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Understanding the Managed Futures Strategy and its Role in an Institutional Policy Portfolio

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Contents

1. Introduction and Background

2. Quantitative Approaches to Understanding CTA Returns

   – Dynamic Beta Properties of CTA Returns

   – Fung and Hsieh—The Lookback Straddle

   – Moving Average Crossover Rules

8. Return Characteristics of Managed Futures versus Endowment Policy Portfolio

   – Conclusions

10. References

11. Important Notes

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Understanding the Managed Futures Strategy and its Role in an Institutional Policy Portfolio

Introduction & Background

Managed futures funds (managed by Commodity Trading Advisors) are a subset of investment programs within the global macro universe that typically apply systematic, quantitative trading strategies to liquid global markets.[1] Some CTAs may also use discretionary trading either exclusively or in combination with quantitative systems. Most of the larger funds in this space are broadly diversified across asset classes, including currencies and futures contracts on commodities, equity indices, bonds and interest rates.

The CTA strategy originated with systematic trend-following, which is still the most common model type and the one that this paper will focus on, but many CTAs use other model types as well, including high frequency trading, different forms of pattern recognition, and fundamentally-driven models. Systematic trend-following attempts to capture broad market movements while controlling the risk of reversals. In its simplest form, trend-following involves taking positions and letting profits run while cutting losses short. While these systems are diverse in terms of preferred entry and exit points, they all capitalize on the tendency of market prices to trend.

Within the broader global macro strategy, CTAs are distinct for what might be termed their agnosticism. Unlike their discretionary, thematic counterparts, trend followers are generally not in the practice of adopting a worldview and then constructing a portfolio around it. Rather, they are empiricists, designing their systems to be based on observed price behavior. The process of identifying trends is, by its nature, data-driven. It follows that in systematic trading, portfolio decisions are based on quantitative models rather than human judgment. However, the trading decisions made by these models are often intuitive despite the "black box" reputation of the strategy.

In *Inside the Black Box,* Rishi Narang observes:

> *The connotation of opaqueness still persists today whenever the term black box is used. Most commonly in the sciences and in finance, a black box refers to any system that is fed inputs and produces outputs, but whose inner workings are either unknown or unknowable… for the most part, quantitative trading strategies are in fact clear boxes that are far easier to understand in most respects than the caprice inherent to most human decision making.*

Narang's point is not trivial: the algorithm's role in the CTA investment process is not to replace or remove manager discretion, but instead to formalize it. Even for strategies where the role of the "machine" is relatively large, a human component is not absent. The systematic investment approach requires back-testing, rigorous questioning of assumptions and continual development and refinement. It may also require overriding model-generated trade signals in extraordinary circumstances. All of these are expressions of a manager's judgment.

While many institutional investors have historically been skeptical of CTAs, that view appears to be changing. In fact, according to hedge fund database BarclayHedge, CTA assets under management as of September 2011 now exceed $320 billion, larger than any other hedge fund strategy type. A primary driver of this growth is the historical ability of CTAs to deliver significant diversification benefits to institutional portfolios, particularly during periods of market stress.

In the sections that follow we will provide an empirical basis for understanding the drivers of returns in the strategy, and present historical evidence that supports the role of managed futures in an institutional policy portfolio.

1 Although Commodity Trading Advisors include investment firms that pursue other types of strategies, including physical commodities and commodities futures, for purposes of this white paper, we will refer to managers who offer managed futures funds as "CTAs."

Quantitative Approaches to Understanding CTA Returns

Historically, CTA returns have demonstrated low correlation to major asset classes (see Table 1), making it an attractive diversifier for an institutional portfolio. In fact, some of the strongest periods of CTA performance have occurred amid broad market stress, when the diversification benefit is needed most. Note especially the strategy's modest correlation properties relative to the four broadly representative asset classes which account for the majority of the risk present in institutional portfolios: equities, fixed income, commodities and currencies. We proxy these asset class exposures with the S&P 500 Index (SPX), the Merrill Lynch Treasury Master Index (ML Treasury Master), the Dow Jones-UBS Commodities Index (DJUBS), and the U.S. Dollar Index (DXY), a trade-weighted measure of the strength of the U.S. dollar relative to other developed market currencies, and use these four factors for the models that follow. In this section our CTA proxy is the Dow Jones-Credit Suisse Managed Futures Index (DJCS).

TABLE 1

Correlation Matrix, 1/94–8/11,* DJCS Managed Futures Index vs. Policy Portfolio Asset Classes

	a	b	c	d	e	f	g	h	i	j	k	l
a		.17	-.12	.30	-.08	-.09	-.02	.12	-.08	.19	.05	-.26
b	.17		.24	.44	.07	-.06	-.04	.05	.00	.07	-.07	-.21
c	-.12	.24		.12	.61	.59	.57	.53	.67	.49	-.05	.38
d	.30	.44	.12		.09	-.12	.01	-.03	.00	.25	-.05	-.13
e	-.08	.07	.61	.09		.83	.72	.59	.57	.60	.22	.71
f	-.09	-.06	.59	-.12	.83		.78	.68	.61	.54	.19	.70
g	-.02	-.04	.57	.01	.72	.78		.73	.61	.59	.04	.54
h	.12	.05	.53	-.03	.59	.68	.73		.80	.57	.23	.75
i	-.08	.00	.67	.00	.57	.61	.61	.80		.52	.18	.57
j	.19	.07	.49	.25	.60	.54	.59	.57	.52		.28	.44
k	.05	-.07	-.05	-.05	.22	.19	.04	.23	.18	.28		.32
l	-.26	-.21	.38	-.13	.71	.70	.54	.75	.57	.44	.32	

a DJCS Managed Futures
b Barclays Aggregate
c Merrill Lynch High Yield
d WGBI non-U.S.
e S&P 500
f MSCI EAFE
g MSCI Emerging Markets
h HFRI Fund of Funds
i HFRI Distressed
j Natural Resources Mix
k NCREIF
l Thomson All Private Equity

*Correlations of monthly returns 1/94–8/11; for private equity/real estate, based on quarterly returns through 6/11 (NCREIF) or 3/11 (private equity)

Sources: Commonfund Hedge Fund Strategies Group, PerTrac, Bloomberg, Thomson Reuters, NCREIF

The relationship of the CTA strategy to each asset class is not as simple as "short when prices are falling, long when they are going up." Rather, it is based on the interplay of trends that develop over different time frames and in a variety of asset classes and markets. The goal of trend-following is almost deceptively simple: detect a trend, build a position to capture it and, when the trend breaks down, exit the position. Rather than relying on fundamental, bottom-up valuation methods, trend-following uses only the information that is embedded in past prices to determine whether and when to enter or exit a position.

Narang suggests the economic basis of the trend-following approach:

> *Trend-following is based on the theory that markets sometimes move for long enough in a given direction that one can identify this trend and ride it. The economic rationale for the existence of trends is based on the idea of consensus-building among market participants…The earliest adopters of this idea place their trades in accordance with it…As more and more data come out to support their thesis and as a growing mass of market participants adopts the same thesis, the price…may take a considerable amount of time to move to its new 'equilibrium,' and this slow migration from one equilibrium to the next is the core opportunity that the trend follower looks to capture.*

The implication is that trend-following systems are continually adapting, taking on selective market exposure. In terms of risk and return properties, this presents an apparent contradiction: how is a strategy that is largely based on taking directional risks distinct for being uncorrelated to major underlying asset classes?

Dynamic Beta Properties of CTA Returns

While in the long term, correlations to major asset classes are low, in the short term, the opposite is often true. CTA market exposures are highly time-varying, shifting frequently in terms of significance, magnitude and sign. To illustrate these shifts, we divide the time series of the DJCS Managed Futures Index returns into short periods of 18 months, and re-fit a model within each period using the four asset class factors.

We construct the model for each period using stepwise regression, a method in which factors are iteratively added and subtracted until a single, optimal fit is reached, which may include some, all, or none of the four candidate asset class factors. The stepwise process "solves" for the best model and calls for no prior assumptions about which factors to include (in other words, there is no bias towards factors to which the trend-following strategy is assumed to have exposure).

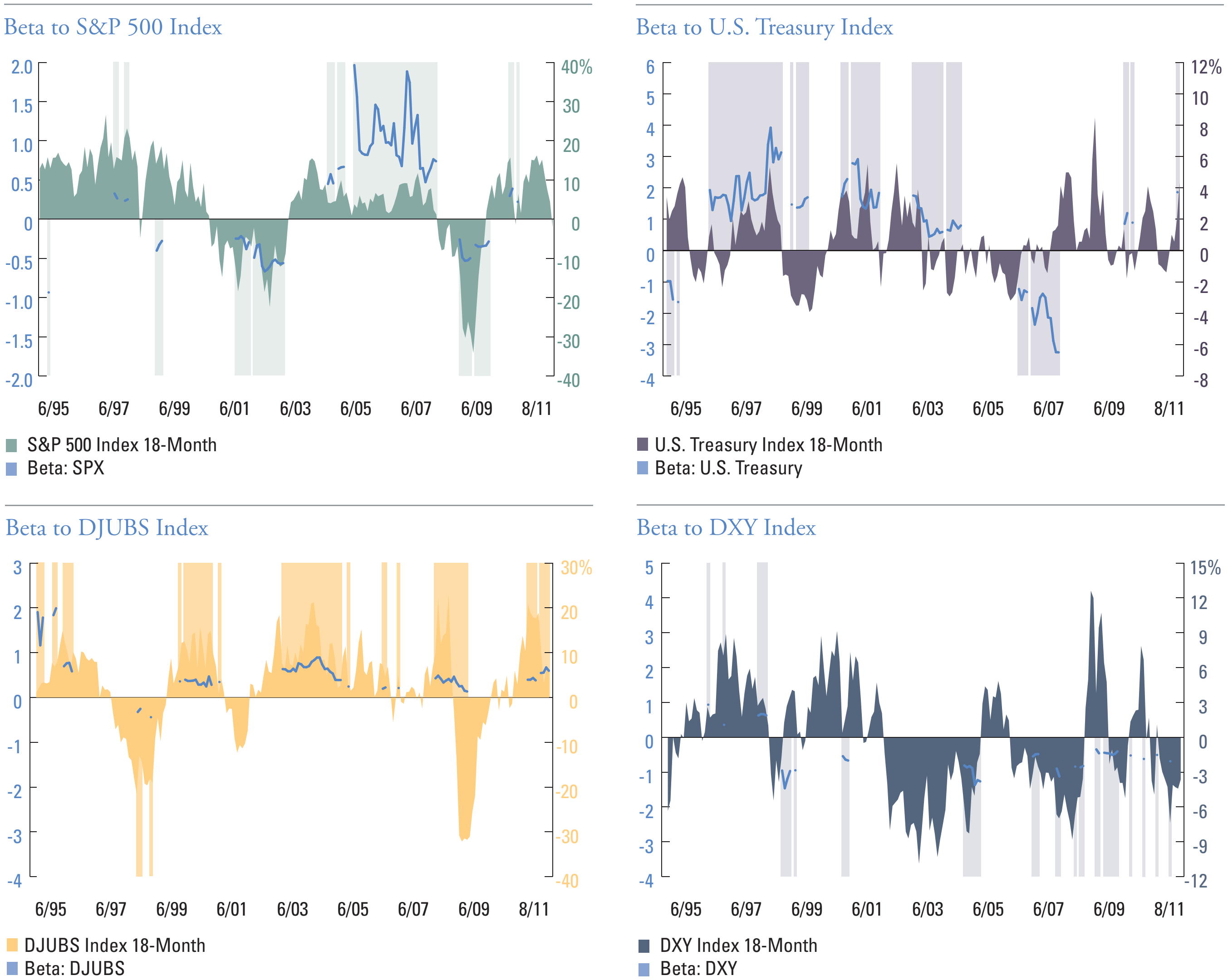
Results are presented in Figure 1. When each factor is included, the beta line is shown in blue (along with shaded columns). When excluded, the factor is not shown, which makes each line appear discontinuous. Also shown are the rolling 18-month returns of the underlying asset class factors in solid color. Both beta and returns are exponentially weighted to give more influence to recent months.

The stepwise beta profiles suggest that the trend-following strategy is not always directionally exposed to the asset class. The strategy does, however, exhibit a general tendency to capture prolonged market moves (i.e., trends).

For example, consider the S&P 500. In the abrupt downtrend during the tech crash in early 2000, following what had been a steadily up-trending equity market, the DJCS Index's beta line suggests negligible initial exposure. However, the strategy established a more substantial short profile soon afterward, as the initial down move continued, and maintained an implied short profile through the credit crunch and bear market of 2002. The CTA strategy was similarly successful in the bull period from 2004 to 2007, with equity beta through that period reflecting positive exposure throughout.

FIGURE 1

Stepwise Regression of DJCS Managed Futures Index (Rolling 18-months)



Sources: Commonfund Hedge Fund Strategies Group, Bloomberg

Another noteworthy period was 2008. Having missed the initial sell-off, the CTA index turned broadly short only as the downturn accelerated. The quarter ending September 2008 was characterized by a sell-off in risk assets; CTAs also produced negative returns, with the stepwise beta profile suggesting that they were caught unfavorably exposed to the direction of the equity market. Conversely, the quarter ended December 2008, when the downtrend accelerated, was one of the strongest quarters in the history of the DJCS Index. Similar cases are visible throughout the four stepwise charts: abrupt reversals are often missed by the CTA strategy, but prolonged moves tend to be captured.

The broad observation is that CTAs' directional exposure to asset classes varies widely within short windows; there are periods when direction of exposure is favorable relative to broad market performance, others when it is not, and very often—about half to two-thirds of the time—there is no significant relationship at all.

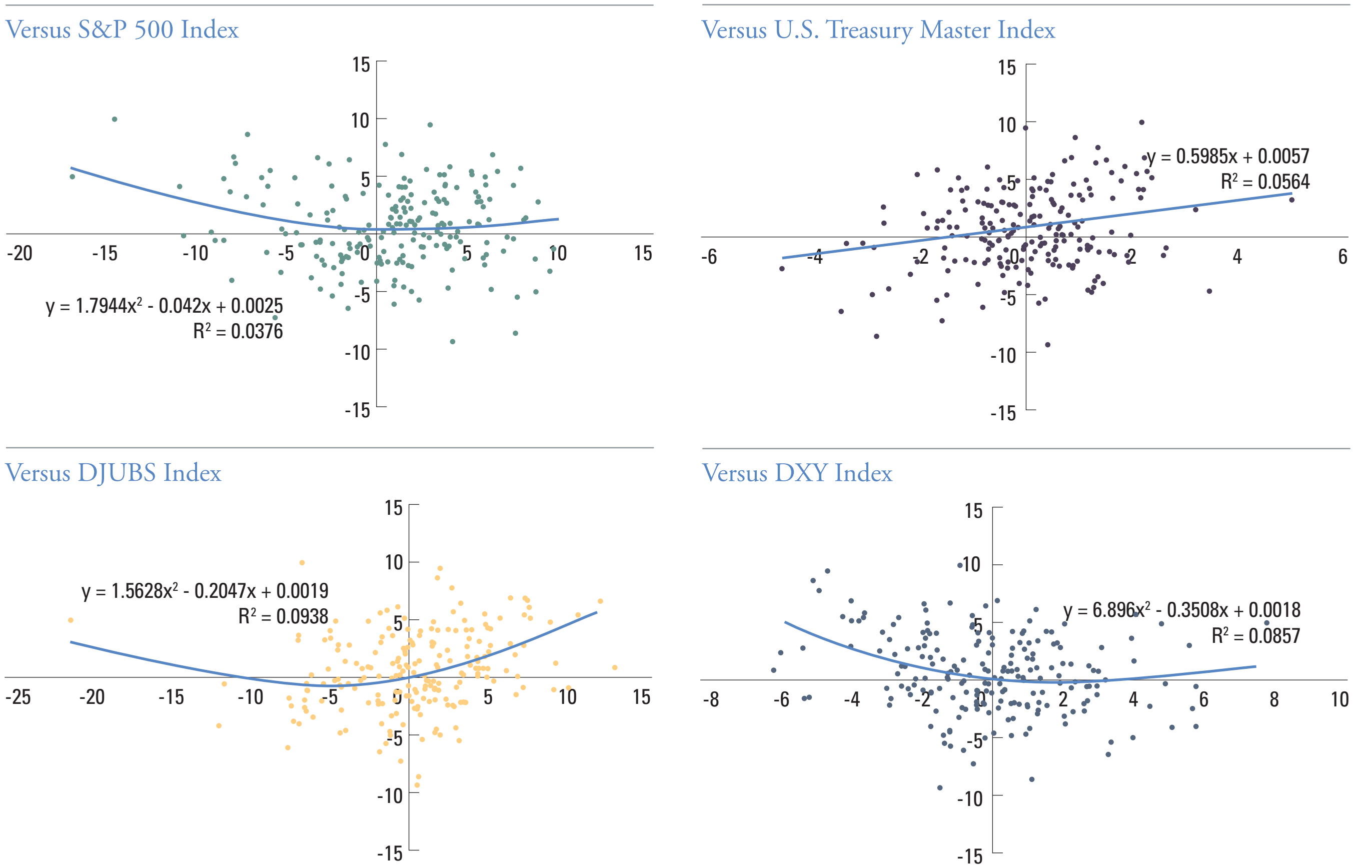
While the flexible beta nature of the strategy is evident, it does not explain the drivers of returns. Applying traditional linear alpha/beta separation with broad market factors to CTA returns is ineffective. Not only is its explanatory power low, as evident in the static correlation properties, but interpretation of the alpha and beta terms is problematic. Whereas conventionally beta is taken to represent market risk and alpha the contribution of manager skill, in the context of a CTA, these results are often ambiguous.

While simple linear correlation using these factors explains very little of the strategy's returns, we will show how relatively simple techniques applied to the same data can do a better job of explaining CTA returns. In particular we will look at two methods which are quite different, but provide unique insights into important aspects of the strategy. Both methods have in common that they utilize some form of transformation of asset class returns. In each case the goal is to use a model that makes intuitive sense in terms of what trend-followers do in practice and is empirically sound as evidenced by explanatory power.

FIGURE 2

CTA Strategy Demonstrates Convex Long-Term Relationship to Broad Asset Classes

DJCS Managed Futures Index vs. Four Asset Class Factors 1/1994–12/2010



Sources: Commonfund Hedge Fund Strategies Group, PerTrac, Bloomberg

These methods will help explain the following two properties:

- Positive convexity, and
- State-dependent beta properties

Fung and Hsieh—The Lookback Straddle

Whether targeting it explicitly or not, many investors have convexity in mind when they introduce CTAs to a portfolio. Positive convexity refers to upward curvature, or bowl-shaped sensitivity to underlying risk factors—in other words, the strategy tends to benefit from large moves up or down in the underlying asset class. Evidence of a convex relationship is visible in Figure 2 (shown on page 4), showing the DJCS Managed Futures Index against each of the four asset class factors' returns.

A significant contribution to the study of CTAs was made by William Fung and David Hsieh in 2001. One of their insights was that replacing the poorly-fitting broad asset class factors with portfolios of lookback straddles better represented the form of trend-follower exposures. They created factors based on series of straddles on futures contracts within different sectors, calling them "Primitive Trend-Following Strategies" (PTFS), with the goal of capturing the positively convex relationship of the CTA strategy to different asset classes.

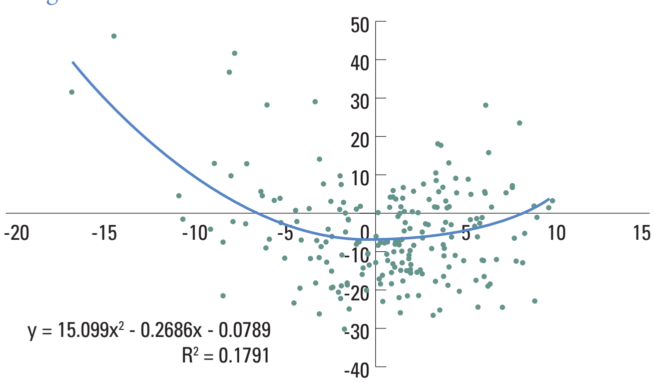
A portfolio of straddles has two prominent characteristic traits. The first trait is a long-volatility profile—gains are realized in large moves, whether up or down, attributable to either the straddle's call (benefiting from a rising price in the underlying asset) or the put that is paired with it (benefiting from a falling price in the underlying asset). The second is a negative return when the underlying security price does not move significantly, reflecting the loss of option premium over time. Figure 3 shows returns of four of Fung and Hsieh's PTFS factors for bonds, stocks, currencies and commodities, each charted against a related asset class index. In each case the long-volatility profile is observable, with positive curvature indicating that the straddle factors benefit from large moves in the underlying asset class in either direction.

FIGURE 3

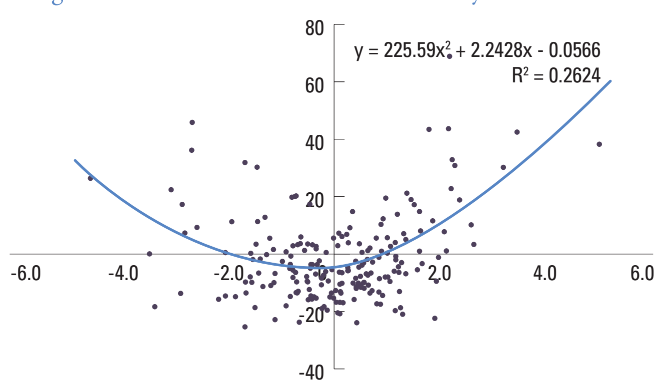
Modeling Risk and Return in CTAs: Fung and Hsieh Approach Uses Lookback Straddles

Fung/Hsieh PTFS Factors vs. Representative Asset Class Indices 1/1994–12/2010

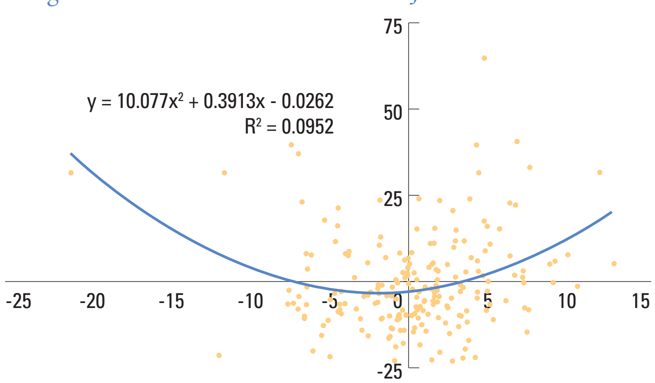
Fung/Hsieh PTFS: Stock vs. S&P 500 Index



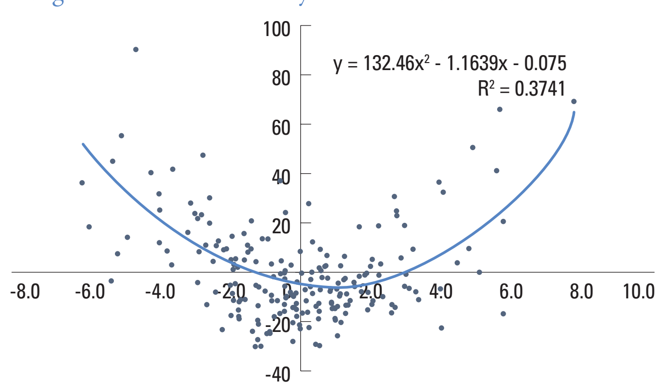
Fung/Hsieh PTFS: Bond vs. BA/ML Treasury Master



Fung/Hsieh PTFS: Commodities vs. DJUBS Index



Fung/Hsieh PTFS: Currency vs. DXY Index



Sources: William Fung and David A. Hsieh, http://faculty.fuqua.duke/edu/~dah7/HFRFData.htm, Commonfund Hedge Fund Strategies Group, Bloomberg

In Fung and Hsieh's original paper, by replacing asset class returns with straddle-based PTFS returns, they increased explanatory power in their sample of trend-following funds (from 1986 to 1997) from 1 percent to nearly 48 percent. In other words, the PTFS factors are better able to explain the positively convex nature of the CTA strategy than standard linear asset class regression.

Straddles, however, are an imperfect representation of CTA risk and return profiles. One drawback to the approach is that most CTAs do not actually hold straddles in their portfolios. While it would be an appealingly simple proposition to suggest that CTAs always have convex exposure to asset classes, which would be observable if straddles were causal in driving returns, this is not the case. While they share the property of convexity, CTAs and the straddle factors demonstrate different primary risks. The principal risk of holding straddles is that the underlying asset stays range-bound and does not move substantially in any direction (premium is paid out, but not recovered). While such a range-bound or choppy environment may be adverse for the CTA strategy, the more pertinent hazard is getting caught in a sharp reversal of a well-established trend. In the case of holding a straddle, there is no wrong direction of a large move. While a long-volatility profile is an observable long-term characteristic of the trend-following strategy, in the shorter term, the relationship to underlying asset classes is more nuanced.

Moving Average Crossover Rules

Galen Burghardt and Brian Walls used moving average crossover rules to examine CTA returns. Like Fung and Hsieh, the authors transformed the underlying asset class returns to better explain CTA returns. However, unlike a transformation that replicates an option payoff, their method uses trend-following techniques.

FIGURE 4

Four Asset Class Indices, with 50- and 150-Day Moving Averages

Sources: Commonfund Hedge Fund Strategies Group, Bloomberg

A simple moving average rule "goes long" whenever a fast average (the average asset price over a recent time-period—for instance, 50 days) is above a slow average (the average over a longer time-period—for example, the past 150 days). The theoretical basis for using any such rule is that it signifies trend. These rules may predict whether the CTA strategy is long or short in a particular asset class. Previously, we examined the time-variability evident in the stepwise approach and the moving average is one way of formally accounting for this.

We apply these moving average rules on the four asset class factors (S&P 500, U.S. Treasury Master, DJUBS, and DXY) using daily return data from the NewEdge CTA Index. Each day, each asset class factor is assigned an either/or condition based on the prior day's close, a 1 for 'yes' when the fast average is above the slow (i.e., the strategy is long), and a 0 for 'no' when the moving average condition is not met (i.e., the strategy is short). Multiplying the index returns by the 1/0 condition, the result can be regressed with the moving average condition as an interaction. Whereas the stepwise regressions divided the return history into different windows, the moving average method effectively divides a return history into two states: one state being when the fast average is above the slow and vice-versa. As with the lookback straddle approach, this transformation results in a substantial increase in explanatory power over the asset class returns alone.

Figure 4 (shown on page 6), graphically depicts where a moving-average system might be long or short the four underlying asset classes. In Figure 4, we consider a 50-day and a 150-day average. When the blue line is above the gray, the model has a long exposure to that asset class; when it is below, the model is short.

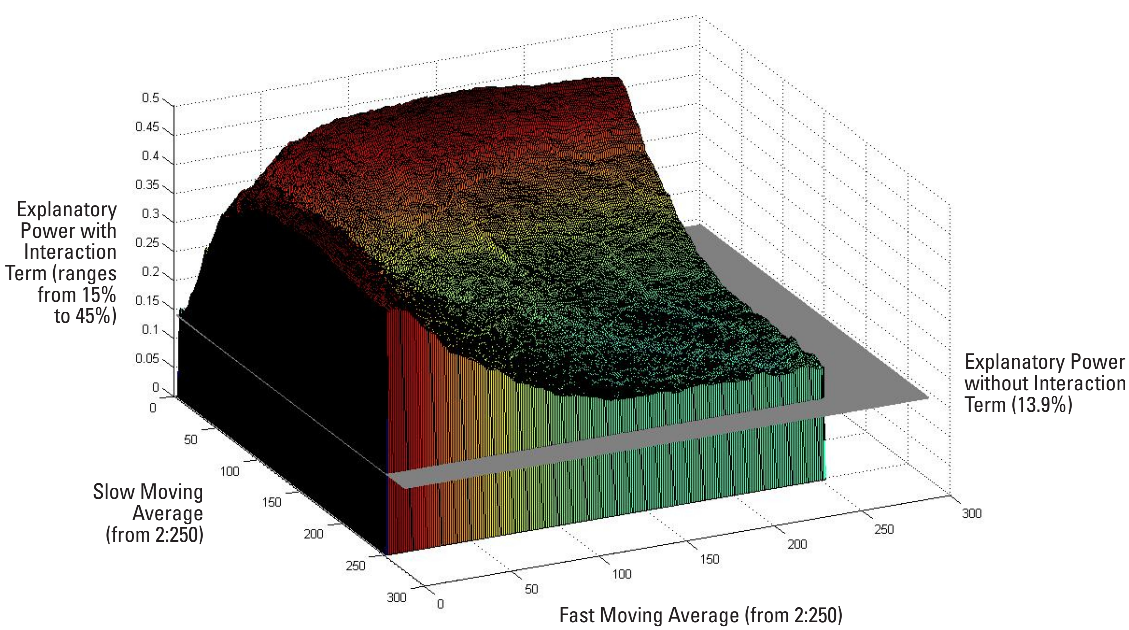
Regressing the NewEdge CTA Index daily returns against the four asset class factors without any moving average transformation yields a modest explanatory power (in terms of adjusted R-squared) of 13.9 percent. By adding a moving average crossover rule, we are able to significantly increase the explanatory power, suggesting that this method does explain the strategy exposure over time.

What cross should be used for the interaction? Any combination is a candidate, from short (e.g., 10-day/15-day) to long (e.g., 200-day/250-day). In their study, Burghardt and Walls conclude that a 20-day/120-day moving average works best. Using the four asset class factors, we calculate the explanatory power for the interactions of every possible combination of crossing moving averages, from 2 days to 250 days for both the slow and fast averages, representing a total of over 30,000 unique combinations.

Our results are presented graphically in Figure 5. The x-axis represents a slow average for each asset class, the y-axis a fast average, and the vertical z-axis the explanatory power of each combination.

FIGURE 5

Moving Average Crossovers Explain CTA Returns Significantly Better than Linear Regression with the Same Factors



Sources: Commonfund Hedge Fund Strategies Group, Bloomberg

The explanatory power rises from the initial 13.9 percent (represented by the gray plane 'slicing' of the figure) from modeling each factor as a linear, untransformed exposure, to as much as 45 percent by including moving average crossover interactions. In the surface diagram, the peak region with the most explanatory power extends from 12 days to 22 days on the fast average and 115 days to 165 days on the slow average, with the absolute peak at 12 days/159 days.

To illustrate the effect of a moving average cross in a model, Figure 6 shows regression results with the expected change in slope at the 16-day/119-day crossover, the model overall having an adjusted R-squared of 43 percent. Each of the four diagrams, representing the four factors, shows two "beta lines"—one, a base term, representing exposure when the moving-average condition is not met, and a second, an interaction term, representing the expected change in slope (beta) when it is met. In three of four cases, the expected result of that change is to reverse the sign of exposure from short to long (the exception is the DJUBS, where the base condition is itself modestly positive). The model can therefore be interpreted as suggesting there is a significant change in slope at the crossover: it should not, however, be interpreted to suggest that CTA beta properties occur in only two states. A two-state model cannot be assumed to capture what are, in fact, highly dynamic changes in terms of both sign and magnitude.

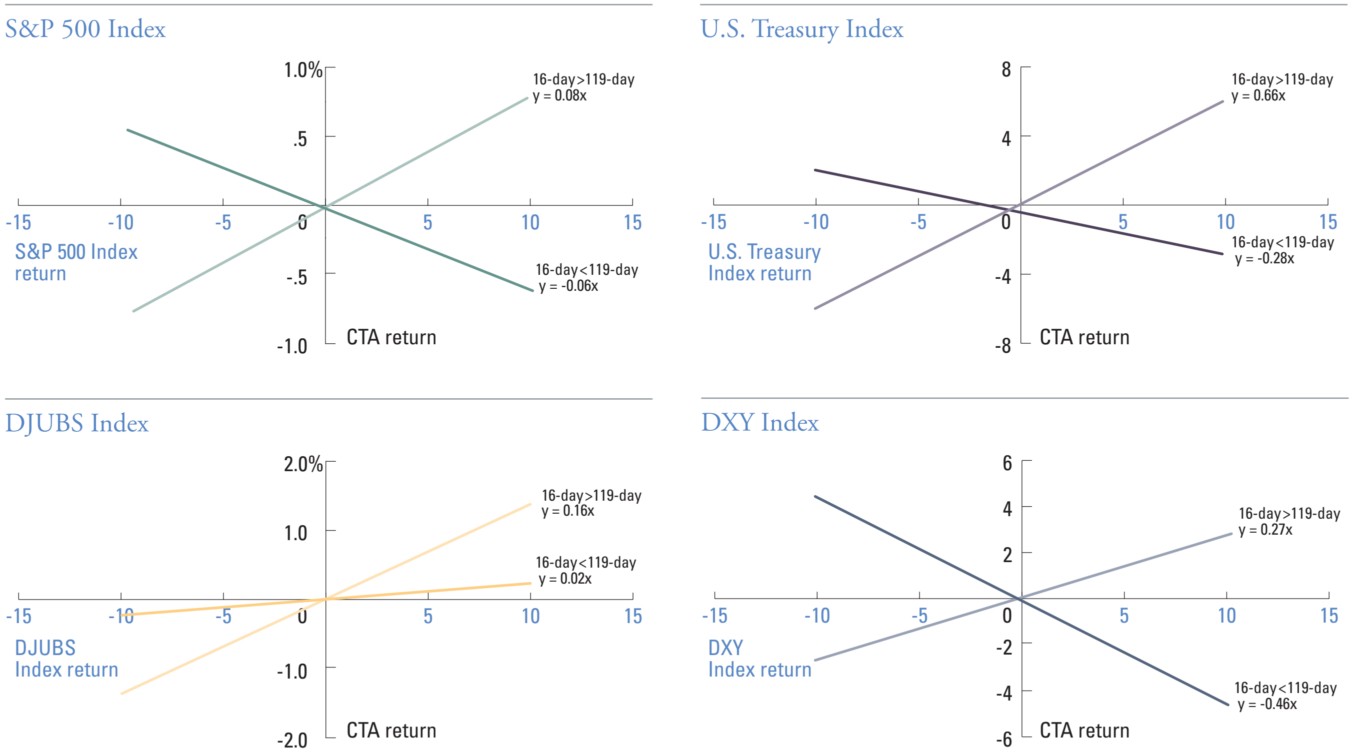
The 16-day/119-day crossover is one example of the models for which explanatory power is represented in Figure 5. Putting these results in context of that diagram, the conclusion is that the NewEdge CTA Index reflects the tendency to have long exposure to an asset class when a fast average (12–20 days) crosses above a slow average (120–150 days) and short exposure when a fast average crosses below a slow average. Moving average crossovers serve as a heuristic device and significantly enhance our ability to explain CTA returns. The results suggest that CTAs broadly exhibit these general tendencies, but in practice, trend-following systems are diverse in terms of how quickly they enter and exit trades.

Return Characteristics of Managed Futures versus Endowment Policy Portfolio

We turn now to the practical question of how the strategy fits in the context of a policy portfolio: in particular, the degree to which it serves as a potential source of downside protection and return generation during periods of broad market stress and the decline of risk assets.

FIGURE 6

NewEdge CTA Index: Moving Average Crossovers Predict Change in Exposure to Asset Class Factors
Example Base & Interaction Terms: 16-Day Moving Average Above/Below 119-Day (adj. R-Squared 44%)



Sources: Commonfund Hedge Fund Strategies Group, NewEdge, Bloomberg

Using asset class weights based on the 2010 NACUBO-Commonfund Study of Endowments (see Table 2) we calculated the historical returns of a pro forma policy portfolio and compared its performance to the CTA strategy. The bar chart in Figure 7 shows this comparison for the policy portfolio's 13 worst calendar quarters, during the period from 1994:Q1 to 2011:Q2.

TABLE 2

Policy Portfolio Index Weights

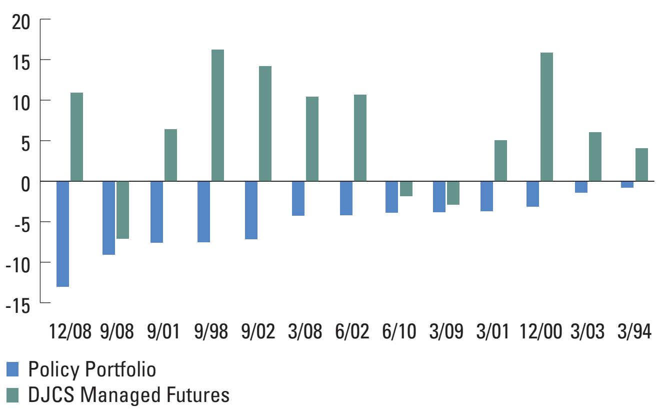
Fixed Income	**12%**	**Alternatives**	**52%**
U.S. Investment Grade	10%	Hedge Funds	21%
U.S. High Quality	1%	Private Equity	12%
International	1%	Venture Capital	3%
Emerging Markets	0%	Private Equity Real Estate	5%
U.S. Equity	**15%**	Natural Resources	7%
International Equity	**16%**	Distressed	3%
EAFE	11%	**Cash/Other**	**5%**
Emerging Markets	5%	**Total**	**100%**

Sources: NACUBO-Commonfund Study of Endowments 2010, Commonfund Hedge Fund Strategies Group.

The policy portfolio is presented for illustrative purposes only and does not represent an advisory recommendation to any investor.

FIGURE 7

Policy Portfolio's Worst Quarters, with DJCS Managed Futures Index Return



Quarter Ending:		Quarter Ending:	
12/08	Credit Crisis Accelerates	6/10	Fear of Double-Dip Recession
9/08	Lehman Failure	3/09	2008 Bear Market Finds Bottom
9/01	Sept 11th Terrorist Attacks	3/01	Economic Downturn
9/98	Russian Debt Crisis/LTCM	12/00	Wake of Tech Bubble
9/02	Credit Crunch of 2002	3/03	2002 Sell-Off Finds Bottom
3/08	Bear Stearns Collapse	3/94	Bond Market Crash
6/02	Onset of 2002 Credit Crunch		

Sources: Commonfund Hedge Fund Strategies Group, PerTrac, Bloomberg, Thomson Reuters, NCREIF

Note that the CTA strategy has not only protected assets during these stress periods, but has also produced substantial positive, outsized returns during many of these periods. Particularly notable is the performance during the policy portfolio's worst quarter, the quarter ending December 2008. As the broad downturn in risk assets accelerated, CTAs were generally short risk assets, with long positions in fixed income.

In Table 3, if we look at the drawdown periods for the policy portfolio, CTAs provided good protection, particularly during the worst drawdowns of 1998, 2000–02 and 2007–09.

TABLE 3

Policy Portfolio Drawdowns (1Q94 to 2Q11)

Drawdown	Length	Recovery	Peak	Valley	DJCS Performance
-29.57%	16	26	10/31/07	2/28/09	16.74%
-18.85%	25	17	8/31/00	9/30/02	37.62%
-8.35%	4	5	4/30/98	8/31/98	13.27%
-3.36%	2	5	1/31/94	3/31/94	3.83%
-2.18%	2	3	3/31/00	5/31/00	-1.71%

Sources: Commonfund Hedge Fund Strategies Group, PerTrac.

Conclusions

Taken together, the different methods we have examined point to several useful properties of CTA strategy performance resulting from its systematic, data-driven investment approach.

- Through stepwise regression in short windows, the variability of the CTA strategy's beta can be observed. The CTA strategy often demonstrates favorable, directional beta exposure during rising and falling broad markets.
- Fung and Hsieh's straddle model captures the convexity of the strategy; the straddle transformation illustrates the strategy's "long-volatility" return properties, regardless of whether underlying managers are literally holding straddles.
- The moving average method utilizes a trend-following technique to better capture the time-varying nature of CTA exposures.

CTA returns have demonstrated substantial long-term diversification properties in the context of a broad, multi-asset class policy portfolio. They also represent one of the few investment strategies that have the potential for outsized positive returns during extended periods of market stress.

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