The Risk in Hedge Fund Strategies: Theory and Evidence from Trend Followers

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Hedge fund strategies typically generate option-like returns. Linear-factor models using benchmark asset indices have difficulty explaining them. Following the suggestions in Glosten and Jagannathan (1994), this article shows how to model hedge fund returns by focusing on the popular "trend-following" strategy. We use lookback straddles to model trend-following strategies, and show that they can explain trend-following funds' returns better than standard asset indices. Though standard straddles lead to similar empirical results, lookback straddles are theoretically closer to the concept of trend following. Our model should be useful in the design of performance benchmarks for trend-following funds.

The last decade has witnessed a growing interest in hedge funds from investors, academics, and regulators. Investors and academics are intrigued by the unconventional performance characteristics in hedge funds, and regulators are concerned with the market impact of their reported speculative activities during major market events.[1] The near bankruptcy of Long-Term Capital Management (LTCM) in 1998 has further heightened attention on hedge fund risk. Because hedge funds are typically organized as private investment vehicles for wealthy individuals and institutional investors,[2] they do not disclose their activities publicly. Hence, little is known about the

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[1] See Fung and Hsieh (2000) and Fung et al. (1999) for analyses on the market impact of hedge fund activities.

[2] See Fung and Hsieh (1999) for an overview for hedge fund organizational structure and their economic rationale.

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risk in hedge fund strategies. This article illustrates a general methodology for understanding hedge fund risk by modeling a particular trading strategy commonly referred to as "trend following" by the investment industry.

As documented in Fung and Hsieh (1997a), hedge fund managers typically employ dynamic trading strategies that have option-like returns with apparently no systematic risk. Linear-factor models of investment styles using standard asset benchmarks, as in Sharpe (1992), are not designed to capture the nonlinear return features commonly found among hedge funds. This may lead investors to conclude erroneously that there are no systematic risks.

A remedy is in Glosten and Jagannathan (1994), where they suggested using benchmark-style indices that have embedded option-like features.[3] This is done in Fung and Hsieh (1997a) for hedge funds where they extracted style factors from a broad sample of hedge fund returns. By construction, these style factors captured much of the option-like features while preserving the general lack of correlation with standard asset benchmarks. To fully capture hedge fund risk, we must model the nonlinear relationships between these style factors and the markets in which hedge funds trade. This is not a simple task. The lack of public disclosure makes it difficult to link hedge fund style factors to asset markets.

Our task is further complicated by the fact that hedge fund managers, who are no strangers to risk, generally diversify their fund's performance across a variety of strategies. Consequently, the observed returns and extracted style factors are generated by portfolios of different strategies, each having a different type of risk. The combination of the dynamic allocation of capital resources to a portfolio of trading strategies, each with nonlinear return characteristics, greatly limits the value of analyzing a general sample of many hedge funds. From a modeling perspective, it is useful to concentrate on a specific trading strategy that is identifiable with a reasonably large number of hedge funds, whose returns are predominantly generated by that strategy.

In this article, we focus on a popular strategy commonly referred to as "trend following."[4] Trend following is a self-described strategy for the majority of commodity trading advisors (CTAs), as shown in Billingsley and

[3] Typically, performance evaluation and attribution models rely on regressing a manager's historical returns on one or more benchmarks. The slope coefficients reflect benchmark-related performance, whereas the constant term ("alpha") measures performance "benchmark risk." This approach dates back to Jensen's (1968) original work. Unfortunately, this type of regression method is sensitive to nonlinear relationships between the manager's returns and the benchmarks and can result in incorrect inferences. For instance, Grinblatt and Titman (1989) showed that a manager can generate positive Jensen's alphas by selling call options on the underlying stocks of a given standard benchmark. Merton (1981) and Dybvig and Ross (1985) showed that a portfolio manager with market-timing ability can switch between stocks and bonds to generate returns with option-like features without explicitly trading options. Empirically, Lehman and Modest (1987) found that a number of mutual funds exhibited option-like return features. A standard way to deal with option-like return features is to add nonlinear functions of the benchmark return as regressors. This was done in Treynor and Mazuy (1966) and Henriksson and Merton (1981).

[4] Studies modeling other trading styles have emerged. See, for example, pairs trading in Gatev et al. (1999), risk arbitrage in Mitchell and Pulvino (1999), and relative-value trading in Richards (1999).

Chance (1996).[5] Also, Fung and Hsieh (1997b) showed that the returns of CTA funds have one dominant style factor. This implies that there is one dominant trading strategy in CTA funds, and that strategy is trend following. We therefore focus our empirical work on the return of CTA funds to develop a model that explains their returns. In addition, this model contributes to explaining the performance of other hedge funds that use trend following as part of their portfolio of strategies.

Trend following is a particularly interesting trading strategy. Not only are returns of trend-following funds uncorrelated with the standard equity, bond, currency, and commodity indices, Fung and Hsieh (1997b) found these returns to exhibit option-like features—they tended to be large and positive during the best and worst performing months of the world equity markets.[6] This is evident in Exhibit 2 of Fung and Hsieh (1997b), reproduced here as Figure 1. The monthly returns of the world equity market, as proxied by the Morgan Stanley (MS) World Equity Index, are sorted into five "states." State 1 consists of the worst months, and State 5 the best months. This figure graphs the average monthly return of an equally weighted portfolio of the six largest trend-following funds, along with that of the world equity markets, in each state. Fung and Hsieh (1997b) noted that a similar pattern holds for an equally weighted portfolio of all trend-following funds.

The return profile shown in Figure 1 indicates that the relationship between trend followers and the equity market is nonlinear. Although returns of trend-following funds have a low beta against equities on average, the state-dependent beta estimates tend to be positive in up markets and negative in down markets. In fact, the return pattern of trend-following funds in Figure 1 is similar to those of contingent claims on the underlying asset and must therefore have systematic risk, albeit in a nonlinear manner. The goal of this article is to model how trend followers achieve this unusual return characteristic in order to provide a framework for assessing the systematic risk of their strategy. Note that, in the presence of nonlinearity, betas from a standard linear-factor model can either overstate the systematic risk or understate it (as in the case of LTCM).

If the trading rules used by trend followers are readily available, we can directly estimate their systematic risk. Unfortunately, but understandably, traders regard their trading systems to be proprietary and are reluctant to disclose them. We can therefore only theorize what trend followers do. Furthermore, although we use the term *trend followers* to describe a certain class

[5] CTAs are individuals or trading organizations, registered with the Commodity Futures Trading Commission (CFTC) through membership in the National Futures Association, who trade primarily futures contracts on behalf of a customer.

[6] August 1998 provides an out-of-sample observation that substantiates this view. While the S&P 500 lost 14.5% of its value, commodity funds generally had positive returns. In a *Barron's* September 9, 1998, article, Jaye Scholl wrote, "Of the 17 commodity trading advisors reporting to MAR, 82% generated positive results in August, with 46 of them posting returns of more than 10%."

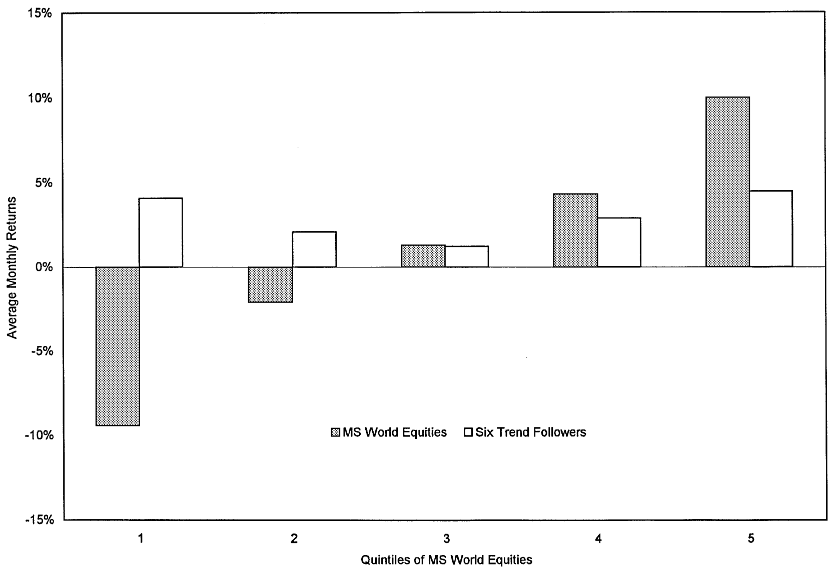

Figure 1
Average monthly returns of six large trend-following funds in five different MS world equity market states
Source: Fung and Hsieh (1997a).

of traders, in practice their respective approaches can differ widely. Trend followers can converge onto the same "trend" for different reasons and have very different "entry and exit" points. From a modeling perspective, we need a level of aggregation that captures the essence of this trading style but avoids some of the distracting idiosyncrasies of individual trend followers.

We posit that the simplest trend-following strategy, which we label as the "primitive trend-following strategy," has the same payout as a structured option known as the "lookback straddle." The owner of a lookback call option has the right to buy the underlying asset at the lowest price over the life of the option. Similarly, a lookback put option allows the owner to sell at the highest price. The combination of these two options is the lookback straddle, which delivers the ex post maximum payout of any trend-following strategy.[7] The concept of a lookback option was first introduced in Goldman et al. (1979). Within this context, trend followers should deliver returns resembling those of a portfolio of bills and lookback straddles. Unlike earlier studies that

[7] In reality, trend followers often make multiple entry and exit decisions over a sufficiently long investment horizon so long as there is sufficient volatility surrounding the underlying trend. This aspect is excluded in our simple model. However, a comparison of our model to the market-timing model of Merton (1981) can be found in Section 2 of this article.

explicitly specify "technical trading rules" to proxy a popular form of trend-following strategy,[8] this particular option strategy is not designed to replicate any specific trend-following strategy. Rather, it is designed to capture the general characteristics of the entire family of trend-following strategies.

We demonstrate empirically that lookback straddle returns resemble the returns of trend-following funds. This provides the key link between the returns of trend-following funds and standard asset markets.

The rest of the article is organized as follows. Section 1 sets out the theoretical foundation of the primitive trend-following strategies as lookback straddles. We explore the similarities and differences between trend following and market timing as trading strategies in the Merton (1981) framework. Given any asset, we show that the lookback straddle is better suited to capture the essence of trend-following strategies than a simple straddle. Section 2 details the data sample used to test our model. Section 3 reports the improvements on explaining trend-following funds' returns using our model versus standard asset benchmarks. It confirms the intuition that trend-following funds' returns are similar to those of contingent claims on standard asset indices. Section 4 discusses the question of performance benchmarks for trend followers. Here we note the opportunistic nature of trend followers. These traders apply capital resources to different markets in a dynamic fashion and do so in a manner peculiar to their individual skill and technology. Summary and conclusions are in Section 5.

1. The Primitive Trend-Following Strategy

The convex return pattern observed in Figure 1 resembles the payout profile of a straddle on the underlying asset. A simple strategy that yields the return pattern of a straddle is that of a "market timer" who can go long and short on the underlying asset, as in Merton (1981). Following his notation, let $Z(t)$ denote the return per dollar invested in the stock market and $R(t)$ the return per dollar invested in Treasury bills in period t. At the start of the period, if the market timer forecasts stocks to outperform bills, only stocks will be held. Otherwise, only bills will be held. This implicitly assumes the presence of short sales constraints. For a perfect market timer, Merton (1981) showed that the return of his portfolio is given by $R(t)+Max\{0, Z(t)-R(t)\}$, which is the return of a portfolio of bills and a call option on stocks.

In the absence of short sale constraints, the market timer's return is modified to reflect the short sale alternative. For a perfect market timer, Merton (1981) showed that the return of his portfolio is given by $R(t)+Max\{0, Z(t)-R(t)\}+Max\{0, R(t)-Z(t)\}$, which is the return of a portfolio of bills and a straddle on stocks. In a follow-up paper, Henriksson

[8] See Alexander (1961).

and Merton (1981) proposed a nonparametric test on whether a market timer had the ability to time the market.

We use a similar approach to model a trend follower. It is helpful to begin with a qualitative comparison of market timing and trend following as trading strategies. Both market timers and trend followers attempt to profit from price movements, but they do so in different ways. In Merton (1981), a market timer forecasts the direction of an asset, going long to capture a price increase, and going short to capture a price decrease. A trend follower attempts to capture "market trends." Trends are commonly related to serial correlation in price changes, a concept featured prominently in the early tests of market efficiency. A trend is a series of asset prices that move persistently in one direction over a given time interval, where price changes exhibit positive serial correlation. A trend follower attempts to identify developing price patterns with this property and trade in the direction of the trend if and when this occurs.[9]

To provide a formal definition of these two trading strategies, we introduce the concepts of Primitive Market-Timing Strategy (PMTS) and Primitive Trend-Following Strategy (PTFS) as follows. Let S, S', S_{max}, and S_{min} represent the initial asset price, the ending price, the maximum price, and the minimum price achieved over a given time interval. Consistent with the Merton (1981) framework, we restrict our strategies to complete a single trade over the given time interval. The standard buy-and-hold strategy buys at the beginning and sells at the end of the period, generating the payout $S' - S$. The PMTS attempts to capture the price movement between S and S'. If S' is expected to be higher (lower) than S, a long (short) position is initiated. The trade is reversed at the end of the period. Thus, the optimal payout of the PMTS is $|S' - S|$. The PTFS, on the other hand, attempts to capture the largest price movement during the time interval. Consequently, the optimal payout of the PTFS is $S_{max} - S_{min}$. Note that the PMTS is defined in a manner consistent with Merton (1981). The construction of the PTFS, on other hand, adds the possibility of trading on S_{max} and S_{min}.[10] Capital allocation to the PMTS or PTFS is determined by comparing the payout of the respective strategy to the return of the risk-free asset.[11]

If we are dealing with perfect market timers and perfect trend followers, they would capture the optimal payouts $|S' - S|$ and $S_{max} - S_{min}$, respectively, without incurring any costs. In reality, these traders cannot perfectly anticipate price movements. A helpful distinction between their approaches can be made as follows. Generally, market timers enter into a trade in anticipation of a price move over a given time period, whereas trend followers trade

[9] Note that we are not advocating that markets trend. That is an empirical issue best deferred to another occasion.

[10] Therefore, if Merton's (1981) assumptions were strictly imposed, the payout of the PTFS must equal that of the PMTS.

[11] The distribution of capital resources between the respective trading strategy and the riskless asset will also depend on the investor's risk preference.

only after they have observed certain price movements during a period. The terms *buying breakouts* and *selling breakdowns* are often used to describe trend followers.[12] These are very common characteristics of trend-following strategies.

Also, in reality, market timers and trend followers do incur costs when they attempt to capture their respective optimal payouts. We cannot estimate these costs without knowledge of their strategies. Instead, we assume that the ex ante cost of the PMTS is the value of an at-the-money standard straddle, and that of the PTFS is the value of a lookback straddle. In other words, the PMTS is a long position in a standard straddle, and the PTFS is a long position in a lookback straddle.

In the next section, we will empirically create returns of the PTFS using lookback straddles on 26 different markets. Before doing so, we have some remarks regarding the differences between the PTFS and the PMTS.

As the PMTS and PTFS are option positions, we can illustrate their theoretical difference via their deltas. For illustrative purposes, assume that Black and Scholes (1973) holds. The price of a standard straddle is then well known, and the prices of lookback options can be found in Goldman et al. (1979). The delta of the standard straddle is given by

$$\delta = 2N(a_1) - 1, \tag{1}$$

where $N()$ is the cumulative standard normal distribution, and

$$a_1 = [\ln(S/X) + \left(r + \tfrac{1}{2}\sigma^2\right)T]/(\sigma T^{1/2}). \tag{2}$$

Here, S is the current price of the underlying asset with instantaneous variance σ, r the instantaneous interest rate, and T the time to maturity of the option. In comparison, the delta of the lookback straddle is given by

$$\begin{aligned}\delta_{LB} = {} & [1 + \tfrac{1}{2}\sigma^2/r]\ N(-b_3) + (u/\sigma)\ \exp(-rT + 2rb/\sigma^2)\ N(b_2) \\ & - [1 + \tfrac{1}{2}\sigma^2/r]\ N(d_3) - (u/\sigma)\ \exp(-rT - 2rd/\sigma^2)\ N(d_2),\end{aligned} \tag{3}$$

where

$$u = (r - \tfrac{1}{2}\sigma^2), \tag{4}$$

$$d = \ln(S/Q) \tag{5}$$

$$d_1 = [\ln(S/Q) + (r - \tfrac{1}{2}\sigma^2)T]/(\sigma T^{1/2}), \tag{6}$$

$$d_2 = [-\ln(S/Q) + (r - \tfrac{1}{2}\sigma^2)T]/(\sigma T^{1/2}), \tag{7}$$

$$d_3 = [-\ln(S/Q) - (r + \tfrac{1}{2}\sigma^2)T]/(\sigma T^{1/2}), \tag{8}$$

[12] *Breakout* means that the price of an asset moves above a recent high, and *buying breakouts* refers to the strategy of going long when a breakout happens. *Breakdown* means that the price moves below a recent low, and *selling breakdowns* refers to the strategy of going short when a breakdown happens.

$$b = \ln(M/S), \tag{9}$$

$$b_1 = [\ln(M/S) - (r - \tfrac{1}{2}\sigma^2)T]/(\sigma T^{1/2}), \tag{10}$$

$$b_2 = [-\ln(M/S) - (r - \tfrac{1}{2}\sigma^2)T]/(\sigma T^{1/2}), \text{ and} \tag{11}$$

$$b_3 = [\ln(M/S) - (r + \tfrac{1}{2}\sigma^2)T]/(\sigma T^{1/2}). \tag{12}$$

Here Q and M denote the minimum and maximum prices, respectively, of the asset since the inception of the lookback straddle. A derivation of Equation (3) is available from the authors on request. Several examples of the difference in the deltas are in Appendix A. The key difference lies in the path-dependency of the lookback option.

Empirically, the difference between the PMTS and the PTFS is much more subtle. Given any investment horizon, the payout of the PMTS equals that of the PTFS if and only if S_{max} and S_{min} occur at the beginning and end of the period in any order. Consequently, as the investment horizon shrinks, the payouts of the two strategies converge. As the investment horizon lengthens, the payout of the two strategies will diverge, because the probability of S_{max} and S_{min} being interior points to the investment horizon increases. In the empirical implementation, we use three-month options, which tend to be the most liquid options; this observation period may be too short to deliver a consistently dramatic payout difference between lookback straddles and standard straddles.

Furthermore, as pointed out in Goldman et al. (1979), the lookback straddle can be replicated by dynamically rolling standard straddles over the life of the option. The rollover process is much reminiscent of the buying breakouts and selling breakdowns characteristics of trend-following strategies.[13] However, as both the PMTS and PTFS make use of standard straddles on the same asset, albeit in a different manner, their returns are likely to be correlated.

Given these two considerations, it may be difficult to distinguish between the PMTS and the PTFS empirically, even though the PTFS better describes trend-following strategies theoretically. This issue is explored in the empirical sections of the article. We note here that the goal of this article is to show that there is at least one option portfolio, involving bills and lookback straddles, that performs like trend-following funds. We do not attempt to answer the question of which option portfolio best describes the returns of trend-following funds. It is conceivable that, depending on the data sample used, alternative strategies to the PTFS can better replicate trend-following funds' returns empirically.

[13] A more detailed description of this process can be found in Section 3.

2. Constructing a Performance Database of PTFSs

To verify if the PTFS can mimic the performance of trend followers, we generated the historical returns of the PTFS applied to the most active markets in the world. For stock indices, we used the futures contracts on the S&P 500 (CME), Nikkei 225 (Osaka), FTSE 100 (LIFFE), DAX 30 (DTB), and the Australian All Ordinary Index (SFE). For bonds, we used the futures contracts on the U.S. 30-year Treasury bonds (CBOT), UK Gilts (LIFFE), German Bunds (LIFFE), the French 10-year Government Bond (MATIF), and the Australian 10-year Government Bond (SFE). For currencies, we used the futures contracts on the British pound, Deutschemark, Japanese yen, and Swiss franc on the CME. For three-month interest rates, we used the futures contracts on the 3-month Eurodollar (CME), Euro-Deutsche Mark (LIFFE), Euro-Yen (TIFFE), the Paris Interbank Offer Rate (PIBOR) (MATIF), 3-month Sterling (LIFFE), and the Australian Bankers Acceptance Rate (SFE). For commodities, we used the futures contracts on soybean, wheat, and corn futures traded on the CBOT and gold, silver, and crude oil traded on the NYMEX.

Futures and option data on the DTB, MATIF, and Osaka were purchased from the Futures Industry Institute (FII). Futures and option data on the LIFFE, SFE, and TIFFE and option data on the CBOT and NYMEX were supplied by the respective exchanges. Option data on the CME were purchased from the FII and updated by the CME. Futures data on the CBOT, CME, and NYMEX came from Datastream. Appendix B provides information on the data.

A number of technical complications arose in the construction of the PTFS returns. First, lookback options are not exchange-traded contracts, so we cannot directly observe their prices. Instead, we replicated the payout of a lookback straddle by rolling a pair of standard straddles, as described in Goldman et al. (1979). The replication process calls for the purchase of two at-the-money straddles at inception using standard puts and calls. We use one straddle to lock in the high price of the underlying asset by rolling this straddle to a higher strike whenever the price of the underlying asset moves above the current strike. At expiration, this straddle's strike must equal the highest price achieved by the underlying asset since inception. We use the other straddle to lock in the lowest price of the underlying asset by rolling the straddle to a lower strike whenever the price of the underlying asset moves below the current strike. At expiration, this latter straddle's strike must equal the low price achieved by the underlying asset since inception. Thus, the pair of standard straddles must pay the difference between the maximum and minimum price achieved by the underlying asset from inception to expiration, which is exactly the payout of the lookback straddle.[14]

[14] An alternative replication strategy is a delta-hedging strategy using the underlying asset. However, a delta-hedging strategy has two problems. First, we need the implied volatility of the option to calculate its delta.

Second, though the strategy of rolling standard straddles can replicate the payout of the lookback straddle, it may not perfectly replicate all the cash flows of the lookback straddle. A lookback straddle has only two cash flows: an upfront premium at inception and a payout equal to the maximum range of the price of the underlying asset at expiration. In replicating this, the straddle rolls may generate additional cash flows when straddles are rolled from one strike price to another. We included these cash flows in calculating the returns of the straddle-rolling strategy.

Third, our straddle-rolling strategy ignores the fact that many exchange-traded options are not European-style options. Most of the options traded on U.S. exchanges are American-style options, which have higher prices than European-style options. This biases downward the returns of the PTFS. There is no problem with options on the LIFFE, which are futures-style options.

Fourth, we frequently do not observe at-the-money options. Because exchange-traded options have discrete strikes, we use the nearest-to-the-money options to approximate at-the-money options. The error is likely to be small.

Fifth, we have to select the horizon of the lookback straddle. The choice is primarily dictated by availability and liquidity of the options in our data set. All the financial options in our data set have quarterly expirations. Even when monthly expirations are available, quarterly expirations tend to have longer history and larger volume. In the case of commodity options, the majority have expirations in March, June, September, and December. To compare results across markets, we used lookback straddles with three months to expiration as close to the end of a quarter as possible to maintain consistency.

Finally, the straddle-rolling strategy should be implemented continuously if we were to match the assumptions in Goldman et al. (1979) exactly. This is impractical, as it requires tick-by-tick data, which are costly to purchase and time-consuming to process. It is also unclear to what extent it is feasible to simulate straddle rolls on a tick-by-tick basis, due to the asynchronous nature of options trading (at different strikes) and the potential distortion of bid-offer spreads. In practice, we rolled the straddles only at the end of each trading day using the settlement prices of the options and the underlying assets. We then aggregated the daily returns up to monthly returns to match the standard reporting interval for hedge funds.

The monthly returns of the PTFS from rolling the straddles are summarized in Table 1. Based on these return series, we formed five portfolios of straddles, one each for stocks, bonds, three-month interest rates, currencies, and commodities. Their correlation matrix is given in panel G of Table 1.

As lookback options are not traded, we will have to make some assumptions to obtain an implied volatility. Second, a delta-hedging strategy can incur substantial transaction costs, as it requires dynamically changing the amount of the underlying asset every time its price changes. The straddle-rolling strategy will incur many fewer transactions.

Table 1
Statistical properties of primitive trend-following strategy (PTFS) returns for 26 markets and 5 portfolios

Panel A: PTFS monthly returns for stock markets

	S&P 500	FTSE 100	DAX 30	Nikkei 225	Australian All Ordinary
Mean	−0.0161	−0.0177	0.0437[c]	−0.0470	−0.0304[c]
SD	0.2774	0.1845	0.2775	0.3978	0.1627
Maximum	2.2932	0.5313	1.0060	1.7349	0.3912
Minimum	−0.4003	−0.3867	−0.3433	−0.7667	−0.2657
Skewness	3.83[a]	0.71[a]	1.19[a]	1.72[a]	0.88[a]
% positive	33	41	44	33	32

Panel B: PTFS monthly returns for government bond markets

	US 30Y	UK Gilt	German Bund	French 10Y	Australian 10Y
Mean	0.0136	0.0097	0.0321[c]	0.0157	0.0189
SD	0.2455	0.2351	0.2333	0.2285	0.2411
Maximum	0.9642	0.8859	1.2051	0.9989	0.6884
Minimum	−0.3503	−0.3110	−0.3117	−0.4464	−0.3881
Skewness	1.55[a]	1.21[a]	2.16[a]	1.43[a]	0.93[a]
% positive	40	40	49	49	39

Panel C: PTFS monthly returns for three-month interest rate markets

	Euro-Dollar	3-month Sterling	Euro-DM	Euro-Yen	Australia Bankers Acceptance	Paris Interbank Rate
Mean	0.0170	0.0449[c]	−0.0375	0.0750[c]	0.0453	0.0513[c]
SD	0.2703	0.3495	0.3077	0.4066	0.4780	0.3167
Maximum	1.0174	1.4412	1.8883	2.2039	2.4999	1.5699
Minimum	−0.5000	−0.4129	−0.4444	−0.4545	−0.4950	−0.4433
Skewness	1.33[a]	1.59[a]	3.20[a]	2.38[a]	2.72[a]	1.70[a]
% positive	40	39	31	45	36	50

Panel D: PTFS monthly returns for currency markets

	British Pound	Deutsche Mark	Japanese Yen	Swiss Franc
Mean	0.0174	0.0232	0.0455[c]	0.0496[a]
SD	0.3070	0.2788	0.3372	0.2577
Maximum	1.2661	1.0783	1.3560	1.1054
Minimum	−0.4391	−0.3992	−0.4223	−0.3513
Skewness	1.73[a]	1.48[a]	1.67[a]	0.99[a]
% positive	41	38	44	48

Panel E: PTFS monthly returns for commodity markets

	Corn	Wheat	Soybean	Crude Oil	Gold	Silver
Mean	−0.0135	0.0435[c]	−0.0355[c]	0.0455[b]	−0.0539[a]	−0.0502[b]
SD	0.2685	0.2977	0.3001	0.3047	0.2927	0.2685
Maximum	1.5408	1.3286	1.1063	2.1573	1.0266	1.0952
Minimum	−0.4286	−0.3914	−0.5556	−0.3716	−0.5119	−0.4982
Skewness	1.87[a]	1.74[a]	1.54[a]	2.93[a]	1.37[a]	1.52[a]
% positive	37	45	33	44	30	33

Before proceeding to compare the PTFS returns to trend-following funds' returns, we examine the empirical difference between the standard straddle and the lookback straddle. We start by comparing the two types of straddles on two quarterly options on the Japanese yen futures contract.

Table 1
(continued)

Panel F: Monthly returns for trend followers and five PTFS portfolios (1989–97)

	Trend-Following Funds	Stock PTFS	Bond PTFS	Interest Rate PTFS	Currency PTFS	Commodity PTFS
Mean	0.0137[a]	−0.0193	0.0181	0.0195	0.0177	−0.0072
SD	0.0491	0.2094	0.1573	0.1867	0.2305	0.1310
Maximum	0.1837	1.3240	0.4739	0.8158	1.0006	0.6413
Minimum	−0.0820	−0.5172	−0.2285	−0.2573	−0.3013	−0.2497
Skewness	0.79[a]	2.62[a]	1.07[a]	1.46[a]	1.68[a]	1.19[a]

Panel G: Correlation matrix of the five PTFS portfolios

	Stock PTFS	Bond PTFS	Interest Rate PTFS	Currency PTFS	Commodity PTFS
Stock PTFS	1.00	0.37	0.06	0.16	0.37
Bond PTFS		1.00	0.32	0.21	0.12
Interest rate PTFS			1.00	0.36	0.07
Currency PTFS				1.00	0.18
Commodity PTFS					1.00

The primitive trend-following strategy (PTFS) is a long position on three-month lookback straddles. The five PTFS portfolios are equally weighted portfolios of the PTFSs in the five groups of markets (panels A through E). Trend-following funds' returns are based on an equally weighted portfolio of 407 defunct and operating commodity funds that had significant correlation with the first principal component from a principal component analysis of 1304 defunct and operating commodity funds. The sample periods for each market is given in Appendix B.
[a] Statistically different from zero at the 1% one-tailed test.
[b] Statistically different from zero at the 5% one-tailed test.
[c] Statistically different from zero at the 10% one-tailed test.
%Positive refers to the percentage of months with positive returns.

The first comparison is graphed in Figure 2, using the March 1994 Japanese yen contract. We initiated the straddles at the end of November 1993, approximately three months prior to expiration. At that time, the March yen futures price was 0.9199. It declined to a low of 0.8878 in early January 1994, rose to a high of 0.9780 by mid-February, and ended at 0.9459 when the contract expired in the middle of March. As the contract's minimum and maximum prices occurred in the middle of the observation period, the payout of the lookback straddle (0.0902) was substantially greater than that of the standard straddle (0.0260).

The second comparison is graphed in Figure 3, using the September 1990 Japanese yen futures contract. Like the first comparison, we initiated the straddles at the end of May 1990, approximately three months prior to expiration. At that time, the September yen futures price was 0.6591. It declined to a low of 0.6444 near the end of June, and then rose to a high of 0.7147 at the expiration of the contract. In this case, the contract's minimum and maximum prices occurred near the beginning and the end of the observation period, so the payout of the lookback straddle (0.0703) was much closer to that of the standard straddle (0.0556). These two graphs show that the two straddles can have different payouts over a given obser-

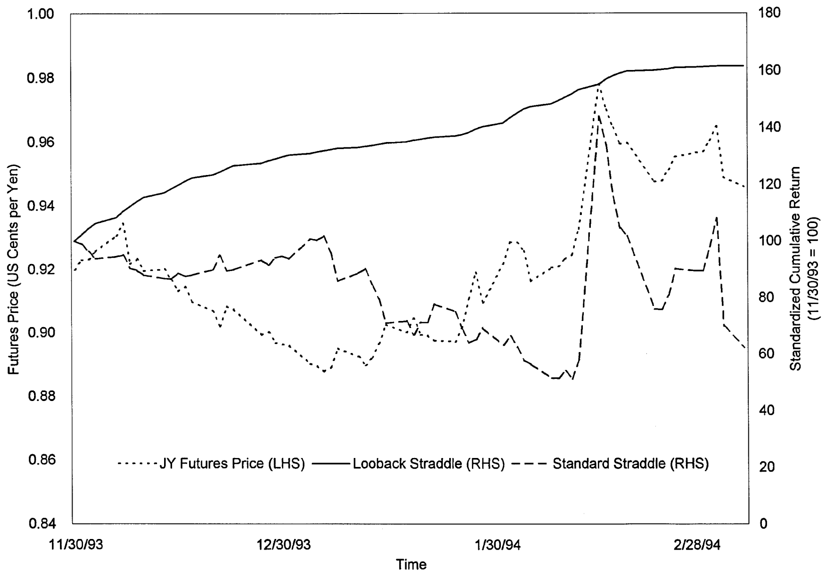

Figure 2
Standardized cumulative returns of the lookback straddle and the standard straddle on the March 1994 Japanese yen futures contract

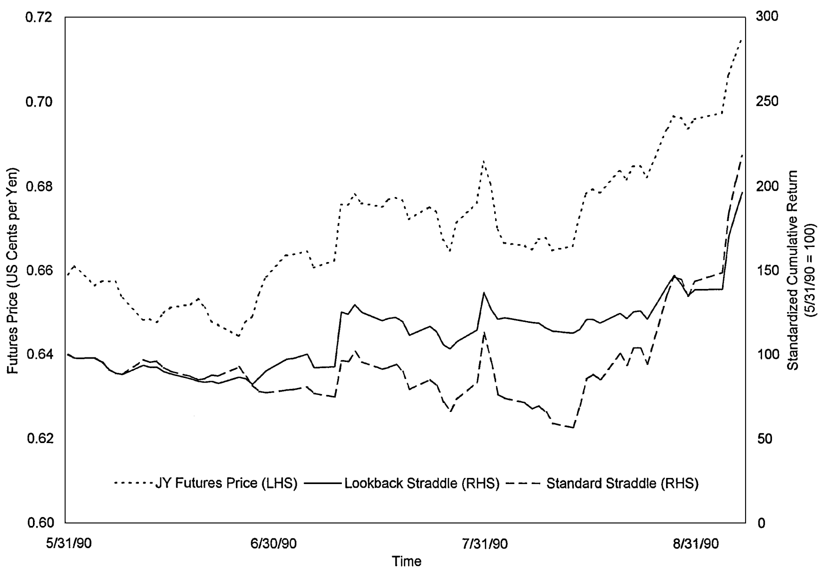

Figure 3
Standardized cumulative returns of the lookback straddle and the standard straddle on the September 1990 Japanese yen futures contract

vation period, depending on when the maximum and minimum prices were reached.

Next, we examine the entire data sample from March 1986 to December 1997. The daily returns of the two types of straddles on the Japanese yen had a correlation of 0.39, and their monthly returns had a correlation of 0.86. This indicates that, in our empirical application using monthly returns, the difference between the PMTS and the PTFS may be hard to discern. This is a consequence of using monthly returns of options that expire quarterly. We are empirically constrained to use quarterly options because data for longer-dated options are generally unreliable and, in most cases, unavailable. In addition, we are also empirically constrained to use monthly returns as higher frequency observations on the performance of trend-following funds are limited. It is an empirical regularity that the standard straddle and the lookback straddle are highly correlated in our data sample, even though this is not necessarily so at a different return interval. Consequently, we apply the lookback straddle in our empirical tests given its superior theoretical properties.

3. Evaluating the Risk in Trend-Following Strategies

In this section we show that the returns of trend-following funds are strongly correlated with the returns of the PTFSs. This is consistent with the notion that trend-following funds have systematic risks, contrary to the prediction of linear-factor models applied to standard asset benchmarks.

3.1 Standard benchmarks do not explain trend-following funds' returns

To explore this issue, we begin with a representative series of trend-following funds' returns. Theoretically, different trend-following funds may use different trading strategies. This may require a tailor-made benchmark for each fund, based on extensive interviews with the manager. Fortunately, despite the theoretical differences in the strategies, there is a high degree of commonality in the returns of trend-following funds, as shown in Fung and Hsieh (1997b). Applying principal components analysis on all defunct and operating CTA funds, Fung and Hsieh (1997b) found a single dominant trading style. This dominant style was interpreted to be a trend-following style, which is the most popular self-described CTA trading style. In this article, we update the results of Fung and Hsieh (1997b) using the Tass CTA database as of March 1998. Out of 1304 defunct and operating CTA funds, 407 are strongly correlated to the first principal component.[15] The returns of the equally weighted

[15] Fung and Hsieh (1997b) noted that the inclusion of defunct funds helps guard against "survivorship bias" in their estimate of the returns of the trend-following trading style. Survivorship bias comes about when only surviving, or operating, funds are used to estimate the returns of a group of funds. This is likely to result in an upward bias, because the omitted defunct funds generally have poorer performance than surviving funds.

portfolio of these 407 funds are used as the representative trend-following funds' returns.

We start with a key distributional feature of trend-following funds' returns. Table 1 shows that the trend-following funds' returns have strongly positively skewed returns. The returns of the five PTFS portfolios as well as all the individual PTFSs are also strongly positively skewed. The difference is that trend-following funds' returns have a positive and statistically significant mean, whereas the PTFS portfolios and most of the individual PTFSs do not. With the exception of the PTFS for the Swiss franc, trend-following funds' returns have a higher mean and greater statistical significance than the PTFS returns. We defer further analysis of this implicit alpha in trend-following funds' returns until Section 4.

3.2 Lookback straddle benchmarks explain trend-following funds' returns

Next, we document the apparent lack of systematic risk in trend-following funds' returns in standard linear-factor models in Table 2. The regression of trend-following funds' returns against the eight major asset classes

Table 2
Explaining trend-following funds' returns: The $\overline{R}^2$s of regressions on ten sets of risk factors

	Sets of Risk Factors	$\overline{R}^2$ of Regression (%)
1.	Eight major asset classes in Fung and Hsieh (1997a) (U.S. equities, non-U.S. equities, U.S. bonds, non-U.S. bonds, gold, U.S. dollar index, Emerging market equities, one-month Eurodollar)	1.0
2.	Five major stock indices (S&P 500, FTSE 100, DAX 30, Nikkei 225, Australian All Ordinary)	−2.1
3.	Five government bond markets (U.S. 30-year, UK Gilt, German Bund, French 10-year, Australian 10-year)	7.5
4.	Six three-month interest rate markets (Eurodollar, 3m Sterling, Euro-DM, Euro-Yen, Australian Bankers Acceptance, Paris Interbank Rate)	1.5
5.	Four currency markets (British pound, deutschemark, Japanese yen, Swiss franc)	−1.1
6.	Six commodity markets (corn, wheat, soybean, crude oil, gold, silver)	−3.2
7.	Goldman Sachs Commodity Index	−0.7
8.	Commodity Research Bureau Index	−0.8
9.	Mount Lucas/BARRA Trend-Following Index	7.5
10.	Five PTFS portfolios (Stock PTFS, Bond PTFS, Currency PTFS, three-month interest rate PTFS, Commodity PTFS)	47.9

$\overline{R}^2$ refers to adjusted R^2 of the regressions of trend-following funds' returns on ten different sets of risk factors.

(U.S. equities, non-U.S. equities, U.S. bonds, non-U.S. bonds, one-month Eurodollar interest rate, gold, U.S. Dollar Index, and emerging market equities) in Fung and Hsieh (1997a) has an $\overline{R}^2$ of 1.0%, and none of the variables are statistically significant. For completeness, we examined the 26 markets used to construct the PTFSs in Table 1. Doing this by groups, the five stock markets have an $\overline{R}^2$ of -2.1%, the five bond markets 7.5%, the six three-month interest rates 1.5%, the four currencies -1.1%, and the six commodities -3.2%. An investor using a linear-factor model on standard asset benchmarks would have concluded that trend followers had no systematic risk.

Other indices frequently associated with commodity traders and trend followers produced similarly poor results. The regression of trend-following funds' returns on the GSCI Total Return Index has an $\overline{R}^2$ of -0.7% and is not statistically significant. The Commodity Research Bureau (CRB) Index has an $\overline{R}^2$ of -0.8% and is also not significant. The Mount Lucas/BARRA Trend-Following Index is slightly better, with an $\overline{R}^2$ of 7.5%, and it is statistically significant. These results are summarized in Table 2.

Next, we document the PTFS's ability to characterize the performance of trend followers using standard linear statistical techniques. The regression of the trend-following funds' returns on the five PTFS portfolios returns has an $\overline{R}^2$ of 47.9%, with currencies and commodities having the largest explanatory power. The F-test that none of the PTFS portfolios is correlated with the trend-following funds' returns is rejected at any conventional significance level. This indicates that trend followers do have systematic risks. These risks are just not evident in a linear-factor model applied to standard asset benchmarks.

Proper diagnostics are needed to guard against nonlinear relationships in regressions. We do so using scatter plots of the trend-following funds' returns against the five PTFS portfolios in the five panels in Figure 4. The first panel graphs the trend-following funds' returns against the stock PTFS returns. It basically shows that there is no apparent relationship between these two variables either in the center of the distribution or at the extremes. The other panels in Figure 4 are the scatter plots of the trend-following funds' returns against the PTFS portfolios in bonds, three-month interest rates, currencies, and commodities, respectively. They show that the currency and commodity PTFSs have the strongest relationship with trend followers. In particular, the panel for currency PTFS contains the most striking scatter plot. It shows that, when trend followers make large profits, the currency PTFS also makes large profits. In fact, the relationship between the currency PTFS returns and the trend-following funds' returns appear reasonably linear. Plots of the residuals of the regression against the explanatory variables (available from the authors on request) do not show any remaining nonlinear relationships.

3.3 Trend-following funds' returns are sensitive to large moves in world equity markets

Next we examine another important characteristic of trend-following funds' returns corresponding to extreme moves in world equity markets. We begin with Table 3, where we report the trend followers' sizable positive returns during downturns in world equity markets. The two worst periods for world equities in the last 10 years, as measured by the MS World Equity index, are: Sep–Nov 1987 (−20.4%) and Aug–Sep 1990 (−18.9%). Trend-following funds recorded large positive returns of 13.0% and 10.2% during these two periods, respectively. Given the lookback option's structure, it was not surprising that the PTFSs for stocks had positive returns during these two down periods for equities. The less obvious results were the positive returns from the PTFSs for most of the government bonds, currencies, and commodities. However, less than half of the PTFSs for three-month interest rates were profitable during these two periods.

To generalize these unusual return characteristics, we provide further collaborating evidence on this relationship between the returns of trend followers and those of the world equity markets over a large sample period. It was first observed in Fung and Hsieh (1997a, 1997b) that the returns of trend followers have option-like payouts relative to world equity markets. We extend this observation to encompass a larger data set using the returns from the PTFSs. The result is reported in Table 4. Here we divided the longer time series for which there were data for all PTFSs (March 1985 to December 1997) into 5 states, based on the performance of the world equity market. State 1 represents the worst 30 months for world equities, which declined on average 4.60%. State 2 consists of the next 30 worst months, when equities fell an average of 0.59% per month. State 5 has the best 30 months for equities, which rose 6.74% on average. State 4 are the next best 30 months, in which equities gained 3.36% on average. State 3 contains the remaining 34 months. We then report the average return and the standard deviation of the PTFSs for stocks, bonds, currencies, three-month interest rates, and commodities during these states.

Consistent with the earlier observation, the returns of the PTFSs tended to be high during extreme states 1 and 5 for stocks. As expected, the PTFSs on stocks had high and positive average returns during the two extreme states. The PTFSs on bonds, three-month interest rates, and currencies also had high and positive average returns in states 1 and 5. However, the PTFSs on commodities did not exhibit this option-like behavior.[16]

It is perhaps not surprising that the PTFSs in bonds, three-month interest rates, and currencies generated high returns during extreme moves in the world equity markets. Theoretically, financial assets (stocks, bonds, three-month interest rates, and currencies) should respond to the same set of

[16] The low average return for the commodity PTFS in state 1 was primarily due to one outlier.

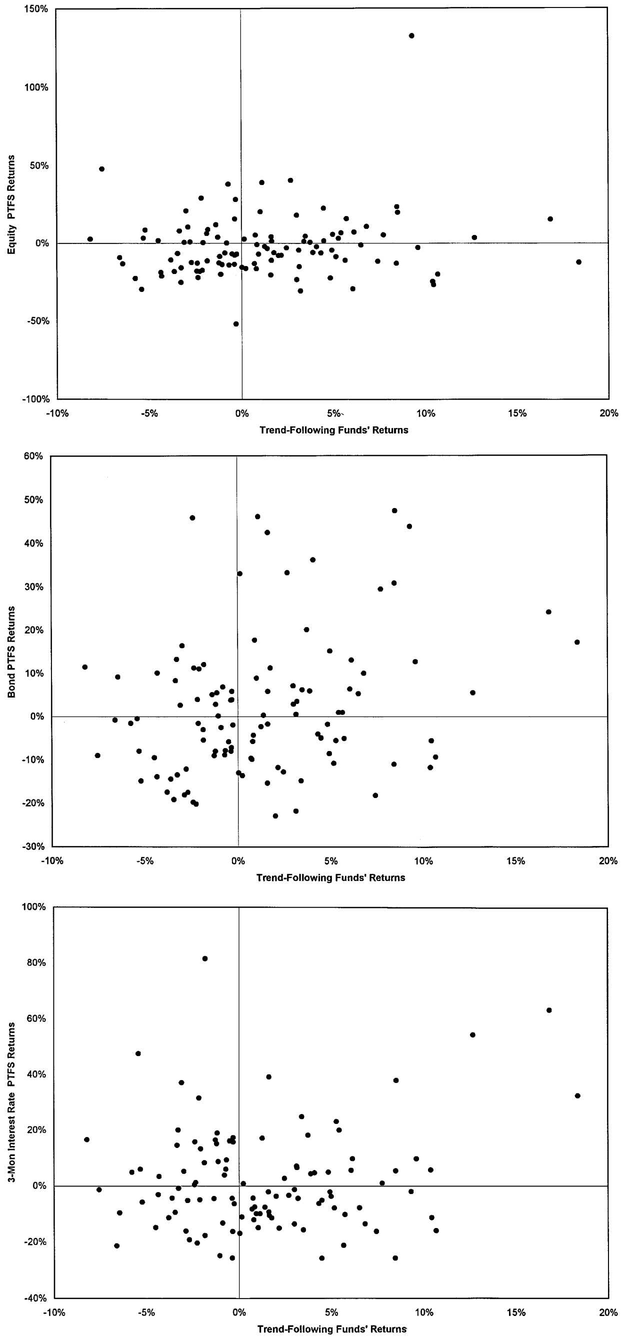

Figure 4
Scatter plots of monthly trend-following funds' returns versus five PTFS portfolio returns

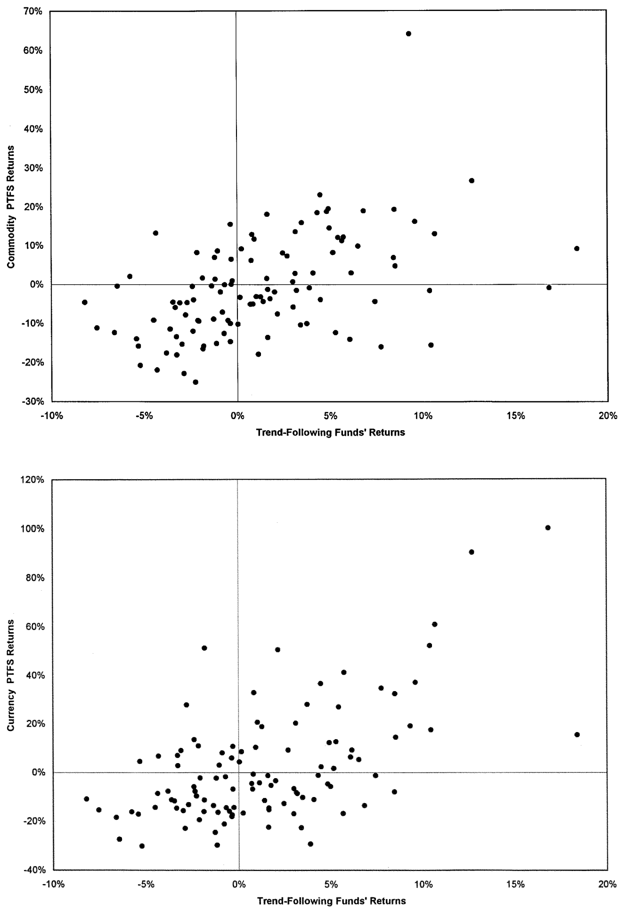

Figure 4
(continued)

macroeconomic events. Historically, extreme moves tended to be caused by a common set of dramatic events (such as the Persian Gulf War in 1990 and the attendant shock to the oil markets), leading all financial markets to move in concert.

To conclude this subsection, we examine the possibility of using standard straddles as an alternative option-replication strategy. We investigated this for two markets: the Swiss franc futures contract because its PTFS returns were most highly correlated to trend-following funds' returns, and the Sydney 90-day Bankers Acceptance futures contract, being the least correlated.

For the Swiss franc, lookback straddle returns had a correlation of 0.834 with those of standard straddles. Both straddles had statistically significant correlation to trend-following funds' returns, 0.444 in the case of lookback

Table 3
Large PTFS returns during the two worst periods for world equities: Sep–Nov 1987 and Aug–Sep 1990

Panel A: World equities and trend-following funds

Period	MS World Equities	Trend-Following Funds
8709–8711	−0.2036	0.1299
9008–9009	−0.1889	0.1019

Panel B: PTFS returns for stock markets

Period	Stock PTFS	S&P 500	FTSE 100	DAX 30	Nikkei 225	Australian All Ordinary
8709–8711	2.1060	2.1060				
9008–9009	0.7744	0.7744				

Panel C: PTFS returns for bond markets

Period	Bond PTFS	US 30Y	UK Gilt	German Bund	French 10Y	Australian 10Y
8709–8711	0.2725	0.3187	0.0753			
9008–9009	0.3557	0.3670	−0.0513	0.1257	1.0377	

Panel D: PTFS returns for three-month interest rate markets

Period	Interest Rate PTFS	Euro-Dollar	3-month Sterling	Euro-DM	Euro-Yen	Australia Bankers Acceptance	Paris Interbank Rates
8709–8711	0.8194	0.8194					
9008–9009	−0.1372	−0.0052	−0.0898	−0.3145			0.4268

Panel E: PTFS returns for currency markets

Period	Currency PTFS	British Pound	Deutsche Dark	Japanese Yen	Swiss Franc
8709–8711	0.7758	1.3368	0.5401	0.3842	0.7448
9008–9009	0.1832	0.1887	−0.0599	0.0882	0.5165

Panel F: PTFS returns for commodity markets

Period	Commodity PTFS	Corn	Wheat	Soybean	Crude Oil	Gold	Silver
8709–8711	0.0220	0.1494		0.8344	−0.3871	−0.3937	
9008–9009	0.8525	0.4336	0.2040	−0.2891	5.4406	0.9578	0.1719

straddles and 0.433 for standard straddles. For the Sydney 90-day Bankers Acceptance, lookback straddle returns had a correlation of 0.924 with those of standard straddles. Neither straddle, however, had statistically significant correlation with trend-following funds' returns, −.006 in the case of lookback straddles and 0.010 in the case of standard straddles. These results indicate that, for quarterly expirations, standard straddles are similar to lookback straddles for the purpose of replicating monthly trend-following funds' returns. Our choice of the lookback straddle in the empirical application rests on its superior theoretical properties given in Section 2.

3.4 Preferred habitat of trend followers

Next we address the question of preferred habitat or which markets trend followers were active in during the extreme equity market moves (i.e., states 1 and 5 in Table 4). To answer this question, we regressed the trend-following funds' returns on the PTFSs' returns during the extreme states 1 and 5. Given

Table 4
Option-like behavior of PTFS returns during five different states for equities: Mar 85–Dec 97

State	Stock PTFS	Bond PTFS	Currency PTFS	Interest Rate PTFS	Commodity PTFS	Trend Following Funds	MS World Equities
1	0.1281	0.0591	0.0827	0.0832	0.0121	0.0203	−0.0460
	0.0928	*0.0375*	*0.0484*	*0.0454*	*0.0321*	*0.0114*	*0.0056*
2	−0.0832	0.0306	−0.0068	0.0588	−0.0362	0.0112	−0.0059
	0.0284	*0.0323*	*0.0390*	*0.0407*	*0.0309*	*0.0130*	*0.0014*
3	−0.0553	−0.0518	−0.0058	−0.0108	−0.0188	0.0132	0.0156
	0.0176	*0.0246*	*0.0375*	*0.0264*	*0.0244*	*0.0098*	*0.0009*
4	−0.0816	−0.0307	0.0170	−0.0146	−0.0183	0.0010	0.0336
	0.0253	*0.0211*	*0.0436*	*0.0355*	*0.0237*	*0.0076*	*0.0012*
5	0.0941	0.1017	0.0821	0.0560	−0.0245	0.0569	0.0674
	0.0453	*0.0470*	*0.0439*	*0.0483*	*0.0267*	*0.0149*	*0.0039*

State 1 consists of the worst 30 months of the MS World Equity Index.
State 2 consists of the next worst 30 months of the MS World Equity Index.
State 5 consists of the best 34 months of the MS World Equity Index.
State 4 consists of the next best 30 months of the MS World Equity Index.
State 3 consists of the remaining 30 months of the MS World Equity Index.
Standard errors are in italics.

the large number of PTFSs and the small number of observations, we ran the regression five times using groups of PTFSs. In the stock PTFS regression, the $\overline{R}^2$ is 9.4%, and none of the equity indices is statistically significant. For bond PTFSs, the $\overline{R}^2$ is 10.1% with U.S. bonds being the only significant variable. For the three-month interest rate PTFSs, the $\overline{R}^2$ is 21.5%, where the significant variables are the Eurodollar and Short Sterling contracts. For currency PTFSs, the $\overline{R}^2$ is 39.5% with the deutschemark and the Japanese yen being the significant variables. For commodity PTFSs, the $\overline{R}^2$ is 30.5% where the wheat and silver futures contracts were the significant variables. The final regression is reported in panel A of Table 5. Using only the significant PTFSs, the $\overline{R}^2$ is 60.7% with U.S. bonds, deutschemark, wheat, and silver being the significant variables. These are the markets that, ex post, can account for trend followers' performance during extreme equity market moves. Figure 5 provides a scatter plot of the fitted values of the regression against the returns of trend-following funds. Table 5 also provides information on the regressions for the overall sample, using all five PTFSs (in panel B) and three statistically significant PTFSs (in panel C).

As the regressors were selected based on previous regressions, statistical inference is not reliable. This, however, is the nature of ex post performance attribution, where data-mining techniques are applied to determine which markets trend followers were active in.

3.5 Relationship to other empirical studies

To complete our analysis, it is helpful to incorporate qualitative results from other independent studies. Billingsley and Chance (1996) found that among the CTAs trading only specialized markets, 41.2% trade bonds and three-month interest rate futures, 30.9% trade currencies, 15.5% trade commodities, and 12.4% trade stock index futures. As Billingsley and Chance (1996)

Table 5
Estimating trend-following funds' preferred habitat: January 1989–December 1997

Regressors	Coefficient Estimate	Standard Errors[a]
Panel A: Regression of trend-following funds' returns on selected PTFSs during two extreme states (1 and 5) for world equities		
Constant	0.0166	0.0052
US bond	0.0478	0.0204
Euro-$	0.0336	0.0259
Short sterling	0.0234	0.0123
DM	0.0544	0.0255
JY	0.0194	0.0180
Wheat	0.0513	0.0169
Silver	0.0540	0.0128
R^2	0.674	
$\overline{R}^2$	0.607	
Panel B: Regression of trend-following funds' returns on five PTFS portfolios using the full sample		
Constant	0.01155	0.00312
PTFS on stocks	−0.03517	0.01713
PTFS on bonds	0.05164	0.02495
PTFS on currencies	0.10994	0.01594
PTFS on interest rates	−0.02096	0.02413
PTFS on commodities	0.14999	0.02468
R^2	0.5032	
$\overline{R}^2$	0.4788	
DW	2.31	
$\chi^2(5)$	163.44 (p-value : 0.0000)	
Panel C: Regression of trend-following funds' returns on selected PTFS portfolios using the full sample		
Constant	0.01229	0.00332
PTFS on stocks	—	—
PTFS on bonds	0.02933	0.02077
PTFS on currencies	0.10308	0.01575
PTFS on interest rates	—	—
PTFS on commodities	0.13913	0.02657
R^2	0.4816	
$\overline{R}^2$	0.4666	
DW	2.28	
$\chi^2(3)$	123.50 (p-value : 0.0000)	

See the note for Table 1 for the definition of PTFS.
See the note for Table 2 for the definition of markets.
[a]With correction for heteroskedasticity.

did not report the split between bonds and three-month interest rates, we assume that the group is evenly divided between the two instruments. This means that the currency market is the most popular market for trend followers attracting, presumably, the lion's share of available risk capital, whereas the equity market is the least popular. Although it is difficult to expect qualitative results to line up closely with quantitative observations, both approaches came to a similar conclusion: Currencies appeared to be the instrument of choice, and stock indices attracted the least trend-following activities.

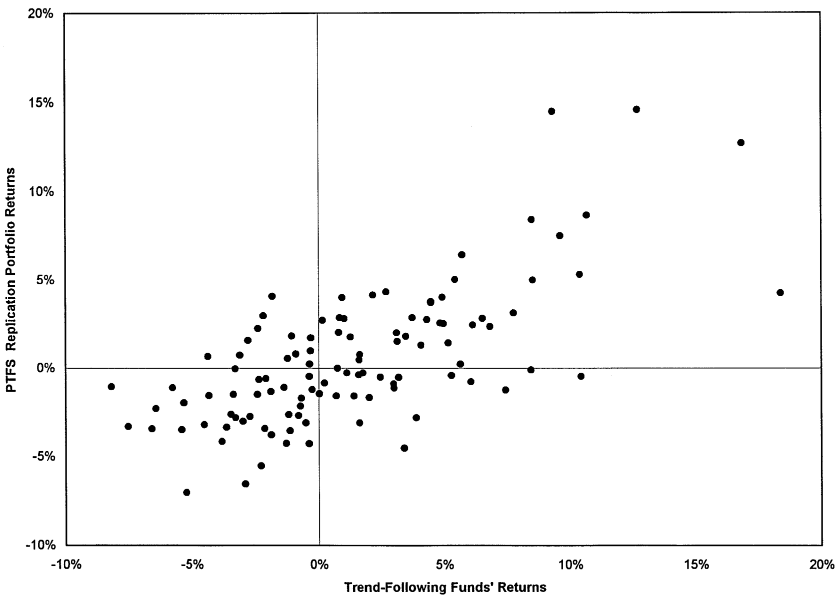

Figure 5
Scatter plots of monthly trend-following fund's returns versus PTFS replication portfolio returns

4. Benchmarking Individual Trend-Following Funds

So far, we have examined the return characteristics of a portfolio of 407 trend-following funds. There can be, however, wide individual variations not reflected in this portfolio that merit documentation. We investigate individual funds in this section.

First, we focus on 163 trend-following funds with at least 24 months of return information through the end of 1997. As a starting point, we assessed the ability of standard asset benchmarks to explain returns of individual funds. We regressed each fund's returns on five portfolios of stocks, bonds, three-month interest rates, currencies, and commodities, formed from their benchmark (i.e., buy-and-hold) returns rather than the PTFS returns. The distribution of $\overline{R}^2$ are given in the third column of Table 6. They ranged from -9% to 58%, with an average of 11%. Eighty-six funds had no regression coefficients significant at the 1% level. Seventy-two funds had one significant coefficient: 2 funds had exposure to stocks, 1 to currencies, 7 to bonds, and 62 to commodities. Five funds had two significant coefficients.

Next, we regressed the returns of each fund on the five PTFS portfolios. The distribution of $\overline{R}^2$ are given in the second column of Table 6. They ranged from -2% to 64%, with an average of 24%. Thirty-nine funds had no regression coefficients significant at the 1% level. Ninety-six funds had one significant coefficient: 12 had exposure to the bond PTFS, 33 to the

Table 6
Explaining the monthly returns of 163 trend-following funds using the five PTFS portfolios and five buy-and-hold portfolios

	Number of Trend-Following Funds	
$\overline{R}^2$ from, to	Regressions Using 5 PTFSs Portfolios	Regressions Using 5 Buy-and-Hold Portfolios
−1.0, −0.9	0	0
−0.9, −0.8	0	0
−0.8, −0.7	0	0
−0.7, −0.6	0	0
−0.6, −0.5	0	0
−0.5, −0.4	0	0
−0.4, −0.3	0	0
−0.3, −0.2	0	0
−0.2, −0.1	0	3
−0.1, 0.0	3	26
0.0, 0.1	21	53
0.1, 0.2	43	44
0.2, 0.3	44	28
0.3, 0.4	26	8
0.4, 0.5	17	1
0.5, 0.6	7	0
0.6, 0.7	2	0
0.7, 0.8	0	0
0.8, 0.9	0	0
0.9, 1.0	0	0

The $\overline{R}^2$s are based on regressions of 163 trend-following funds with 24 months of returns on the five PTFS portfolios and on five buy-and-hold portfolios based on the underlying markets of the PTFS portfolios.

currency PTFS, and 51 to the commodity PTFS. Twenty-seven funds had two regression coefficients significant at the 1% level: 5 were exposed to the bond and currency PTFSs, 11 to the bond and commodity PTFSs, 10 to the currency and commodity PTFSs, and 1 to the currency and three-month interest rate PTFS. Last, one fund had exposure to the bond, three-month interest rate, and commodity PTFSs. It is worth noting that no fund had any significant exposure to the stock PTFS.

In terms of magnitudes, the statistically significant exposure to the bond PTFS ranged from 4% to 65%, averaging 20%. The currency PTFS exposure ranged from 3% to 44%, averaging 16%. The commodity PTFS exposure ranged from 9% to 87%, averaging 26%. The three-month interest rate PTFS exposure ranged from 18% to 22%, averaging 20%.

Last, we demonstrate that the PTFSs can provide reasonable results for identifying the preferred habitat of traders. We examined 21 trend-following funds whose names imply they trade only currencies. Of these, 18 had statistically significant exposure to the currency PTFS only; 2 had exposure to the currency PTFS along with either the three-month interest rate PTFS or the commodity PTFS; and 1 fund had no significant exposure to any PTFSs.

These results indicate that the PTFS returns (particularly bond, currency, and commodity) had much higher explanatory power than the benchmark asset returns even at the level of individual trend-following funds. They can also help in performance attribution. However, the results also indicate substantial differences in preferred habitats across trend-following funds. In light of these results, it would be difficult to find a single benchmark for monitoring the performance of trend-following funds. In fact, Glosten and Jagannathan (1994) recommended extensive discussions with each fund manager to understand how he or she operates, in determining whether a fund-specific benchmark is necessary. Nonetheless, our model contributes to the design of benchmarks for trend-following funds by capturing the nonlinear dynamics of their strategy.

5. Conclusions

In this article, we created a simple trend-following strategy using a lookback straddle. This strategy delivers the performance of a perfect foresight trend follower. The cost of implementing this strategy can be established using observable, exchange-traded option prices. For each asset market, we label this the Primitive Trend-Following Strategy (PTFS) for that market. Empirically, we show that these PTFSs capture three essential performance features of trend-following funds.

First, the PTFS returns replicate key features of trend-following funds' returns. They both have strong positive skewness. Both tend to have positive returns during extreme up and down moves in the world equity markets.

Second, trend-following funds' returns during extreme market moves can be explained by a combination of PTFSs on currencies (deutschemark and Japanese yen), commodities (wheat and silver), three-month interest rates (Eurodollar and Short Sterling), and U.S. bonds, but not the PTFSs on stock indices. This is in agreement with qualitative results in previous studies that indicate that stock indices are the least popular market to CTAs. In addition, the PTFSs are better able to explain trend-following funds' returns than standard buy-and-hold benchmark returns on major asset classes, as well as benchmarks used by the hedge fund industry.

Third, the superior explanatory power of the PTFSs over standard buy-and-hold benchmarks supports our contention that trend followers have nonlinear, option-like trading strategies. Specifically, trend followers tend to perform as if they are long "volatility" and "market event risk," in the sense that they tend to deliver positive performance in extreme market environments.

The implications of these performance features are threefold. One implication is that trend-following funds do have systematic risk. However, this risk cannot be observed in the context of a linear-factor model applied to standard asset benchmarks. The second implication is that trend followers, or a portfolio of lookback straddles on currencies, bonds, and commodities, can reduce the volatility of a typical stock and bond portfolio during extreme market downturns. This view is corroborated by the out-of-sample events in the third quarter of 1998, when the S&P declined more than 10% and the vast majority of trend-following funds made large gains. The third implication is that the PTFSs are key building blocks for the construction of a performance benchmark for trend-following funds, as well as any fund that uses trend-following strategies. However, the evidence indicates that there are substantial differences in trading strategies among trend-following funds. Thus, it may not be possible to find a single benchmark that can be used to monitor the performance of all trend followers. As suggested in Glosten and Jagannathan (1994), the benchmarking of an individual fund's performance may need to incorporate specific aspects of the manager's operations. Nonetheless, the PTFSs are useful tools for the construction of benchmarks for trend-following funds.

Appendix A: The Illustrated Difference between the Deltas of the Lookback Straddle and the Standard Straddle

This appendix compares the replication strategy of the standard straddle and the lookback straddle to gain further insights into the difference between market timing and trend following. Let S denote the price of the underlying asset. Its instantaneous volatility, σ, is assumed to be 20%. The interest rate, r, is 6%. Consider a standard straddle and a lookback straddle that were purchased when the asset price was 100. At inception, both were at-the-money options, that is, their strike prices were 100. Both options have 60 days to expiration. Because the standard straddle's payout is not path-dependent, its delta can be calculated without knowing the path of the underlying asset's price. However, the lookback straddle's payout is path-dependent, so its delta depends on the ex post range of the underlying asset's price. Consider the following cases.

Suppose the asset price stays at 100. Then the deltas of the standard straddle and the lookback straddle are zero, and both payouts are also zero. We consider their deltas in four more scenarios graphed in Figure 6.

In scenario A, illustrated in panel A, the asset price rises steadily from 100 to 160 over the life of the straddles. The deltas of the two straddles are similar and rise with the price. Also, the payouts of the two straddles are identical. In scenario C, illustrated in panel C, the asset price falls steadily from 100 to 40 over the life of the straddles. Again, the two straddles have similar deltas and identical payouts. These two cases show that, in strongly trending markets, the two straddles are virtually identical.

In scenario B, shown in panel B, the asset price rises to 130, fell back to 110, and rose to 150. Here, the two straddles have different deltas but the same payouts. Throughout this entire period, the standard straddle has a positive delta. However, the lookback straddle's delta is quite different. It is similar to the delta of the standard straddle when the asset price rises from 100 to 130 for the first time. When the asset price declines from 130 toward 110, the delta of the lookback straddle declines sharply and actually turns negative, resembling a trend follower selling breakdown. When the asset price subsequently rises from 110, past 130, to 150, the delta of the lookback straddle turns positive and rises sharply once more, resembling a trend follower buying breakouts.

In scenario D, the asset price rises to 130 and falls back to 100, as shown in panel D. Here, the two straddles have different deltas and different payouts. The delta of the standard straddle stays positive over the entire period. In contrast, the delta of the lookback straddle declines rapidly as the asset price falls back from the high of 130. The delta in fact turns negative as the asset price returns to 100, resembling a trend follower selling breakdowns. Note that the payouts of the two straddles are also different: The standard straddle pays out 0, while the lookback straddle pays out 30.

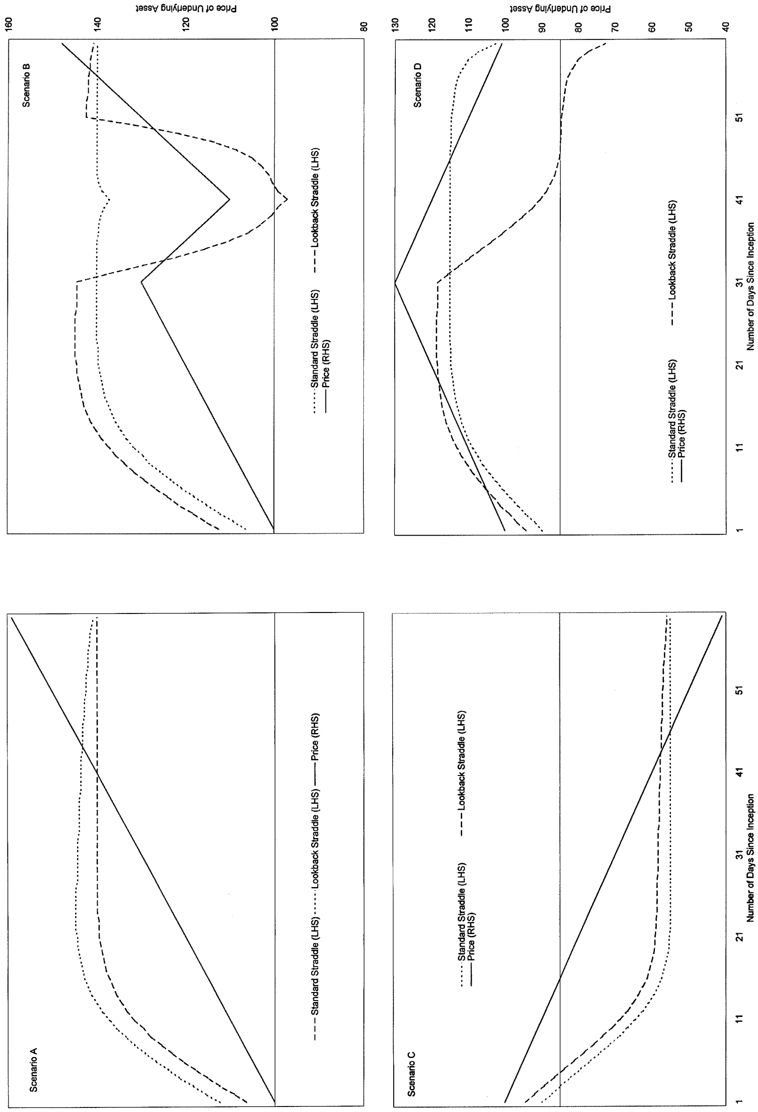

Figure 6
Deltas of the standard straddle and lookback straddle in scenarios A, B, C, and D of the underlying asset's price path

To summarize, the standard straddle's delta mimics a trader whose actions depend only on the relationship between the current price and the inception price of 100, but not any intermediate prices. The trader is long if the current price is above the inception price and short otherwise. This is what a market timer would do. The lookback straddle's delta mimics a trader whose actions depend on the relationship between the current price to the maximum and minimum prices since inception. The trader is long (short) when the current price is near the maximum (minimum) price. This is what a trend follower would do.

Appendix B: Data Description and Data Sources

Futures and option data on the DTB, MATIF, and Osaka were purchased from the Futures Industry Institute (FII). Futures and option data on the LIFFE, SFE, and TIFFE, and option data on the CBOT and NYMEX, were supplied by the respective exchanges. Option data on the CME were purchased from the FII and updated by the CME. Futures data on the CBOT, CME, and NYMEX came from Datastream. The following table provides information on the option data.

			No. of Observations			
Option Contract	Exchange	Start Date[a]	Month	Futures	Options	Source
S&P 500	CME	83/01/28	180	79,310	497,679	FII & CME
FTSE 100	LIFFE	92/03/13	70	NA	286,558	LIFFE
DAX 30	DTB	92/01/02	72	NA	324,714	FII
Nikkei 225	Osaka	89/06/12[b]	96	51,385	94,090	FII
All Ordinary	SFE	92/01/02	72	45,785	626,348	SFE
30-year US bond	CBOT	82/10/04	183	162,525	332,651	CBOT
10-year Gilts	LIFFE	86/03/13	142	38,700	245,282	LIFFE
10-year Bund	LIFFE	89/05/02	104	26,545	309,124	LIFFE
10-year French bd	MATIF	90/01/02	92	34,250	56,883	FII
10-year Aus. bd	SFE	92/01/02	72	15,065	110,247	SFE
Euro-$	CME	85/03/21	154	213,665	443,693	FII & CME
Short Sterling	LIFFE	87/12/01	121	118,410	348,894	LIFFE
Euro-DM	LIFFE	90/03/01	94	91,335	214,473	LIFFE
Euro-Yen	TIFFE	91/08/01[b]	77	70,470	52,368	TIFFE
Aus. Bank. Acc.	SFE	92/01/02	72	81,970	519,398	SFE
PIBOR	MATIF	90/03/01	84	71,960	68,505	FII
British pound	CME	85/03/01	154	56,680	267,469	FII & CME
Deutschemark	CME	84/01/24[c]	168	70,800	359,483	FII & CME
Japanese yen	CME	86/03/06[d]	142	63,545	406,352	FII & CME
Swiss franc	CME	85/02/25[c]	149	61,015	341,497	FII & CME
Corn	CBOT	85/02/27	155	120,970	333,622	CBOT
Wheat	CBOT	88/01/04	120	80,295	227,495	CBOT
Soybean	CBOT	84/10/31	158	153,175	368,338	CBOT
Crude oil	NYMEX	86/11/14	134	269,200	408,309	NYMEX
Gold	NYMEX	82/10/04	180	230,560	622,578	NYMEX
Silver	NYMEX	88/01/04	120	160,275	463,070	NYMEX

[a] All samples end on December 31, 1997.
[b] Data missing from many dates.
[c] Portions of data missing during 1993.
[d] Portions of data missing during 1987 and 1988.
NA = not applicable for cash options.

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