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MULTIPLE TIME SCALE ATTRIBUTION FOR COMMODITY TRADING ADVISOR (CTA) FUNDS*

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Commodity trading advisors (CTAs) make directional investments in liquid futures and forward markets. Since CTAs generally do not engage in security selection or relative value trades, their performance depends to a large extent on funds' ability to "time" market exposures. We analyze CTA return attribution, splitting returns into contributions from asset class (beta) factors and market timing factors. For each asset, we use timing factors at several frequencies. The highest frequency (e.g., daily) timing factors are absolute values of asset returns, while lower frequency (e.g., weekly or monthly) timing factors also use high-frequency returns. Average fund returns net of beta and market timing contributions are called residual alpha. For CTAs, the market timing contribution varies by frequency. By combining timing factors at different frequencies, we estimate aggregate market timing alpha and residual alpha; this latter quantity is around −8% per year for CTA indexes, with transaction costs being a potential contributor.

Commodity trading advisors (CTAs) are funds that invest in liquid futures and forward markets for equities, fixed income, currencies, and commodities. They are often referred to as managed futures funds or trend followers, although the latter term does not apply to all managers in the space. By taking long or short positions in these markets, CTAs make bets on market direction. Generally, trading signals for these funds are produced by systematic models. The directional approach of most CTAs differs from that of relative value hedge funds that seek to profit from the spread between two quantities, regardless of whether their respective markets rise or fall.

While CTA fund returns tend to be correlated with each other,[1] funds differ in their size, the markets they trade, the holding period of their investments,

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and the models that they use to forecast market direction. CTAs range in size from under \$10 mm to over \$10 bn in assets[2]; smaller funds typically trade in the same markets as large funds, but may be overweight smaller markets (e.g., cotton). Holding periods for CTAs can range from minutes to several months, but most assets are in the multi-month category, due to capacity limitations of short-term trading. Most CTAs use systematic trend-following models (i.e., continuation or momentum) to predict market direction, although some funds use mean reversion or pattern recognition as signals.[3] Funds also differ in their leverage, often expressed as a margin to equity.

We focus on attribution analysis of CTA funds in this paper. If a fund has net exposure to markets over the measurement period (e.g., long bonds), a portion of its returns are attributable to directional (beta) contributions. Consistent with Fung and Hsieh (2001), however, we find that these contributions are relatively small. The average return net of beta contributions is called excess return or alpha. For many hedge funds, alpha comes from selection of stocks or bonds. Since CTAs do not generally invest in individual stocks or bonds, their alpha comes mainly from market timing gains; that is, from tactical adjustments in asset exposure that are coordinated with market movements. We use a model to estimate the contribution from directional (beta) exposure, as well as the alpha due to market timing skill; the average return net of beta contribution and market timing alpha is called the *residual alpha*. Absent market timing skill, residual alpha is just the usual excess return.

For CTA funds, what comprises residual alpha? Since we use liquid indexes in each asset class to measure the beta contribution and market timing alpha, gains from exposure to and timing skill in less-liquid markets could appear as residual alpha; this effect should be more pronounced in smaller funds, however. For the minority of CTAs that trade individual equities or emerging markets, gains from these activities would also show up as residual alpha. Fees are a possible (negative) contributor; however, management and incentive fees exert opposing influences on residual alpha,[4] and their combined impact is smaller than our estimated residual alphas. A remaining contributor to residual alpha is transaction cost. Since funds incur these costs on all trades, successful or not, they will be uncorrelated with market timing factors. Due to such costs, we expect to see *negative* residual alpha in many CTAs, after extracting beta contributions and market timing alpha. Indeed, we find residual alphas of around −8% for CTA indexes.

Our analysis of market timing alpha in CTA funds is motivated by their trading approach. A manager who can predict the market direction over some horizon would be long the market when it rises and short the market when it falls[5]; i.e., her returns associated with this market would be the absolute value of market returns.[6] While some CTAs forecast the magnitude and direction of market returns, many focus solely on direction; at these funds, the allocation to an asset is independent of the signal strength and only the sign matters. This motivates our choice of absolute values of index returns as proxies for market timing skill. Therefore, instead of simply including equity, fixed income, currency, and commodity returns in our model, we also include their absolute values. Positive and significant coefficients on absolute value factors are evidence of market timing ability. Since the absolute value factors have positive averages, their presence in a regression model accounts for some of a fund's positive average return. In fact, we find that this estimated contribution exceeds CTA index average returns, resulting in negative residual alphas.

CTA funds differ in their forecast horizons (e.g., long-term or short-term) and some funds use models with multiple horizons.[7] This mixing of time scales is compounded in CTA indexes, which combine the returns of many funds. In fact, we observe market timing alpha at a range of frequencies for CTA indexes. Market timing skill at a range of time scales complicates attribution analysis. For asset class returns (beta factors), absent the effects of compounding or serial correlation,[8] contributions are independent of time scale of measurement.[9] This is not necessarily so for the nonlinear factors we use to measure market timing ability, as the sum of absolute values of daily returns within a month can be equal to or much larger than the absolute value of monthly returns.[10] Consequently, contributions from market timing at different time scales may either be additive or redundant.[11] To compute a fund's aggregate market timing alpha, we need to sum the orthogonal contributions from different time scales.

To estimate the combined market timing skill of a fund at multiple time scales, we introduce variables that express low-frequency timing ability through high-frequency data. Suppose a manager has monthly market timing skill[12]; i.e., she can predict whether a market will be up or down for the month, but not at daily or weekly time scales, and only trades at month-end. During the month, she will be long (short) the market each day, depending on whether it will be up (down) for that month. For each index, we therefore introduce four sets of sign factors that are $+1$ or -1 each day of a week, month, quarter, or year, depending on whether that index is up or down, respectively, for the week, month, quarter, or year containing that day. We then multiply daily index returns and sign factors to obtain market timing variables at different time scales.

For a given fund, the time scales used in attribution analysis depend on its strategy, the frequency and length of available data, and the correlations among timing factors during the fund's history. For short-term traders, it is more important to include daily and weekly timing factors, whereas these may be less relevant for longer term CTAs. To get meaningful results from long-term timing factors, such as quarterly or annual timing, several years of fund data are necessary—otherwise, low-frequency timing ability may appear as beta. Also, if timing factors for an asset are highly correlated, only one or two time scales may ultimately appear in a multi-factor model for the fund. Since timing factors for an asset may be correlated at different frequencies, and timing factors for different assets may also be correlated, analysts must conduct due diligence to ensure that the timing factors included in the model are truly relevant to the fund's strategy.

Isolating market timing contributions and computing residual alpha can provide useful insights into CTA funds. Investors may prefer funds that exhibit consistent market timing ability at a given time scale, seeing this as evidence of a proprietary advantage. Also, in studying a fund's performance over time, a more-negative residual alpha or ratio of residual alpha to market timing alpha could indicate higher trading costs, possibly associated with greater assets. Our results also indicate the potentially large role that transaction costs play even in ostensibly liquid and low-frequency CTAs. In principle, our approach can be extended to other strategies; however, security selection ability and illiquid assets—both generally irrelevant for CTAs—can produce spurious market timing results in other strategies.

Section 1 contains a monthly attribution analysis of CTA and hedge fund indexes, illustrating differences between CTAs and other hedge fund strategies. In Section 2, we conduct full-period and rolling attribution analyses of CTA indexes at different time scales. Our technical contribution is in Section 3, where we construct sets of market timing factors at different frequencies and use them to estimate attribution over a range of time scales in a single model, thus capturing aggregate timing skill across multiple horizons. We then apply this analysis to CTA and Macro indexes. In Section 4, we illustrate our approach on individual CTA funds.

Related research

Much of the returns-based market timing research traces back to papers by Treynor and Mazuy (1966) [TM] and Henriksson and Merton (1981) [HM]. In TM, the authors add a quadratic term to the regression model; a positive and significant coefficient for this term corresponds to convexity and market timing skill. In HM, the authors include a term that is the maximum of the equity market return and the risk-free rate, and a positive coefficient indicates skill at tactically shifting between equities and cash. Glosten and Jagannathan (1994) generalize the HM approach, approximating the value of a managed portfolio by the value of the set of options used to replicate its payout. Their work resembles HM when just one option on the index is used. Jiang (2003) uses a non-parametric approach to market timing analysis, based on the idea that a fund with timing ability should rise significantly when a market is up and fall slightly when it is down.

Research on market timing ability has focused on actively managed mutual funds. One challenge has therefore been to disentangle market timing effects from security selection and style effects; Admati *et al.* (1986) show that it is difficult to arrive at rigorous and consistent definitions of timing and selection activities. By focusing a set of funds—CTAs—that do not engage in individual security selection, we reduce this difficulty.[13] Another challenge in isolating market timing skill is that some lagged, publicly available data have been shown to have predictive power for markets; an example is the dividend yield for equity markets. Ferson and Schadt (1996) include lagged conditioning variables to account for the use of public information that otherwise might be confused with timing skill. Because CTAs are systematic funds that only use past prices of the indexes themselves to trade, however, lagged macroeconomic data are not an important part of their timing decisions. For Macro hedge funds, however, security selection and lagged public information may need to be included.

Some recent papers have studied market timing by hedge funds. Agarwal and Naik (2004) use at-the-money and out-of-the-money S&P 500 calls and puts to examine equity-oriented hedge funds. Chen (2005) studies the timing ability of hedge funds in their focus markets (determined by factor analysis and fund disclosures), finding significant timing skill. His use of a single focus market underscores the importance of parsimony in timing models; the four factors we use are all relevant to the CTAs we study, and even though we have hundreds of months or thousands of days of data, our multi-factor models typically have just 3–5 factors. Chen and Liang (2007) find evidence that self-classified market timing hedge funds can time the market, although small funds tend to do better. They also test for volatility timing and joint return/volatility timing skill.

Several authors have examined market timing across multiple assets. Aragon (2005) studies switching between stocks, bonds, and cash in balanced mutual funds. In his model, expected return rankings by asset class matter; i.e., a competitive dynamic asset allocation occurs. For CTAs, dynamic asset allocation generally arises from aggregating independent models that are long, short, or flat a given asset. Usually, the magnitude of the long/short signal does not affect the weight of a fund in each asset; it is only the directional forecast that is important. Chen *et al.* (2008) study challenges associated with measuring fixed income market timing skill. Spurious (i.e., non-market timing) convexity can enter from callable or convertible bonds; interim trading (higher frequency than available data) can affect results; stale bond pricing can shift returns from timing to selection skill; and public information about future asset returns can mimic timing skill. Since CTAs trade futures on bonds without call or convert features, in the most liquid bond markets, and since we use high-frequency data (relative to funds' models) for systematic funds, these concerns are lessened in our data set.

Fung and Hsieh (2001) study trend followers (CTAs) by using the payoffs from lookback straddle options. They compute primitive trend-following strategy (PTFS) returns for 26 markets, then combine them into five portfolios: stocks, bonds, currency, commodities, and three-month interest rates. These PTFS portfolios are much better at explaining CTA returns than standard asset class factors, producing an adjusted R-squared of 48%. While we construct factors from four of their five asset classes (excluding short-term rates), our focus is not on *how* CTAs produce their forecasts, but rather on their effectiveness at timing these markets over different time scales and the resulting attribution.

A recent development with hedge funds is the availability of daily data, whereas monthly or even quarterly data were once the highest available frequency. Billio *et al.* (2009) study returns of four daily hedge fund indexes and compare them with those of monthly hedge fund indexes. Several authors have recognized the importance of funds' trading frequency relative to that of their reported return data in measuring timing ability. Goetzmann *et al.* (2000) show that the HM timing measures are weak and biased down when applied to monthly returns of daily market timers. They construct a monthly factor based on cumulated daily put options on an index to capture daily timing skill. Bollen and Busse (2001) find evidence of market timing in the daily returns of mutual funds and run separate tests for daily and monthly timing ability.

1 Monthly attribution analysis for hedge funds and CTAs

In this section, we use a model with directional and absolute factor returns to decompose hedge fund and CTA index returns into a beta contribution, market timing alpha, and residual alpha. We chose 17 indexes from HFRI, representing a cross-section of hedge fund strategies[14] from January 1990–May 2009, a total of 233 months. For CTA index returns, we use the BarclayHedge CTA Index, obtained through Bloomberg, over this same 233-month period. Although the BarclayHedge Index has a longer history, we used the same time period as the HFRI indexes both to facilitate comparison and because the volatility of the BarclayHedge Index was higher prior to 1990; see Figure 1. A vertical bar indicates the subperiod we use. Self-reporting of returns by managers to these indexes induces a potential bias: managers not wishing to report an unfavorable return may simply stop reporting; alternatively, managers who have done well and no longer need to raise assets may also cease reporting. Academic research indicates that self-reporting exerts an upward bias on index returns.[15]

We use a set of four benchmark indexes—one for each major asset class (equities, fixed income, currencies, and commodities)—along with the absolute values of their returns to analyze hedge fund and CTA index returns. We chose as factors

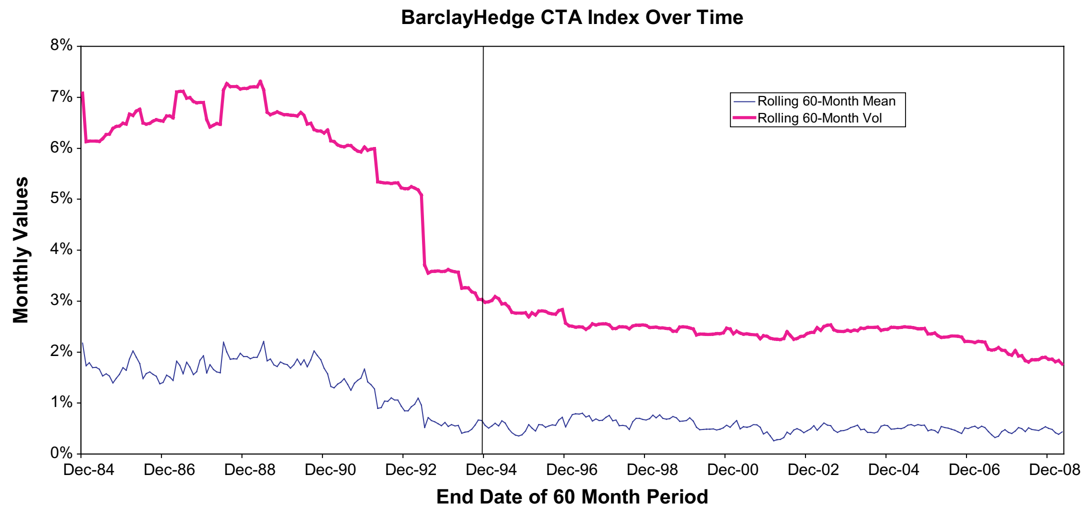

Figure 1 Rolling 60-month average return and volatility for the BarclayHedge CTA Index (Source: Bloomberg).

the S&P 500, the US 10-year Treasury Note,[16] the US dollar index (DXY), and the Goldman Sachs Commodity Index (GSCI), because of their relevance to the trading by CTAs, their liquidity, and their low long-run correlations. Absolute values of returns for these factors are included as proxies for market timing abilities of funds in these markets. At a given frequency—monthly, say—a fund with perfect foresight as to the direction of market return, and that can adjust its exposure once per period, would have a return stream proportional to the absolute value of returns for that market. The model is:

$$R_t = \alpha + \sum_{j=1}^{4} \beta_j F_{j,t} + \sum_{j=1}^{4} \gamma_j |F_{j,t}| + \varepsilon_t. \quad (1)$$

In Eq. (1), subscript j denotes the four indexes (equities, fixed income, currencies, or commodities); coefficients β_j are the directional factor sensitivities; and coefficients γ_j are the sensitivities to absolute asset class returns. We interpret positive and significant estimates, $\hat{\gamma}_j$, as evidence of market timing ability.

We display the average contributions for each index from three sources in Figure 2: beta contribution is shown in yellow, market timing alpha is shown in red, and residual alpha is shown in blue. The multi-factor models are parsimonious: typically 3–4 factors are used per index for 233 months of data. For each index, we only included factors with significant individual correlations, then combined them to maximize the adjusted R-squared of the multi-factor model. In some cases, individually significant factors did not appear because they were correlated with other factors. Segments lying below zero in Figure 2 correspond to negative average contributions, while the overall average return of each index is the *net* height of the positive segments minus the negative segments. For most strategies, yellow segments, corresponding to beta contributions, are relatively small—exceptions are Quantitative Directional funds, Emerging Market funds, and Short Bias funds (a negative contribution, as short equity exposure reduced average returns in this period).

For most strategies, the red segments for absolute factor return contributions are negative. One interpretation of this result is that funds comprising these indexes exhibited negative market timing alpha. However, this implies that thousands of managers, across most hedge-fund strategies, and

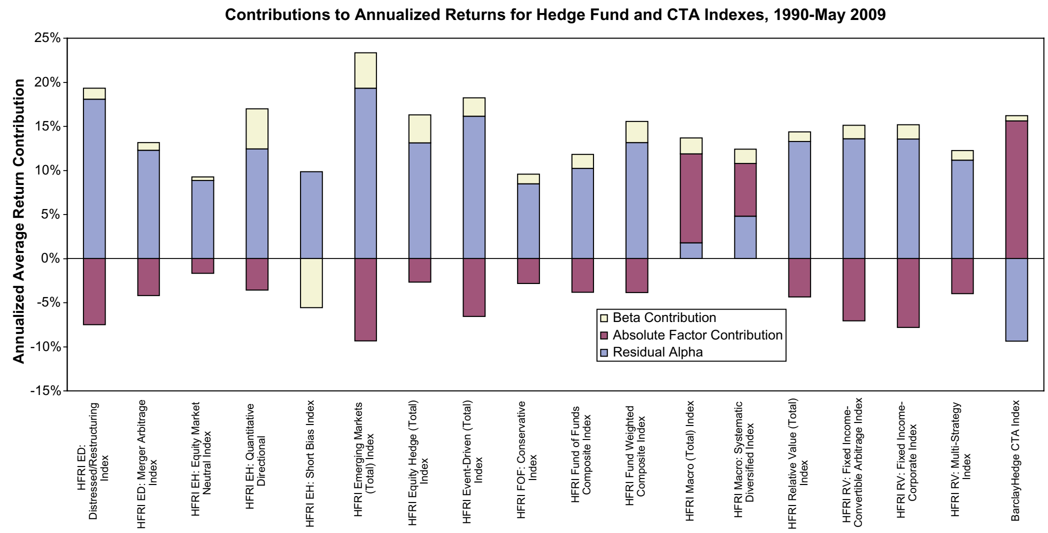

Figure 2 Attribution analysis for 17 HFRI hedge fund indexes and the BarclayHedge CTA Index (Sources: Hedge Fund Research, Bloomberg, and FactSet).

over a 20-year period had significant and economically meaningful negative market timing skill. While this may be possible, it seems to strain credibility. More importantly, timing market direction is an insignificant part of most of these strategies, as the relative value nature of their trades or the idiosyncratic details of a stock or bond drive returns. From this standpoint, it would be coincidental if managers' trades occurred with (or against) market moves.

Alternatively, negative contributions from market timing factors could be due to security selection ability[17] or sensitivity to market illiquidity. Regarding this latter point, the factors we chose are among the most liquid indexes, while many hedge funds are sensitive to a number of less-liquid markets: small-cap equities, emerging markets, convertible bonds, distressed securities, etc. In declining markets, correlations between liquid and less-liquid markets often increase, giving the appearance of higher liquid market sensitivity; this would give apparent negative timing alpha. Previous research has shown that, for example, merger arbitrage funds have higher equity betas in down markets than in up markets; this is not due to poor market timing *per se*, but rather to the widening of spreads on deals as conditions worsen.[18] Negative timing contributions in Figure 2 are, in fact, largest for strategies sensitive to market illiquidity: Distressed Securities, Emerging Markets, Event Driven, Convertible Arbitrage, and Corporate Credit.

Four strategies have non-negative timing contributions: Short Bias, Macro—both Macro Total and Macro Systematic Directional–and CTAs. Of these, Short Bias funds do not exhibit market timing skill, whereas timing gains are a substantial portion of macro funds' returns. This latter point is natural, as macro funds use directional strategies, among others. Residual alpha is negative for the CTA index. In other words, over 100% of CTA index average return comes from gains due to tactical adjustment of exposure to liquid indexes. What does the negative residual alpha for the CTA index represent? A potential explanation is transaction cost. Since funds must pay these costs irrespective of whether their bet was correct, they should be uncorrelated with market timing returns, and therefore appear as (negative) alpha. Anecdotally, many CTAs are aware of their

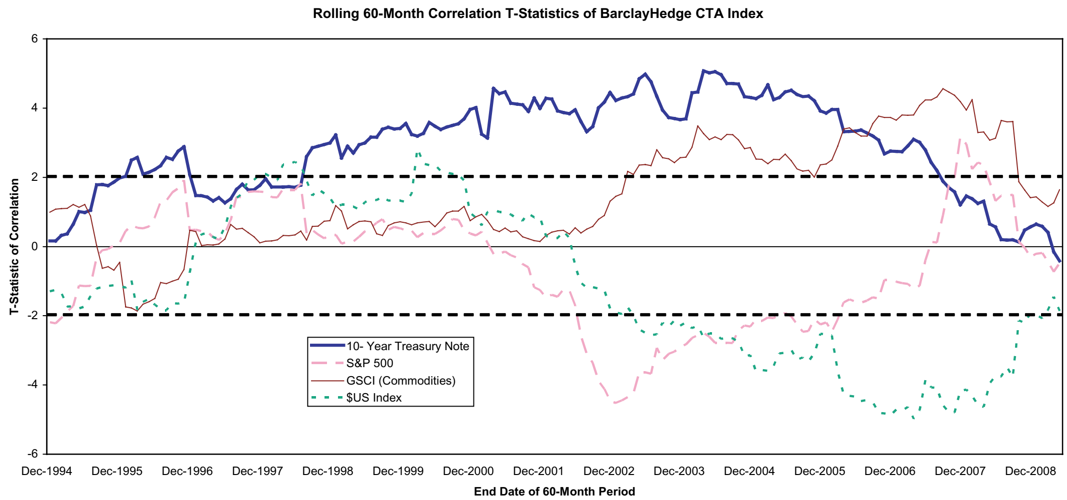

Figure 3 Rolling 60-month correlation T-statistics of the BarclayHedge CTA Index with directional factors (Sources: Bloomberg and FactSet).

size and its impact on transaction costs. While longer term funds may have more capacity than short-term funds, some long-term funds are also much larger.

Rolling Correlations of CTAs to Beta and Timing Factors

Exposures of CTA funds to the four asset classes evolve gradually over time. In Figure 3, rolling 60-month factor correlations show how directional exposure evolved over time for CTAs. The T-statistics (i.e., statistical significance) of correlation are shown for the four beta factors; values over 2 in magnitude–indicated by dashed lines—are significant. Until recently, CTAs, in aggregate, were long bonds (positive blue curve) in every 60-month period. Equity exposure (dashed pink curve) varied from positive to negative over time. Since 2002, CTAs have been long commodities (brown curve) over 60-month periods. They also began cutting their US dollar exposure in 1999 (dotted green curve) and have been short dollars since 2002.

At a monthly time scale, the market timing ability of CTAs varies by factor. Figure 4 shows rolling 60-month correlation T-statistics of CTAs with the four *absolute return* factors; positive and significant values (i.e., over 2) are consistent with timing ability. For example, the dotted green curve consistently exceeds two, indicating that CTAs were successful in tactically adjusting US Dollar exposure. In addition, the dotted pink curve is always positive and often above two, indicating that CTAs also had some success in adjusting their equity market exposure during this time. In aggregate, CTAs were less successful at tactically adjusting exposures to bonds and commodities. The blue curve (bonds) is only significant in 2001 and 2002, and is frequently negative. The thin brown curve for commodities also veers from negative to positive, but is rarely significant. None of the rolling correlations are significantly negative, however.

2 Variation in market timing alpha with time scale

In this section, we study how the market timing ability of CTAs varies depending on the time scale of measurement. If we repeat the preceding rolling correlation analysis on a daily time scale,

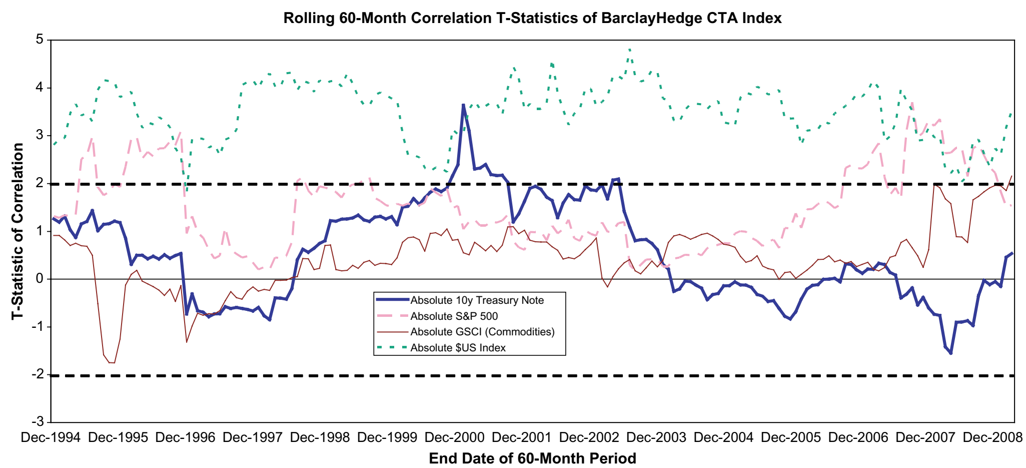

Figure 4 Rolling 60-month correlation T-statistics of the BarclayHedge CTA Index with monthly absolute returns of four indexes (Sources: Bloomberg and FactSet).

instead of a monthly time scale, the results are similar for the directional (beta) factors, but different for the market timing factors. Using daily data for the Newedge CTA Index since 2000, in Figure 5, we show the rolling 60-day T-statistics to four indexes.[19] While the rolling periods are smaller than before (less than 3 months vs 60 months), the month-to-month behavior is similar to that of the rolling exposures[20] in Figure 3. For example, bond exposure (pink curve) is generally positive in Figure 5 (as in Figure 3), while equity exposure (blue curve) in Figure 5 is negative prior to 2003, then generally positive through 2007, before turning negative until early 2009. This traces the fall, rise and fall of the rolling equity correlation curve in Figure 3.

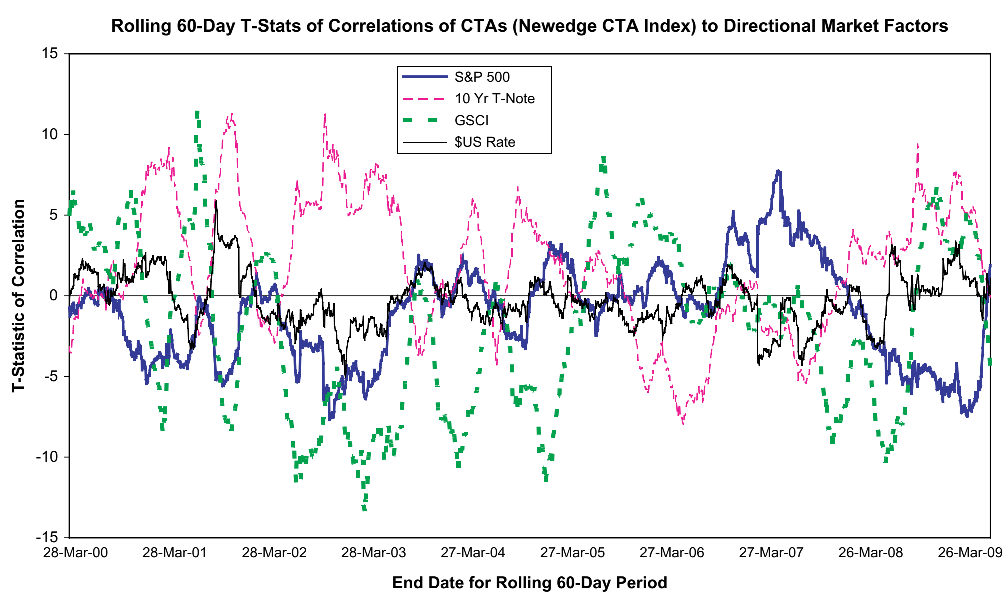

Figure 5 Rolling 60-day correlation T-statistics of the Newedge CTA Index with four directional factors (Sources: Newedge, Bloomberg and FactSet).

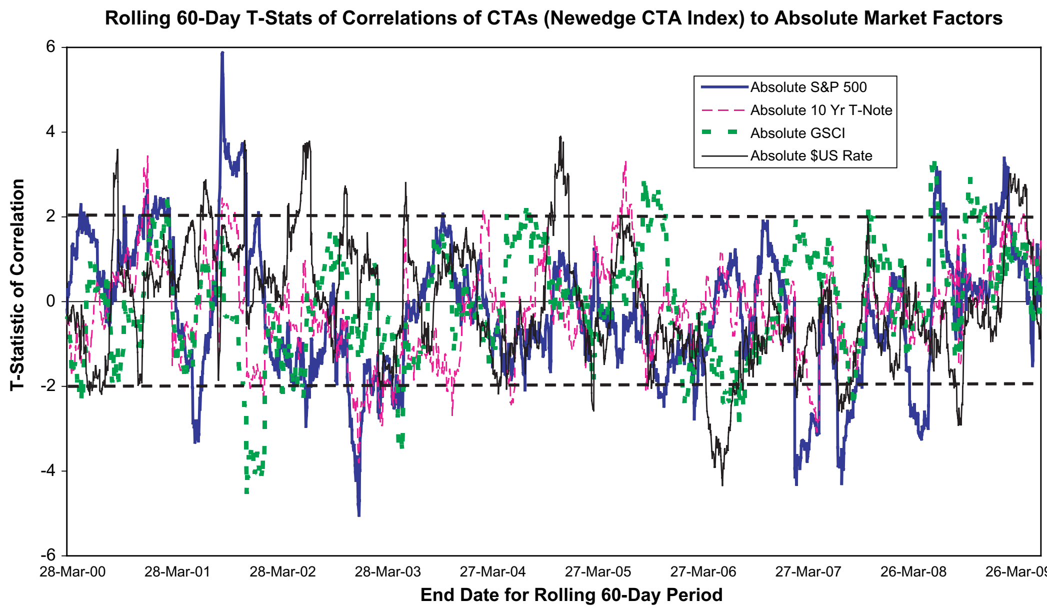

Figure 6 Rolling 60-day T-statistics of correlations of the Newedge CTA Index with four absolute daily index returns (Sources: Newedge, Bloomberg and FactSet).

Rolling 60-day correlations of the Newedge CTA Index with four daily *absolute return* factors, shown in Figure 6, are generally insignificant and more-often negatively significant than positively significant. The evidence in Figure 6 is therefore negative regarding consistent *daily* market timing ability by CTAs. For example, while CTAs were fortuitously short equities going into the September 11, 2001 terrorist attack (upward spike in blue curve), they also missed the rally in equities in the spring of 2003 (downward spike in blue curve). Given the multi-month nature of CTA holding periods and the potential lack of correlation between daily and monthly absolute returns, this result is not surprising.

A more recent index, the Newedge STTI Index, tracks the performance of short-term futures traders. In Figure 7, rolling 60-day correlation T-statistics to the four index returns are shown over the STTI's 18-month (377 trading day) history. Short-term traders were short equities until quite recently, while they were generally long bonds.

Evidence for daily market timing ability in the Newedge STTI Index is more compelling than that for the Newedge CTA index. In Figure 8, the rolling 60-day correlation T-statistics for equity (blue curve) and currency (green curve) are consistently positive and often significant. For bonds, the correlation is less-often significantly positive, but still rarely negative. Meanwhile, none of the rolling correlations is ever significantly negative. This result is consistent with funds in the STTI index using shorter term forecasting models.

Multi-factor attribution analysis at different time scales

We compare attribution from beta contributions, market timing alpha and residual alpha at several time scales by estimating model (1) at different data frequencies. Results, including T-statistics for each factor are shown in *Table 1* (Appendix A). Each row in Table 1 represents a different time scale; i.e., a different set of estimates for (1). Shaded factors within each row are the factors that were ultimately present in the multi-factor model

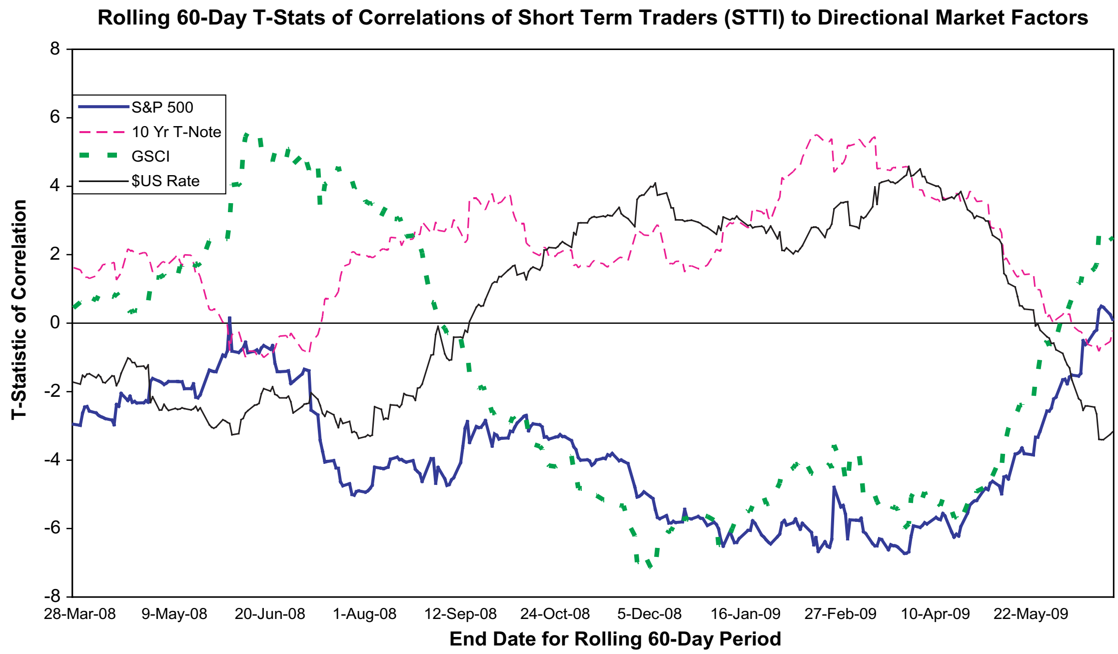

Figure 7 Rolling daily correlation T-statistics of the Newedge STTI Index with four market factors (Sources: Newedge, Bloomberg, and FactSet).

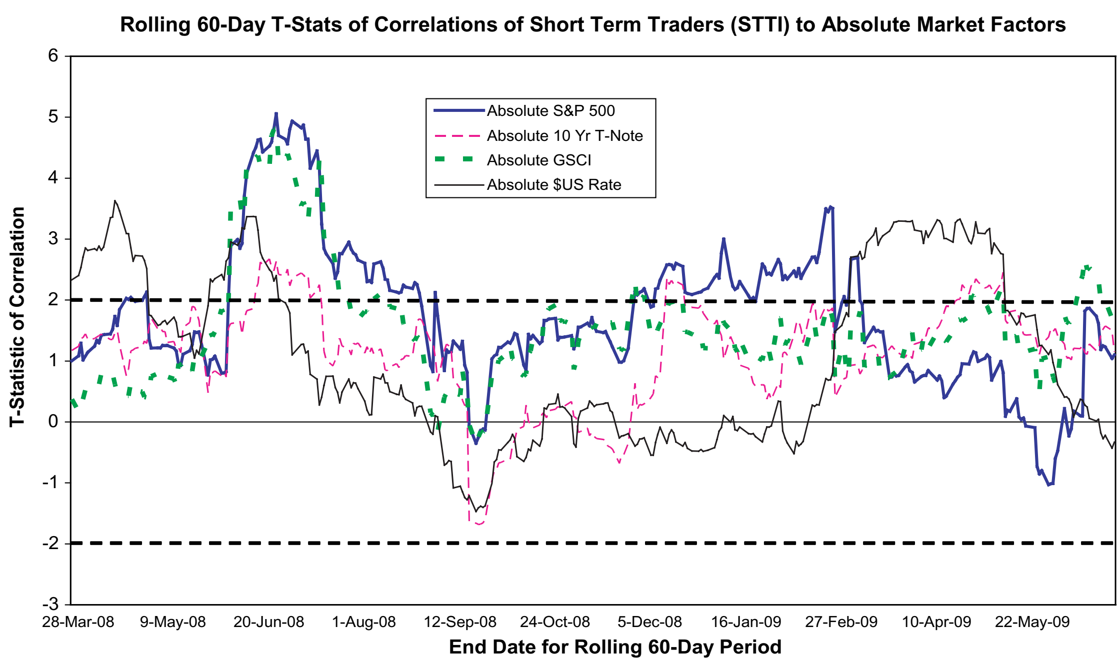

Figure 8 Rolling 60-day correlation T-statistics of the Newedge STTI Index with four absolute daily factor returns (Sources: Newedge, Bloomberg and FactSet).

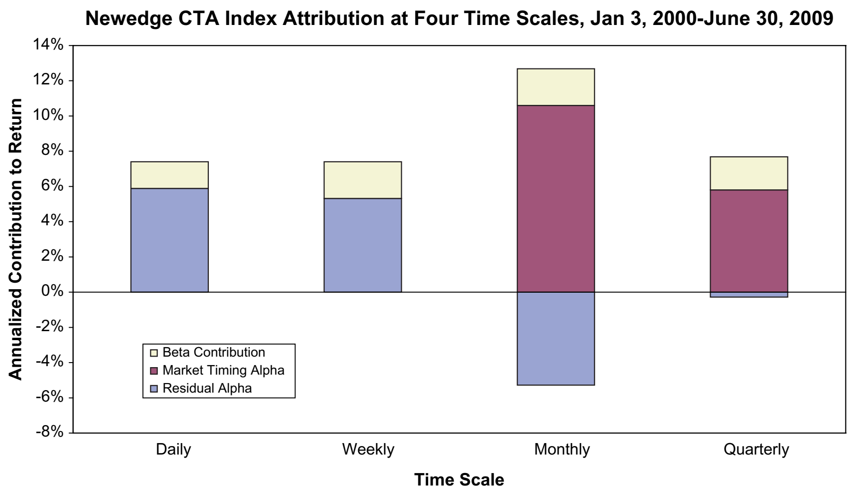

Figure 9 Attribution Analysis for the Newedge CTA Index at Four Time Scales, Jan 2000–June 2009 (Sources: Newedge, Bloomberg, and FactSet).

for that index/time scale. From the green-shaded multi-factor models, we compute attribution by time scale for the three CTA indexes. Contributions from the first set of four columns comprise the directional (beta) attribution; contributions from the second set of four columns comprise the market timing alpha, and residual alpha is the remaining contribution.

For the Newedge CTA and BarclayHedge CTA indexes, directional beta T-statistics are similar in whether or not they are significant at each time scale. The selected (i.e., green-shaded) beta factors for the multi-factor models are also quite similar, despite different time periods for each index; the only difference is that DXY appears in the monthly model for Newedge, but not for BarclayHedge, although it is significant for both. For both indexes, significance of absolute return factors varies greatly with data frequency. Absolute return factor significance is similar for both indexes at the monthly and quarterly time scales, although currency timing is the only significant factor for Newedge monthly, while equity and currency timings are both significant for BarclayHedge. Only equity timing is significant for both indexes at a quarterly time scale.

In Figure 9, we show attribution for the Newedge CTA Index over the January 2000–June 2009 period for daily, weekly, monthly, and quarterly data. In all four columns, the beta contribution (yellow segment) is quite similar in Figure 9. This is as expected: excluding compounding and estimation error, the factor sensitivities should be unchanged at different time scales. Absolute return contributions vary dramatically by time scale, however. Since annualized average returns in each column are identical, residual alpha (blue component) must make up the difference with this fixed total; it is positive at daily and weekly frequencies and negative at monthly and quarterly frequencies.

In the Jan 3, 2000–June 30, 2009 period, the Newedge CTA Index does not exhibit market timing skill at daily or weekly time scales. At the monthly time scale, however, market timing is the dominant contributor to returns, with residual alpha being negative. At the quarterly time scale, where we have 38 data points, market timing is also important, though less dramatic than the monthly time scale. With just nine non-overlapping years of history, we do not include annual frequency attribution in Figure 9. One

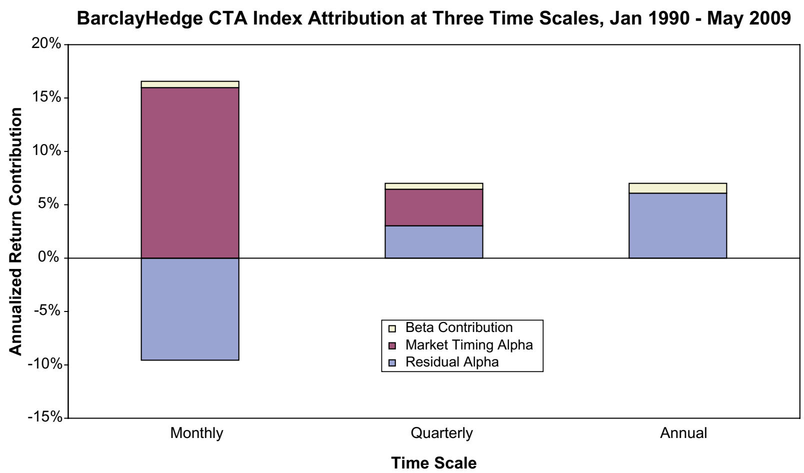

Figure 10 Attribution analysis on three time scales for the BarclayHedge CTA Index, Jan 1990–June 2009 (Sources: Bloomberg and FactSet).

question we cannot address from this analysis is the extent to which the market timing ability present at the monthly and quarterly time scales is incremental or capturing the same effect; we address this issue through multiple time scale analysis.

For the BarclayHedge CTA Index, we use monthly data from January 1990 to May 2009 (233 months), allowing us to estimate monthly, quarterly and annual attribution; these three time scales are shown in Figure 10. Annual attribution is only through December 2008. All columns are normalized to have the same annualized return (i.e., same height of the net positive minus negative segments for each bar). Beta contributions (yellow bars) are small and similar across time scales. Like the Newedge CTA Index, market timing is the dominant contribution at the monthly time scale. Also like Newedge, there is a large but less significant contribution at the quarterly time scale. At the annual time scale, we do not observe market timing alpha, although the annual equity timing factor is significant at the 10% level.

In Figure 11, we show attribution at daily, weekly and monthly time scales for the Newedge STTI Index, an index of short-term futures traders. It is available daily from Jan 2, 2008 and we use values through June 30, 2009. Columns are normalized to an annualized return of 7.4% (i.e., *net* height of each column is the same). Beta contribution (yellow segment) is similar across time scales and relatively small in magnitude; this contribution is somewhat larger at the monthly time scale, possibly due to estimation error with only 18 monthly data points. Market timing alpha (red segment) is economically significant at all time scales, but is more pronounced at a daily frequency. Significant timing variables from Table 1 are equities at the daily time scale and commodities at weekly and monthly time scales.

While Figure 11 shows apparent market timing alphas at several time scales, it is unclear whether these alphas represent distinct effects or whether they are actually picking up the same effect. In the latter case, it might be that weekly market timing is highly correlated with daily market timing, and weekly timing alpha would be subsumed by daily timing alpha if we could measure them simultaneously. As a corollary, unless we can measure the combined effects of market timing across time

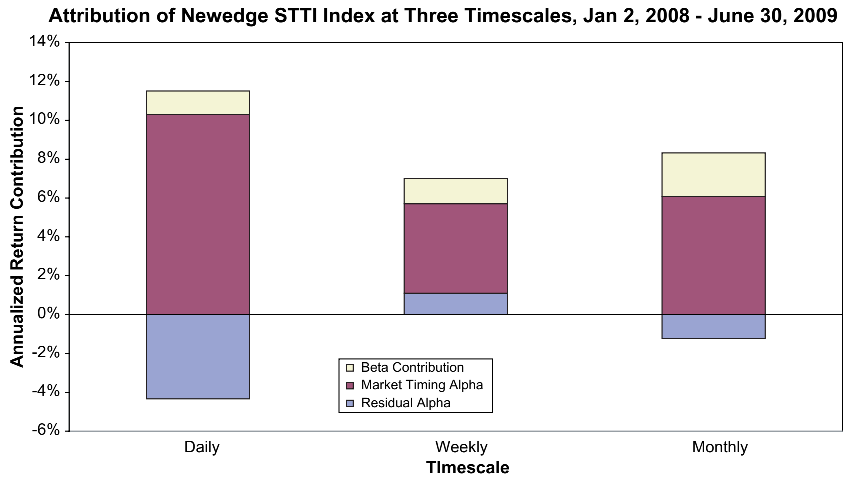

Figure 11 Attribution analysis for the Newedge STTI Index on three time scales, Jan 2008–June 2009 (Sources: Newedge, Bloomberg, and FactSet).

scales, we cannot accurately estimate residual alpha. In the next section, we use a model that combines market timing factors at different time scales into a single equation, thus enabling a more comprehensive market timing analysis.

3 Multiple time scale analysis of market timing

In this section we describe a method for combining market timing variables over multiple time scales into a single regression model. We then apply this model to CTA and Macro Hedge Fund indexes.[21] Last section, we saw that CTA indexes exhibited varying degrees of market timing skill, depending on the time scale of data used. In some cases, such as the STTI Index, positive timing alpha was seen across a wide range of time scales. This difference in time scales poses a technical challenge to modeling: if we use, say, a model with daily CTA returns, daily index returns and daily absolute returns, then append quarterly absolute return factors to the equation, the quarterly variables will have extreme autocorrelation at a daily time scale (barely changing from day-to-day). This autocorrelation makes it difficult to estimate models. We therefore use a different approach to incorporate low-frequency timing variables into models using high-frequency data.

Our approach starts with the observation that absolute return timing factors at a given horizon are equivalent to once-per-period trading—at the beginning of the period and with advance knowledge of the direction of return for the period. If a fund is "long" a factor for the period, each sub-period timing-factor return has the same sign as the index return; if it is "short" the factor for the period, each sub-period timing-factor return has the opposite sign as the index return. We form a set of sign factors, one per index, at weekly, monthly, quarterly, and annual time scales, and create non-linear timing factors by multiplying daily index returns by sign factors corresponding to timing at different scales. For a daily series of fund returns, R_t, and index returns, $F_{j,t}$, for $j = 1, \ldots, 4$, we define a daily series of weekly sign factors, $S^{(W)}_{j,t}$ for each factor $j = 1, \ldots, 4$ by:

$$S^{(W)}_{j,t} = \begin{cases} +1, & \{\text{return of factor } j\} \geq 0 \text{ in } \textbf{week} \\ & \text{in which day } t \text{ is located} \\ -1, & \text{otherwise.} \end{cases}$$

To make this more concrete, suppose that over a three-week period (without any market holidays), factor j is consecutively down, up, and up by week (i.e., negative, positive, and positive returns by week). Then the corresponding 15-day sequence for the weekly sign factor, $S_{j,t}^{(W)}$, is: "$-1, -1, -1, -1, -1$, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1". If a fund's historical return stream begins mid-week, the weekly sign factors are available starting on its first day—there is no need to wait until the start of the next week. However, in the middle of the *current* week, the weekly sign factors are not yet available: it is only when the sign if the weekly returns for those factors are known that the daily sign factors for that week can be determined.[22] By construction, sign factors are forward looking; that is, they require knowledge of the sign of upcoming index returns.

Similar to the weekly sign factors, we also define monthly sign factors, $S_{j,t}^{(M)}$; quarterly sign factors, $S_{j,t}^{(Q)}$; and annual sign factors, $S_{j,t}^{(A)}$. For a given daily index return series, monthly sign factors are either $+1$ each day of a month or -1 each day of a month, depending on whether the index is up or down, respectively, for the month. Likewise, quarterly and annual sign factors have the same value for each day within a given quarter or (calendar) year, depending on the sign of the factor return in those periods. We then multiply the sign factors by the daily factor returns to create timing variables at each time scale; these multiple time scale factors are then combined in a daily regression model[23]:

$$R_t = \alpha + \sum_{j=1}^{4} \{\beta_j F_{j,t} + \gamma_j^D |F_{j,t}| + (\gamma_j^W S_{j,t}^{(W)} + \gamma_j^M S_{j,t}^{(M)} + \gamma_j^Q S_{j,t}^{(Q)} + \gamma_j^A S_{j,t}^{(A)}) F_{j,t}\} + \varepsilon_t. \quad (2)$$

The first two sets of terms within the sum carry over from last section: daily index returns, with coefficients β_j, and daily market timing terms, with coefficients γ_j. Now there are additional terms, with coefficients that correspond to weekly, monthly, etc. timing. By construction (and ignoring compounding effects), the average over (daily) time of the weekly timing factor (sign factor times factor return) is the average weekly absolute return for the factor; see Appendix B for a derivation. This equivalence establishes that the timing factors in Eq. (2) are capturing effects similar to the separate absolute value models at different time scales. Thus, estimated gamma coefficients in Eq. (2) represent sensitivity to market timing at the corresponding time scales.[24]

In Table 9, Appendix A, we show the correlations of the timing factors for daily data from January 2000–June 2009; correlations are similar in the recent STTI period. Correlations above 0.3 in magnitude are shaded. In general, correlations among directional and timing factors are low; exceptions are daily/weekly timing correlations for the same asset (i.e., equity timing at daily and weekly time scales has a 0.46 correlation—not redundant, but we might not observe separate contributions from daily and weekly timing in a multifactor model). Weekly/monthly timing correlations are generally low, while monthly/quarterly correlations are larger.

Since daily data is not available for some funds and indexes, we also define quarterly and annual sign factors for *monthly* index return data.[25] We use a T subscript for monthly returns, to distinguish them from daily returns. Monthly sign factors are constructed similarly to daily sign factors; e.g., if index returns are positive/negative/positive over three consecutive quarters, the corresponding sequence of nine monthly sign factors is: "1, 1, 1, -1, -1, -1, 1, 1, 1". The resulting monthly multi-scale timing model is:

$$R_T = \alpha + \sum_{j=1}^{4}\{\beta_j F_{j,T} + \gamma_j^M |F_{j,T}| + (\gamma_j^Q S_{j,T}^{(Q)} + \gamma_j^A S_{j,T}^{(A)}) F_{j,T}\} + \varepsilon_T. \quad (3)$$

Correlations of these monthly scale timing factors with each other and with directional factors are shown in Table 6 for the January 1990–June 2009 period. Correlations between beta factors and timing factors are low, except for annual timing factors in the same asset. Quarterly and monthly timing variables in the same asset have high correlations (over 0.7). Quarterly/annual and monthly/annual correlations among timing variables for the same asset are moderately high (around 0.4), as well.

Application of multiple time scale analysis to CTA and Macro indexes

We now apply the above analysis to six CTA and Macro indexes. Results are summarized in Table 10, at the conclusion of this section. Since annual timing factors are not yet available for 2009, we conduct separate analyses on two CTA indexes over the full period (through June 2009) and through December 2008. For each index, there is a table in Appendix A, showing details by factor, and a bar chart showing attribution with beta-only factors (first column); beta and highest frequency timing factors (second column); and beta and multiple scale timing factors (third column). The third column has market timing alpha broken down by time scale; residual alpha generally differs between the second and third columns, as well.

We begin with the BarclayHedge CTA Index over the January 1990–June 2009 period, showing monthly and quarterly timing. Next is the Newedge CTA index over the January 2000–June 2009 period, again omitting annual timing variables. We then re-run the analysis on both indexes through December 2008, so that we can include annual timing factors. Next, we conduct analyses for the HFRI Macro Total and HFRI Macro Systematic Diversified Indexes for 1990–2008. In all cases thus far, the monthly model (3) is used. We then turn to the STTI index over the January 2008–June 2009 period, using the daily model (2). Finally, we use the daily model for the HFRX Macro index from April 2003–December 2008.

Figure 12 shows multiple time scale attribution for the BarclayHedge CTA Index from January 1990–June 2009; details are in Table 2. Across all columns, the beta contribution is consistently small. With only monthly timing factors, equity timing contributes 4.1% per year and currency timing contributes 11.6%; adjusted R-squared rises from 0.098 to 0.228 when monthly timing is included. When quarterly timing variables are also included, monthly equity timing drops out, while quarterly equity timing contributes 2.2%; this is consistent with the greater significance of quarterly equity timing in Table 1. Meanwhile, monthly currency timing is reduced to 8.2% per annum, while quarterly currency timing contributes 2.4%. Although the currency timing variables are correlated, each is significant in the multi-factor regression. Residual alpha increases from −9.5% (monthly only) to −6.7% (monthly/quarterly), while adjusted R-squared rises to 0.245 in the monthly/quarterly timing model.

Figure 13 shows multiple time scale analysis for the Newedge CTA Index for January 2000–June 2009; details are in Table 3. Beta contributions are consistent across models—though relatively larger than in Figure 12—and quarterly timing variables contribute when

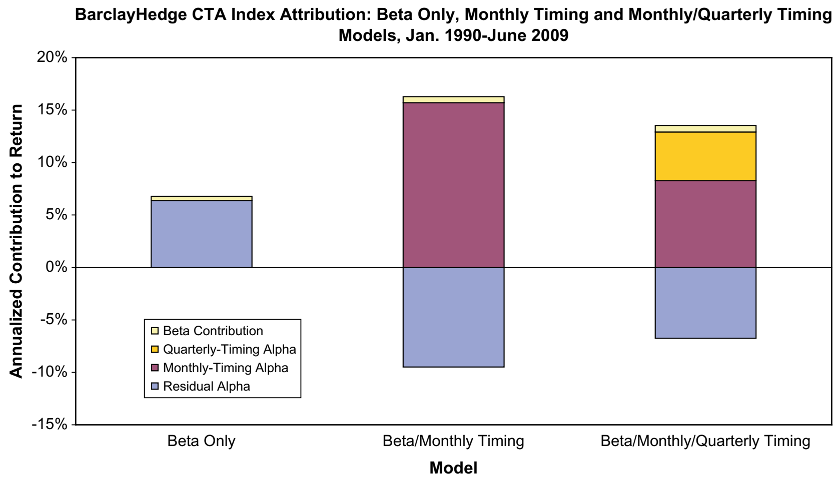

Figure 12 Multiple time scale attribution analysis of the BarclayHedge CTA Index, Jan 1990–Jun 2009 (Sources: Bloomberg, and FactSet).

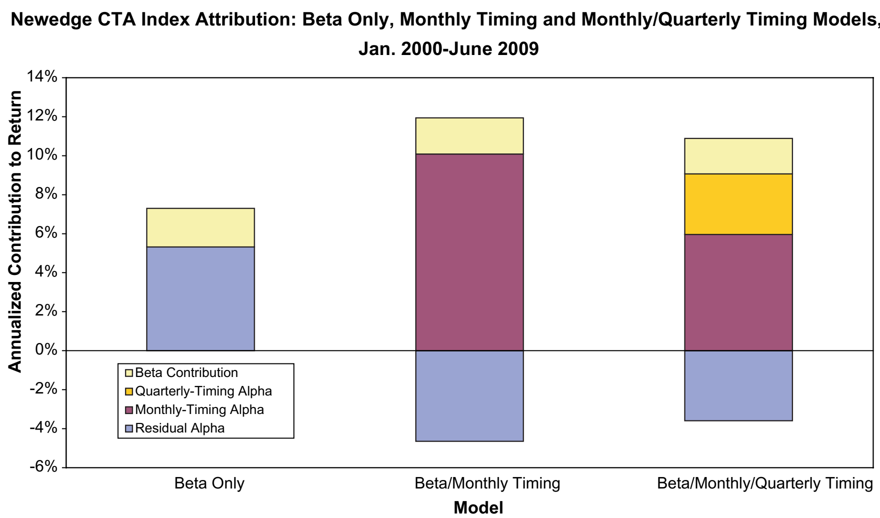

Figure 13 Multiple time scale analysis of the Newedge CTA Index, Jan 2000–June 2009 (Sources: Newedge, Bloomberg, and FactSet).

included (third column). With only monthly timing variables, currency timing contributes 10.1% per year, raising adjusted R-squared from 0.14 to 0.20. Including quarterly variables increases adjusted R-squared to 0.21, as monthly and quarterly currency timing contribute 6.0% and 3.1%, per year, respectively. Residual alpha increases from -4.6% to -3.6% when quarterly timing is included. Given the small increase in adjusted R-squared, the case for including quarterly currency timing is not especially strong in this example.

Since annual timing factors are significant, but not yet known for 2009 (at least not by us!), we re-run the prior two examples through December 2008 with annual timing factors. Figure 14 shows multiple time scale attribution for the BarclayHedge

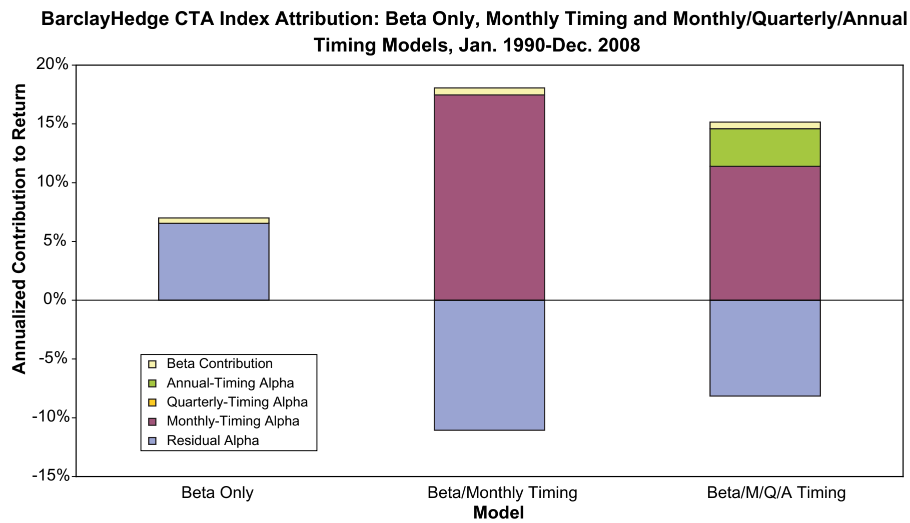

Figure 14 Multiple time scale analysis for the BarclayHedge CTA Index (with annual timing factors), Jan 1990–Dec 2008 (Sources: Bloomberg, and FactSet).

Index; details are in Table 4. While quarterly market timing alpha is subsumed by annual market timing alpha, the overall impact on residual alpha is not large compared with Figure 12; residual alpha again increases in the multi-scale case, rising from −11.1% to −8.1%. In the monthly timing only model, equity and currency timing again contribute. When quarterly and annual timing variables are also considered, monthly currency timing, annual equity timing, and fixed income timing contribute. Although annual timing alpha was not present in Figure 10, S&P 500 annual timing alpha, the main annual contribution in Figure 14, was significant at the 10% level in the single time scale case. In this context, the single- and multiple time scale results are not too dissimilar. Adjusted R-squared rises from 0.10 (beta only) to 0.24 (monthly timing only) to 0.29 (monthly and annual timing).

We show the 2000–2008 results for the Newedge CTA Index in Figure 15; details are in Table 5. In this case, when effects from both monthly and annual timing are included, alpha is more negative than with monthly timing alone. With monthly timing factors only, currency timing contributes 12.1% per year. When quarterly and annual variables are added, only annual equity timing contributes, at 4.9% per year, while the monthly currency timing contribution falls to 9.6% annually. Although there are only 9 years of data, four are positive for equities and five are negative; this 5/4 split is the best case for differentiating annual timing and equity beta factors. Equity returns were also quite volatile for several of these years. This combination helps to explain the presence of the annual equity timing factor. Adjusted R-squared increases from 0.13 (beta only) to 0.22 (monthly timing only) to 0.36 (monthly and annual timing).

This multiple time scale approach can be used for attribution of Macro hedge funds. In this strategy, due to variety of approaches, there may be positive alpha net of market timing ability due to stock or bond selection, and less-liquid market exposures. In Figure 16, we show the multiple time scale attribution for the HFRI Macro Total Index. While there is a small annual timing alpha and residual alpha decreases relative to the monthly

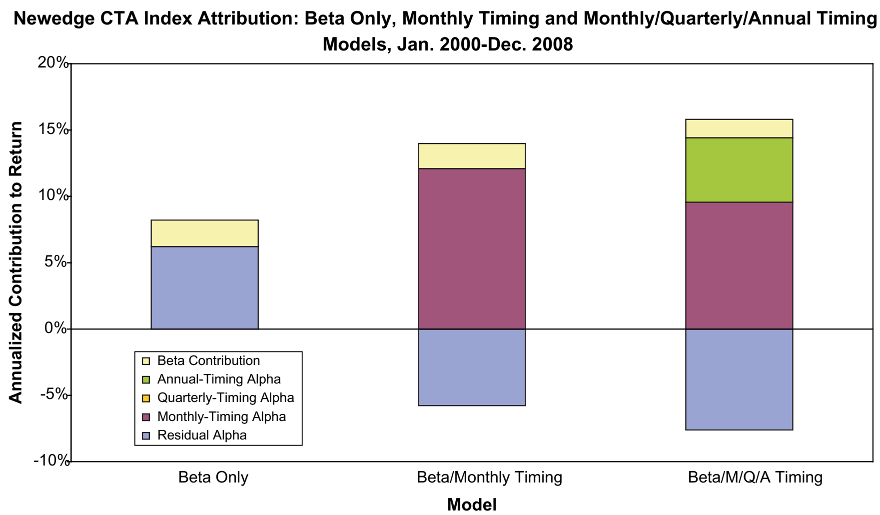

Figure 15 Multiple time scale analysis for the Newedge CTA Index (with annual timing factors), Jan 2000–Dec 2008 (Sources: Newedge, Bloomberg, and FactSet).

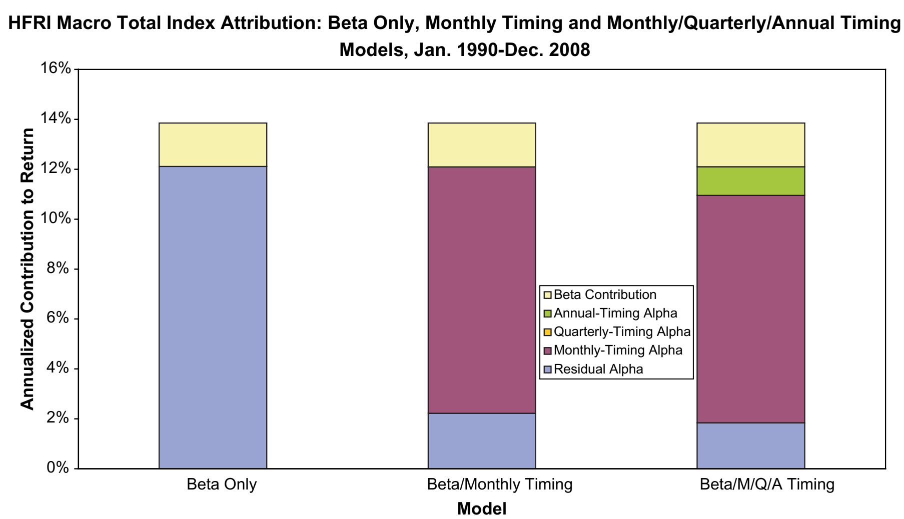

Figure 16 Multiple time scale attribution for the HFRI Macro Total Index, Jan 1990–Dec 2008 (Sources: Hedge Fund Research, Bloomberg, and FactSet).

timing only model, residual alpha remains positive. See Table 4, second-from-bottom row, for details.

In Figure 17, we display the multiple time scale analysis for the HFRI Macro Systematic Diversified Index; details are in Table 4 (bottom row). For this index, monthly timing alpha disappears entirely once quarterly and annual timing variables are included. The net effect on residual alpha is minor, however.

In Figure 18, we show the daily multiple time scale analysis for the Newedge STTI index; details are in Table 7. Daily timing alpha (equity) remains significant, but both weekly (currency) and monthly (commodity) timing effects enter in the third column. These variables, at their

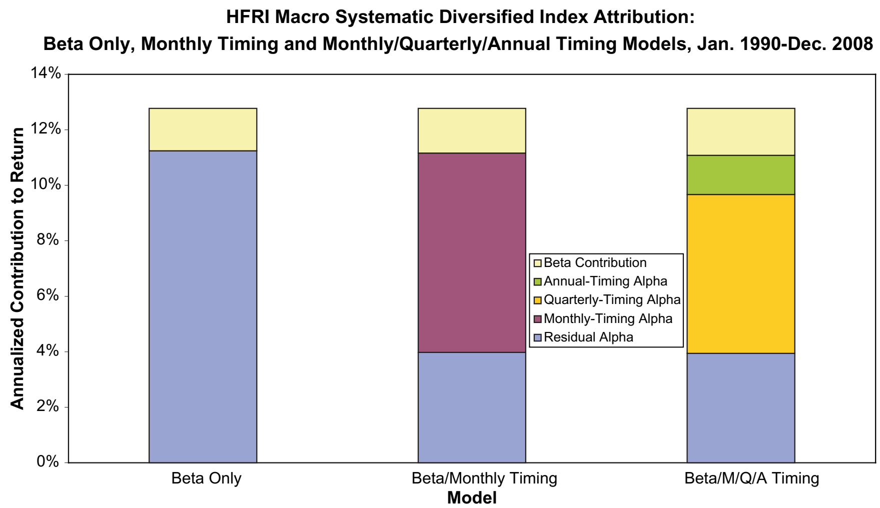

Figure 17 Multiple scale attribution for the HFRI Macro Systematic Diversified Index, Jan 1990–Dec 2008 (Sources: Hedge Fund Research, Bloomberg, and FactSet).

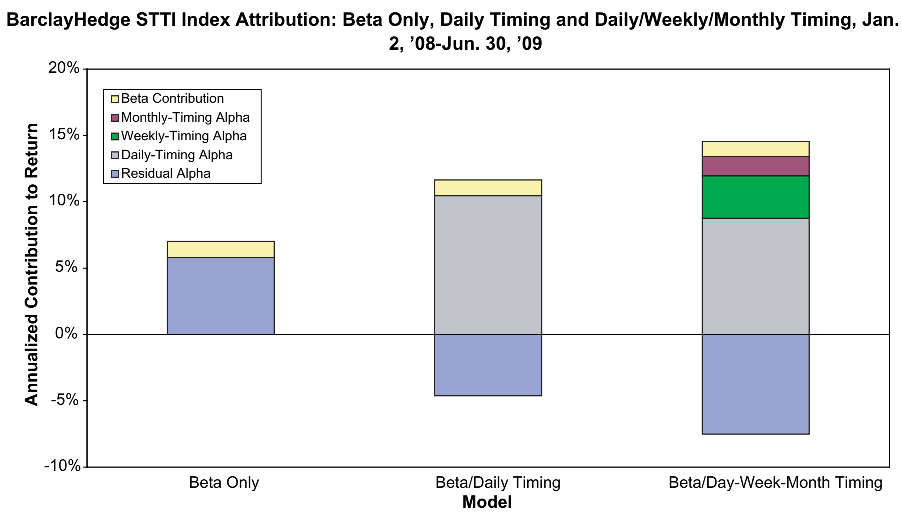

Figure 18 Multiple time scale attribution analysis for the Newedge STTI Index, Jan 2008–June 2009 (Sources: Newedge, Bloomberg, and FactSet).

respective frequencies, were also significant in the single time scale analysis in Table 1, bottom 3 rows.[26] Residual alpha is more negative, −7.5%, with weekly and monthly timing factors than with daily alone, −4.6%, and is statistically significant, as well. The beta contribution is constant across columns, differing by only 10 bp per year. Adjusted R-squared rises from 0.204 (beta only) to 0.226 (daily timing only) to 0.252 (daily/weekly/monthly timing).

We show daily multiple time scale analysis for the HFRX Macro index in Figure 19; details are contained in Table 8 (none of the daily or weekly timing variables is significant, and we omit these columns to make the results more legible).

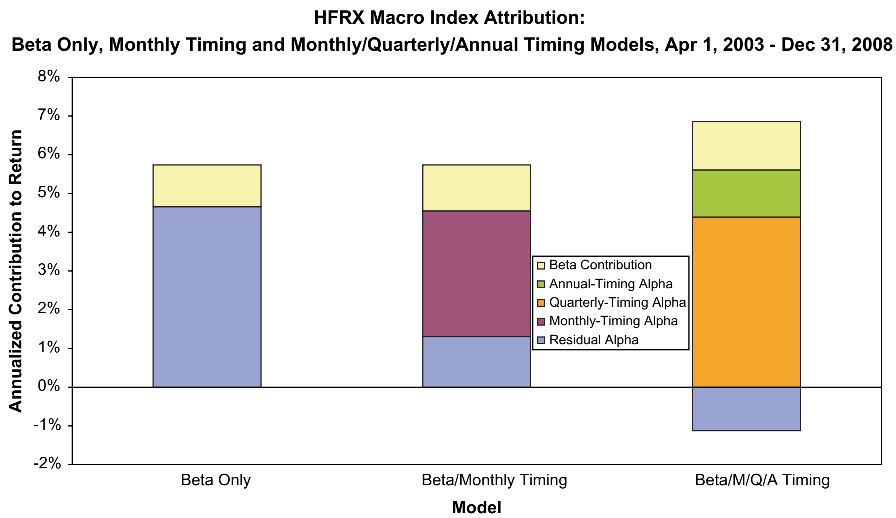

Figure 19 Multiple scale attribution for the HFRX Macro Index, Apr 2003–Dec 2008 (Sources: Hedge Fund Research, Inc., Bloomberg and FactSet).

When quarterly and annual timing variables are included, monthly timing alpha vanishes. Overall market timing alpha is higher in the third column—enough so that residual alpha is negative. Thus, even with the other avenues available to macro funds for generating returns (relative value, equity sectors, individual stocks and bonds, geographic focus, etc.), once market timing alpha at the quarterly and annual scales is isolated, residual alpha is negative. This does not mean that these non-timing activities do not produce alpha; rather, their alpha is insufficient to fully compensate for the transaction costs associated with market timing activities.

Quantitative results for all multiple time-scale models are summarized in Table 10, below.

4 Application to analysis of individual funds

In this section, we illustrate how multiple time scale analysis can be used to enhance understanding of individual managers. Investors can see whether a fund had consistent market timing ability at a single time scale, or whether its attribution was more haphazard. Also, a fund's residual alpha or its ratio of residual alpha-to-timing alpha and beta contribution can be compared with its peers and with itself over time; a more negative value can indicate higher trading costs. The two funds we discuss use modified (scaled and/or shifted) returns taken from the track records of actual funds. Our objective is not to make statements about the funds themselves; rather, it is to describe the types of issues this approach can raise.

Fund 1: Short-Term futures trader

We focus on annual returns, but use a June 30 year-end, to conceal the fund's identity. On days when Fund 1 strikes a NAV, but the NYSE is closed, we compound daily fund returns with those on the next NYSE open date to obtain Fund 1's return on that NYSE open date.

Daily equity market timing alpha is statistically significant for Fund 1, with a T-statistic of 7.1 over 1,259 trading days; this alpha was present throughout the period. In Figure 20, we plot the rolling 252-day (i.e., one year) T-statistics of absolute daily S&P 500 returns. For periods starting July 2005 and later, this quantity

Table 10 Summary of multiple time scale attribution for CTA and Macro Indexes (Sources: Hedge Fund Research, Inc., Newedge, Bloomberg and FactSet).
Multiple Time Scale Attribution Analysis for CTA and Macro Indexes

Index	Barclay Hedge CTA	Newedge CTA	Barclay Hedge CTA	Newedge CTA	HFRI Macro Total	HFRI Macro Systematic Diversified	Newedge STTI	HFRX Macro
Time Period	Jan 1990–Jun 2009	Jan 2000–Jun 2009	Jan 1990–Dec 2008	Jan 2000–Dec 2008	Jan 1990–Dec 2008	Jan 1990–Dec 2008	Jan 2008–Jun 2009	Apr 2003–Dec 2008
Number of Observations	234 mos.	114 mos.	228 mos.	108 mos.	228 mos.	228 mos.	377 days	1450 days
Residual Alpha*	−6.75%	−3.59%	−8.15%	−7.60%	1.84%	3.94%	−7.51%	−1.13%
Daily-Timing Alpha^	na	na	na	na	na	na	8.75%	0.00%
Weekly Timing Alpha	na	na	na	na	na	na	3.19%	0.00%
Monthly-Timing Alpha	8.28%	5.96%	11.39%	9.56%	9.11%	0.00%	1.45%	0.00%
Quarterly-Timing Alpha	4.64%	3.10%	0.00%	0.00%	0.00%	5.73%	na	4.39%
Annual-Timing Alpha&	na	na	3.21%	4.86%	1.15%	1.41%	na	1.22%
Beta Contribution	0.62%	1.82%	0.55%	1.39%	1.75%	1.70%	1.12%	1.26%
Number of Factors	6	5	6	4	4	4	5	5
T-Statistics of Residual Alpha	−2.38	−0.83	−3.08	−1.91	0.78	2.42	−1.99	−0.39
R-Squared	0.26	0.24	0.31	0.39	0.29	0.42	0.30	0.20
Adjusted R-squared	0.24	0.21	0.29	0.36	0.28	0.41	0.29	0.20

*All returns, including residual alpha are annualized values: 12× monthly average values or 252× daily average values.
^Contributions are annualized sums over all significant timing factors at a given time scale of products of coefficient times average factor return Daily or weekly data must be available for the index in order to estimate contributions at these frequencies.
For the Newedge CTA index, we omit daily and weekly contributions because single-factor analysis indicates they are not significant.
&It is not possible to use annual timing factors for 2009 data until the calendar year is finished and the direction of market return is known.

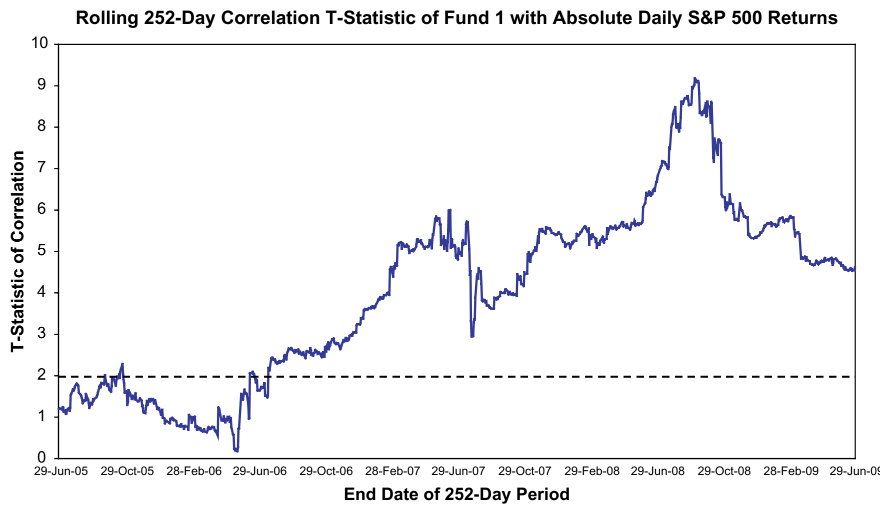

Figure 20 Rolling 252-day correlation T-statistics of Fund 1 with Daily Absolute S&P 500 Returns (Sources: Bloomberg, FactSet, and private).

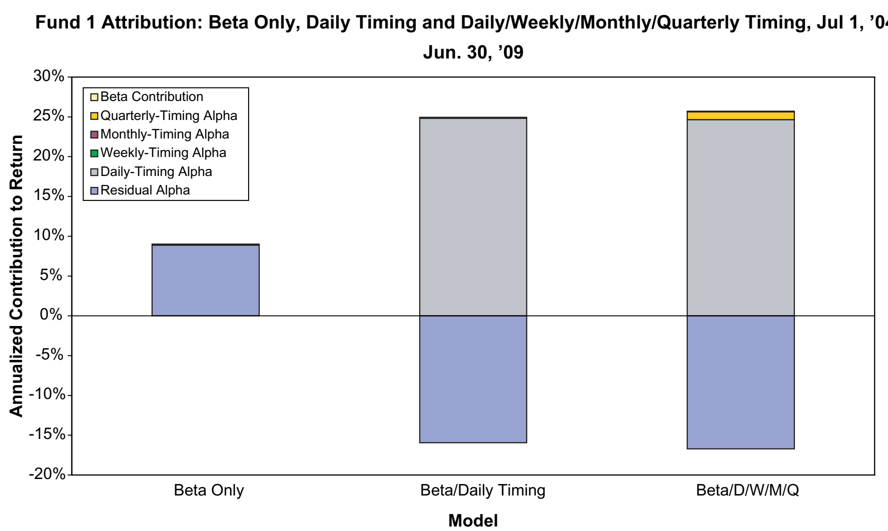

Figure 21 Multiple time-scale analysis for Fund 1, 2004–2009 (Sources: Bloomberg, FactSet, and private).

remains above two (i.e., statistically significant). It appears that daily-timing model performance has improved during this period, either due to model enhancements or a more-conducive market environment.

Not surprisingly, daily equity market timing factor dominates Fund 1's attribution in Figure 21. Interestingly, there is also a contribution from quarterly S&P 500 market timing; due diligence may (or may not) reveal this to be spurious. The beta contribution for Fund 1 is near zero over this period. While the magnitudes of the positive market timing and negative alpha are both large relative to the STTI index, the ratio of alpha-to-beta plus timing contributions is not much larger for Fund 1 than for the index: −0.65 for Fund 1, compared with −0.55 for STTI. The more negative ratio for Fund 1 could be due to its near-exclusive daily timing attribution, compared with

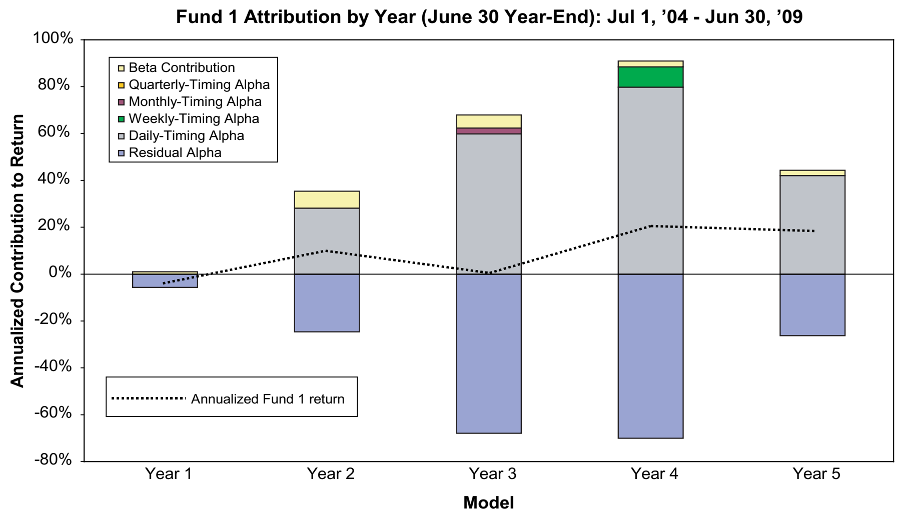

Figure 22 Annual multiple time scale analysis for Fund 1 (Sources: Bloomberg, FactSet, and private).

mixed daily/weekly/monthly (i.e., lower average turnover) source for STTI. Both ratios are more negative than those of the Newedge CTA and BarclayHedge CTA Indexes (−0.36 for Newedge and −0.51 for BarclayHedge through June 2009); these latter CTA indexes comprised longer term funds.

To better understand the dynamics of the alpha-to-timing attribution for Fund 1, we did a yearly analysis (252 trading days, ending June 30). There were no significant timing factors in Year 1, but daily equity timing dominates thereafter; see Figure 22. Also shown in this figure (dashed black line) is the annualized daily average return for Fund 1 in each period. Year 1 and Year 3 were the only negative years, but they were quite different from each other: in Year 1, none of the models appeared to "work"; i.e., no significant market timing factors. In Year 3, the daily and monthly timing models worked, but alpha was inordinately large and negative, more than canceling the timing gains. In Year 3, the blue (negative) bar for alpha is slightly longer than the combined daily (gray), monthly (red), and beta (yellow) contributions. Recall that over the 5-year period, the ratio of alpha-to-timing plus beta is −0.65. By year (excluding Year 1), it is −0.70 in Year 2, −1.00 in Year 3, −0.77 in Year 4, and −0.59 in Year 5.

One potential explanation for this result is that transaction costs rose in Year 3. This analysis might motivate an analyst to discuss the Jul 1, 2006–June 30, 2007 period in more detail with the fund. Did market liquidity change or did assets increase? Did fund alter its trading models subsequently to become more efficient? How big is the risk of a repeat of this scenario? This is a case where a manager appears to have an edge in daily market timing, yet the fund can still incur losses if alpha (presumably trading costs) becomes too negative.

Fund 2: Long-Term CTA

We conduct a multiple time scale analysis over 120 months, through December 2008 (ending here to allow inclusion of annual timing factors for Fund 2). Results are shown in Figure 23. The decomposition is similar to that of the Newedge CTA Index: monthly currency market timing and annual equity market timing are again significant. In terms of directional exposure, both Fund 2 and Newedge CTA Index were long commodities, but Fund 2 was short the US dollar, whereas

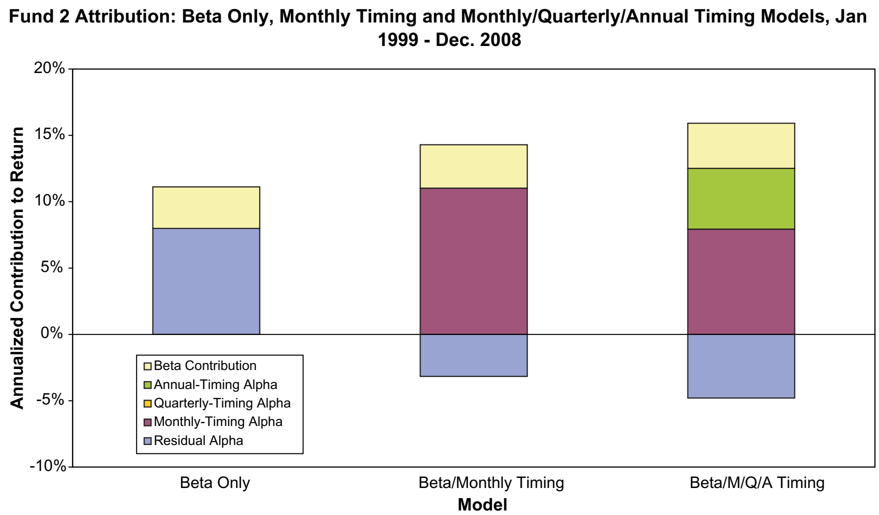

Figure 23 Multi-time scale analysis of Fund 2, Jan 1999–Dec 2008 (Sources: Bloomberg, FactSet, and private).

the Newedge CTA Index had long US bonds as the other beta factor.

However, two differences stand out for Fund 2 relative to Newedge CTA Index (Figure 15): First, the (negative) height of the blue segment (i.e., the negative alpha) is relatively smaller for Fund 2 than for Newedge CTA. The ratio of alpha-to-timing plus beta, is only -0.3 for Fund 2, whereas it is -0.48 over nearly the same period for Newedge CTA (BarclayHedge has a -0.54 ratio over a longer period). This 0.18 difference (less negative alpha) is worth about 2.9% per year to Fund 2. A second difference between Fund 2 and Newedge CTA attribution is that the beta contribution (yellow segment) is relatively larger for Fund 2 than for Newedge CTA. What might account for these differences? We offer two explanations.

One explanation for the comparative results of Fund 2 is that it is skilled in executing its trades (perhaps being smaller than its peers—this could account for some positive alpha contribution from timing small, uncorrelated markets) and it was merely lucky in its proportionately high beta contribution. If we omit a relevant time scale for market timing, its contribution would generally appear as residual alpha, if it is uncorrelated with other timing factors. However, if the omitted time scale is of very low frequency (e.g., multiple years) it could be correlated with index returns (beta factors). Thus, an alternative explanation is that Fund 2 has market timing skill at a multi-year time scale, so that true overall timing alpha is higher and residual alpha more negative—moving the alpha-to-beta plus timing ratio nearer to that of the CTA indexes. Under this scenario, the beta contribution would be partly subsumed by long-term market timing alpha.

Alas, these two interpretations are hard to distinguish quantitatively without a longer data set. Perhaps with 25 years of data, we could isolate 3-year market timing skill. One indication that we have "enough" data would be that the beta segment on the left-most (beta only) bar in Figure 23 becomes relatively smaller; i.e., that long-term timing becomes uncorrelated with index returns. To settle this question in the near-term requires due diligence, in which time scales for the fund's models are broken out by management and the fund's trading strategy can be better assessed.

5 Conclusion

We conduct return attribution for hedge funds and CTAs, splitting returns into beta contributions, market timing alpha and residual alpha. Among hedge fund strategies, only CTAs and Macro funds exhibit positive market timing alpha. We show that CTA index market timing alpha depends on the time scale of data used to measure it. CTAs do not display daily or weekly market timing alpha, but have monthly and quarterly timing alpha. Short-term future traders exhibit market timing alpha at daily through monthly time scales. We use a model that combines market timing variables at multiple time scales to estimate overall market timing alpha, and apply it to analyze CTA indexes and individual funds. Multiple time scale residual alphas for CTA indexes are between −7% and −8% per year. This analysis can be useful in evaluating CTA funds; it may also be adapted for other hedge fund strategies, provided a suitable set of factors is used and security selection is taken into account.

Appendix A: Data tables

Table 1 Single time scale factor correlation T-Statistics.
Factor Performance for CTAs and Short-Term Trend Followers by Time-scale

				Factor Correlation T-Statistics							
				Factors (Directional)				Absolute Values of Factors			
Index	Period	Timescale	Number of Periods	S&P 500	US 10Y T-Note	GSCI	DXY	S&P 500	US 10Y T-Note	GSCI	DXY
Newedge CTA Index	Jan 3, 2000– June 30, 2009	Daily	2387	**−10.72**	**12.35**	**5.71**	**−8.97**	0.23	−0.77	0.43	0.18
		Weekly	500	**−6.14**	**5.30**	**4.23**	**−4.39**	0.60	−0.89	0.54	0.69
		Monthly	114	**−2.60**	**2.27**	*1.83*	**−2.33**	1.07	−0.52	1.50	**3.55**
		Quarterly	38	*−1.75*	**3.14**	−0.91	**−2.51**	**3.06**	1.49	−0.32	0.67
Barclay Hedge CTA Index	January 1990– May 2009	Monthly	233	**−2.14**	**3.43**	**2.75**	**−2.17**	**2.35**	1.32	*1.83*	**5.80**
		Quarterly	77	**−2.55**	**3.68**	0.97	**−3.80**	**2.59**	*1.95*	*1.77*	1.01
		Annual	19	−0.64	**2.54**	−0.67	−1.31	*1.76*	0.43	−0.39	0.26
Newedge STTI Index	Jan 2, 2008– June 30, 2009	Daily	377	**−9.55**	**5.12**	**−5.37**	**2.49**	**3.47**	**2.41**	**3.05**	1.42
		Weekly	79	**−3.81**	1.63	**−3.26**	**2.52**	0.69	1.24	**2.29**	1.63
		Monthly	18	**−2.96**	−0.68	−0.29	0.81	0.68	−0.60	**2.29**	0.93

Significance at 5% threshold indicated by bold tyupe; 10% significance shown in italics.
Shaded cells indicate factors present in the multifactor model with highest adjusted R-squared; some individually significant factors may be excluded due to high correlations with other factors.
Sources: Newedge, Bloomberg and FactSet

Table 2 Multiple time scale monthly factor properties, 1990–2009 (Sources: Bloomberg and FactSet).
Properties of Beta and Timing Factors for Monthly Data
From Jan 1990–June 2009 (234 Months)
Time period for BarclayHedge CTA Index

	Directional (Beta) Factors				Monthly Timing Factors				Quarterly Timing Factors			
	SP50	US10YR	GSCI	DXY	SP50	US10YR	GSCI	DXY	SP50	US10YR	GSCI	DXY
Factor Properties												
Average Monthly Return (%)	0.50	0.02	0.53	−0.03	3.35	0.22	4.65	1.84	2.11	0.15	2.96	1.21
Monthly Volatility (%)	4.3	0.3	6.2	2.4	2.8	0.2	4.2	1.6	3.8	0.2	5.5	2.1
Serial Correlation (%)	8.3	9.3	17.2	14.3	18.1	4.7	23.2	−0.6	−9.5	−6.7	−3.3	−10.7
Factor T-Statistics												
BarclayHedge CTA	***−2.14***	***3.44***	***2.76***	−2.19	*2.39*	1.36	1.87	*5.84*	2.25	1.51	1.75	5.56

Annual timing factors are excluded because they are not available during 2009 YTD (requires knowledge of calendar year 2009 factor returns).
Monthly timing factors are absolute monthly factor returns; quarterly and annual timing factors are monthly factor returns times +/ − 1, with sign chosen to produce absolute quarterly and annual returns.
Bolded cells are factors appearing in the beta-only models.
Italicized cells are those appearing in beta and monthly-only timing models.
Shaded cells are those appearing in the beta/monthly/quarterly timing models.

Table 3 Multiple time scale monthly factor properties, 2000–2009 (Sources: Newedge, Bloomberg and FactSet).

Properties of Beta and Timing Factors for Monthly Data
From Jan 2000–June 2009 (114 Months)
Time period for Newedge CTA Index

	Directional (Beta) Factors				Monthly Timing Factors				Quarterly Timing Factors			
	SP50	US10YR	GSCI	DXY	SP50	US10YR	GSCI	DXY	SP50	US10YR	GSCI	DXY
Factor Properties												
Average Monthly Return (%)	−0.30	0.03	1.01	−0.18	3.47	0.22	5.81	1.88	2.21	0.15	3.56	1.21
Monthly Volatility (%)	4.7	0.3	7.3	2.5	3.1	0.2	4.6	1.6	4.1	0.3	6.5	2.1
Serial Correlation (%)	17.8	2.2	17.9	12.3	22.9	8.4	10.1	−3.2	2.4	−7.5	−10.3	−10.0
Factor T-Statistics												
Newedge CTA	***−2.60***	2.27	***1.83***	***−2.33***	1.07	−0.52	1.50	***3.55***	1.55	−0.50	0.98	3.49

Annual timing factors are excluded because they are not available during 2009 YTD (requires knowledge of calendar year 2009 factor returns).
Monthly timing factors are absolute monthly factor returns; quarterly and annual timing factors are monthly factor returns times +/−1, with sign chosen to produce absolute quarterly and annual returns.
Bolded cells are factors appearing in the beta-only models.
Italicized cells are those appearing in beta and monthly-only timing models.
Shaded cells are those appearing in the beta/monthly/quarterly timing models.

Table 4 Multiple time scale monthly factor properties, 1990–2008 (Sources: Hedge Fund Research, Inc., Bloomberg and FactSet).
Properties of Beta and Timing Factors for Monthly Data
From Jan 1990–Dec 2008 (228 Months)
Time period for BarclayHedge CTA and HFRI Hedge Fund Indexes

	Directional (Beta) Factors				Monthly Timing Factors				Quarterly Timing Factors				Annual Timing Factors			
	SP50	US10YR	GSCI	DXY	SP50	US10YR	GSCI	DXY	SP50	US10YR	GSCI	DXY	SP50	US10YR	GSCI	DXY
Factor Properties																
Average Monthly Return (%)	0.50	0.02	0.42	−0.03	3.25	0.21	4.61	1.80	2.05	0.15	2.91	1.19	1.36	0.08	1.80	0.69
Monthly Volatility (%)	4.2	0.3	6.1	2.4	2.7	0.2	4.1	1.6	3.7	0.2	5.4	2.1	4.0	0.3	5.9	2.3
Serial Correlation (%)	6.1	11.8	17.0	17.5	13.5	1.8	28.2	−2.6	−6.6	−8.3	−2.2	−7.2	−3.6	4.6	8.6	10.9
Factor T-Statistics																
BarclayHedge CTA	***−2.21***	***3.52***	***2.68***	−2.09	2.70	1.42	1.64	*5.90*	2.27	1.44	1.58	5.45	4.84	3.57	3.10	2.41
HFRI Macro Total	***5.59***	***3.80***	1.80	0.97	−0.69	−0.85	−1.24	*4.78*	0.78	−0.47	0.68	4.21	2.79	−0.66	1.19	1.41
HFRI Macro Systematic	***8.83***	0.28	1.50	−0.45	*2.62*	−0.89	1.55	0.93	4.27	−0.30	2.82	−0.14	3.85	−1.19	1.94	0.49

Monthly timing factors are absolute monthly factor returns; quarterly and annual timing factors are monthly factor returns times +/−1, with sign chosen to produce absolute quarterly and annual returns.
Bolded cells are factors appearing in the beta-only models.
Italicized cells are those appearing in beta and monthly-only timing models.
Shaded cells are those appearing in the beta/monthly/quarterly/annual timing models.

Table 5 Multiple time scale monthly factor properties, 1990–2008 (Sources: Newedge, Bloomberg and FactSet).

Properties of Beta and Timing Factors for Monthly Data
From Jan 2000–Dec 2008 (108 Months)
Time period for Newedge CTA Index

	Directional (Beta) Factors				Monthly Timing Factors				Quarterly Timing Factors				Annual Timing Factors			
	SP50	US10YR	GSCI	DXY	SP50	US10YR	GSCI	DXY	SP50	US10YR	GSCI	DXY	SP50	US10YR	GSCI	DXY
Factor Properties																
Average Monthly Return (%)	−0.35	0.04	0.81	−0.18	3.26	0.22	5.80	1.80	2.09	0.14	3.51	1.17	1.34	0.06	2.33	0.79
Monthly Volatility (%)	4.4	0.3	7.3	2.4	2.9	0.2	4.4	1.5	3.9	0.2	6.4	2.1	4.2	0.3	6.9	2.2
Serial Correlation (%)	15.0	6.1	18.0	19.3	15.8	3.5	17.8	−8.3	10.4	−10.6	−9.0	−1.8	4.6	4.5	9.1	9.5
Factor T-Statistics																
Newedge CTA	**−2.52**	2.35	***1.97***	***−2.54***	1.54	−0.41	1.37	***3.85***	1.58	−0.66	0.95	3.44	5.46	1.72	2.66	1.65

Monthly timing factors are absolute monthly factor returns; quarterly and annual timing factors are monthly factor returns times +/−1, with sign chosen to produce absolute quarterly and annual returns.
Bolded cells are factors appearing in the beta-only models.
Italicized cells are those appearing in beta and monthly-only timing models.
Shaded cells are those appearing in the beta/monthly/quarterly/annual timing models.

Table 6 Correlations between the monthly beta and timing factors (Sources: Bloomberg and FactSet).
Correlations Between Factors—Monthly Data
Time Period of BarclayHedge CTA and HFRI Hedge Fund Indexes
From January 1990–June 2009 (234 Months)

	Beta Factors				Monthly Absolute Value				Quarterly Timing				Annual Timing			
	S&P 500 Return (%)	Neg 10Y T-Note (%)	GSCI (%)	DXY (%)	S&P 500 Return (%)	Neg 10Y T-Note (%)	GSCI (%)	DXY (%)	S&P 500 Return (%)	Neg 10Y T-Note (%)	GSCI (%)	DXY (%)	S&P 500 Return (%)	Neg 10Y T-Note (%)	GSCI (%)	DXY (%)
Beta Factors																
S&P 500 Return	100															
Neg 10Y T-Note	2	100														
GSCI	9	−4	100													
DXY	−9	−23	−24	100												
Monthly Absolute Value																
S&P 500 Return	−12	8	−11	2	100											
Neg 10Y T-Note	−6	5	1	−7	27	100										
GSCI	−12	6	11	−6	24	0	100									
DXY	−8	4	−6	13	10	8	11	100								
Quarterly Timing																
S&P 500 Return	−5	7	−19	11	**70**	9	8	6	100							
Neg 10Y T-Note	0	1	−2	2	20	**73**	−6	4	23	100						
GSCI	−13	4	11	−5	20	−1	**71**	9	9	−7	100					
DXY	−12	−1	−3	18	14	0	8	**72**	14	2	5	100				
Annual Timing																
S&P 500 Return	−6	11	−7	4	35	−4	16	21	45	−1	17	21	100			
Neg 10Y T-Note	−18	27	−5	−16	8	38	−7	−2	6	36	−8	−10	23	100		
GSCI	−18	4	28	6	15	−5	46	11	12	−8	55	4	17	−2	100	
DXY	−2	−11	−1	33	8	−8	15	40	6	−13	10	51	16	−19	13	100

Note: The monthly data series for the annual timing factors end with December 2008 (i.e., missing final 6 months), since these factors require knowledge of the full year return Quarterly and Annual Timing Factors are computed monthly, using *ex post* information about the sign of the corresponding factor return during the quarter or calendar year.

Table 7 Multiple time scale daily factor properties, Jan 2, 2008–June 30, 2009 (Sources: Newedge, Bloomberg, and FactSet).

Properties of Beta and Timing Factors for Daily Data
From Jan 2, 2008–June 30, 2009 (377 Days)
Time period for Newedge STTI Index

	Directional (Beta) Factors				Daily Timing Factors				Weekly Timing Factors				Monthly Timing Factors			
	SP50	US10YR	GSCI	DXY	SP50	US10YR	GSCI	DXY	SP50	US10YR	GSCI	DXY	SP50	US10YR	GSCI	DXY
Factor Properties																
Average Monthly Return (%)	−0.09	0.14	−0.05	0.01	1.72	7.04	1.94	0.57	0.69	2.80	0.84	0.27	0.27	1.42	0.42	0.14
Monthly Volatility (%)	2.5	9.2	2.6	0.8	1.8	5.9	1.7	0.5	2.4	8.8	2.4	0.7	2.4	9.1	2.5	0.8
Serial Correlation (%)	−14.9	−2.7	−8.6	3.6	16.2	2.5	7.9	0.9	−25.9	−13.0	−23.4	−8.3	−17.1	−6.1	−11.7	−0.9
Factor T-Statistics																
Newedge STTI	***−9.55***	5.12	***−5.37***	2.49	***3.47***	2.41	3.05	1.42	3.36	2.62	4.20	2.91	3.95	−0.46	4.30	2.68

Daily timing factors are absolute daily factor returns; weekly, monthly, and quarterly timing factors are monthly factor returns times +/−1, with sign chosen to produce absolute returns for the given period.
Bolded cells are factors appearing in the beta-only models.
Italicized cells are those appearing in beta and daily-only timing models.
Shaded cells are those appearing in the beta/daily/weekly/monthly/quarterly timing models.

Table 8 Multiple time scale daily factor properties, Apr 1, 2003–June 30, 2009 (Sources: Hedge Fund Research, Inc., Bloomberg and FactSet).

Properties of Beta and Timing Factors for Daily Data
From Apr 1, 200–Dec 31, 2008 (1,450 Days)
Time period for HFRX Macro Index

	Directional (Beta) Factors				Monthly Timing Factors				Quarterly Timing Factors				Annual Timing Factors			
	SP50	US10YR	GSCI	DXY	SP50	US10YR	GSCI	DXY	SP50	US10YR	GSCI	DXY	SP50	US10YR	GSCI	DXY
Factor Properties																
Average Monthly Return (%)	0.01	0.11	0.04	−0.01	0.12	0.99	0.29	0.09	0.08	0.67	0.20	0.05	0.07	0.24	0.11	0.04
Monthly Volatility (%)	1.3	6.0	1.7	0.5	1.3	5.9	1.6	0.5	1.3	6.0	1.7	0.5	1.3	6.0	1.7	0.5
Serial Correlation (%)	−13.5	−0.3	−6.9	−1.2	−14.9	−3.8	−10.2	−4.3	−14.1	−2.3	−9.2	−2.2	−13.9	0.8	−6.6	−0.8
Factor T-Statistics																
HFRX Macro	0.82	1.77	***9.27***	***−9.69***	1.55	−1.67	*3.52*	1.74	5.71	1.91	10.12	3.55	7.04	1.88	5.51	3.49

Daily timing factors are absolute daily factor returns; weekly, monthly, and quarterly timing factors are monthly factor returns times +/−1, with sign chosen to produce absolute returns for the given period.
Bolded cells are factors appearing in the beta-only model.
Italicized cells are those appearing in beta and monthly-only timing model.
Shaded cells are those appearing in the beta/monthly/quarterly/annual timing model.

Table 9 Correlations between the daily beta and timing factors (Sources: Bloomberg and FactSet).

Correlations Between Factors—Daily Data
Time Period of NewEdge CTA Index
From Jan 2, 2000–June 30, 2009 (2,387 Days)

	Beta Factors				Daily Absolute Value				Weekly Timing				Monthly Timing				Quarterly Timing			
	S&P 500 Return (%)	Neg 10Y T-Note (%)	GSCI (%)	DXY (%)	S&P 500 Return (%)	Neg 10Y T-Note (%)	GSCI (%)	DXY (%)	S&P 500 Return (%)	Neg 10Y T-Note (%)	GSCI (%)	DXY (%)	S&P 500 Return (%)	Neg 10Y T-Note (%)	GSCI (%)	DXY (%)	S&P 500 Return (%)	Neg 10Y T-Note (%)	GSCI (%)	DXY (%)
Beta Factors																				
S&P 500 Return	100																			
Neg 10Y T-Note	−31	100																		
GSCI	15	−12	100																	
DXY	1	−22	−22	100																
Daily Absolute Value																				
S&P 500 Return	−1	5	−7	4	100															
Neg 10Y T-Note	−4	−4	−1	−4	31	100														
GSCI	−5	0	−1	−1	25	14	100													
DXY	−4	2	1	−3	21	25	20	100												
Weekly Timing																				
S&P 500 Return	−7	5	−5	0	46	14	10	11	100											
Neg 10Y T-Note	−9	0	−2	−2	12	47	4	11	17	100										
GSCI	−8	−2	−4	−1	11	6	49	9	10	7	100									
DXY	−5	3	1	−3	10	13	12	54	12	11	10	100								
Monthly Timing																				
S&P 500 Return	−24	9	−6	2	13	4	2	5	25	7	7	5	100							
Neg 10Y T-Note	−2	−5	3	−7	6	28	0	7	7	40	0	3	6	100						
GSCI	−3	2	−11	3	5	0	22	−6	7	1	28	−1	12	−1	100					
DXY	−9	9	−2	4	4	5	3	24	3	1	4	33	9	6	3	100				
Quarterly Timing																				
S&P 500 Return	−48	18	−11	−1	6	4	7	1	14	8	12	2	51	7	8	7	100			
Neg 10Y T-Note	−14	0	−3	0	6	12	1	1	4	18	1	−2	11	35	6	2	19	100		
GSCI	−1	−3	17	0	3	2	13	−3	4	2	13	−1	9	0	47	8	6	8	100	
DXY	−7	2	−5	22	1	−3	−2	11	−1	−2	4	14	6	−5	4	46	6	3	10	100

Note: Weekly, Monthly, and Quarterly Timing factors are computed daily using *ex post* information on the direction of the corresponding factor return during these periods.

Appendix B: Relation of weekly timing factor to weekly absolute return

Lemma. *If the following assumptions hold, then the daily average of each weekly timing factor is a constant times the average of the corresponding weekly absolute factor return.*

(i) *There are an even number of weeks, K, contained in the set of N trading days;*
(ii) *There is an invertible map between trading day $t = 1, \ldots, N$ and week number $k = 1, \ldots, K$ and day of the week, $l = 1, \ldots, N_k$, where $N_k \leq 5$; i.e. $F_{j,t} \leftrightarrow F_{j,k,l}$;*
(iii) *We can ignore compounding effects, so that the weekly factor return, $F^{(W)}_{j,k}$, is the sum of (mapped) daily factor returns; i.e., $F^{(W)}_{j,k} = \sum_{l=1}^{N_k} F_{j,k,l}$; and*
(iv) *The number of trading days per week is approximately constant (i.e., large sample).*

Proof. We compute the average daily return of the weekly timing factor over the sample period. In the first equality below, we use mapping (ii). Next, we use the definition of the weekly sign factor, $S^{(W)}_{j,t}$, followed by condition (iii) ignoring compounding. Finally, we use assumption (iv), so that the ratio of K to N is independent of either variable.

$$
\begin{aligned}
N^{-1}\sum_{t=1}^{N} S^{(W)}_{j,t} F_{j,t} &= N^{-1}\sum_{k=1}^{K}\sum_{l=1}^{N_k} S^{(W)}_{j,k,l} F_{j,k,l} \\
&= N^{-1}\sum_{k=1}^{K}\left|\sum_{l=1}^{N_k} F_{j,k,l}\right| \\
&= N^{-1}\sum_{k=1}^{K} |F^{(W)}_{j,k}| = (K/N) \\
&\quad \times \overline{|F^{(W)}_{j}|} \approx \text{constant}^* \overline{|F^{(W)}_{j}|}.
\end{aligned}
$$

Similar arguments hold for monthly, quarterly, and annual timing factors. At the daily time scale, the compounding error grows with the time scale, while the trading days per period error decrease with time scale. In analyzing a longer term fund, a monthly-scale model (with less compounding error for quarterly and annual returns) may be more accurate than a daily-scale model, particularly if there is a fairly long history of monthly returns for the fund. □

Notes

[1] Vuille and Crisan (2004) find that 50% of all CTAs in their sample and 65% of trend followers had correlations of at least 0.5 with CTA indexes such as Barclay's and CISDM.

[2] *The Wall Street Journal*, Nov 5, 2008, reports that, "Most managed futures funds … are less than $1 billion in size, although some are larger. The sector's heavyweight players include Man Group PLC's $24.9 billion AHL program, Winton Capital Management's $15.7 billion fund and Campbell & Co's FME Large Portfolio with $4.7 billion in assets."

[3] See Vuille and Crisan (2004) for detailed strategy taxonomy.

[4] CTAs typically charge management fees (1–2% is common) and incentive fees (often 15–25% of positive returns). The two fees exert opposite influences on gross (pre-fee) residual alpha relative to net (post-fee) residual alpha: management fees raise (i.e., make less negative) gross residual alpha relative to net residual alpha, while incentive fees scale up gross returns—both positive market timing alpha and negative residual alpha. The relationship between net and gross residual alpha therefore depends on the fund's fee structure and performance. Since the negative residual alphas we observe are much larger than typical management fees, such fees do not appear to be responsible for the effect we describe.

[5] In our example, the manager trades once per period; we also assume that the manager keeps a constant weight in the asset, regardless of the magnitude of return; this is consistent with a direction-only forecast.

[6] Although fund returns are scaled due to leverage and imperfect correlation, and shifted down by trading costs.

[7] Why might a fund that has market timing ability at a short (e.g., daily) time scale also use long time-scale models, whose performance would be dominated by the former? (1) Capacity—it might only be possible to run

limited assets in the short-term model before transaction costs become uneconomical; and (2) diversification—returns from short-term models may be noisy. For indexes, only some of the funds may use short-term models.

8 Serial correlation (autocorrelation) of returns refers to the phenomenon where the return of a fund in a given period depends on its return in a prior period. Some hedge fund strategies, such as distressed securities and convertible arbitrage, have large positive monthly serial correlations: above average months tend to follow above average months, and vice versa. This effect is believed to be due to illiquidity in the assets they trade, as price shocks may take multiple periods to fully be impounded; see Getmansky *et al.* (2004). CTA funds generally have near-zero serial correlation due to their focus on liquid markets.

9 Estimation error in small samples may produce different estimates for these coefficients.

10 By the triangle inequality, the sum of absolute values is greater than or equal to the absolute value of the sum. For index returns, equality holds if the index went straight up or down each day for a month. Alternatively, summed absolute returns would be higher if the index was alternately up and down each day of the month.

11 Return contributions from omitted time scales would appear as alpha, if these omitted timing factors are uncorrelated with those that are included. If the omitted timing factors are correlated, their contributions will be subsumed—at least in part—by included timing factors.

12 This might be more properly referred to as calendar month timing ability, since we do not roll forward the monthly directional forecast each day during the month. However, monthly returns shifted by a few days are highly correlated, and it is therefore redundant to include separate factors for shifted monthly timing skill.

13 Because we use a small number of indexes for parsimony, some degree of selection among indexes is possible. However, index returns are often highly correlated and at many CTAs allocations by index are driven more by liquidity and capacity than by variations in, say, expected return.

14 See www.hedgefundresearch.com for a description of the strategies; data was downloaded as of the June 15, 2009 update. In this update, returns from February–May 2009 were still preliminary, rather than final.

15 See Jagannathan *et al.* (2010) for a discussion.

16 The actual variable used is the change in yield on 10 year US Treasury Notes; the US dollar index is a proxy for the baskets of currencies that CTAs might use to produce a net long or short dollar position.

17 See Jiang (2003) for a discussion of spurious negative correlations between sampling errors from security selection and market timing factors.

18 Mitchell and Pulvino (2001) show that spreads on risk (merger) arbitrage deals widen in down markets.

19 The specific days with available data vary by index, as well as from fund to fund (often depending on where an offshore fund is domiciled, for example). To reconcile the various holidays among our indexes, we use the US Composite market calendar (i.e., days when the NYSE is open). If a fund or index has returns on other days, we compound those daily returns until the next open day for the NYSE. In some cases, there are indexes (such as US Government bonds) that are closed when the NYSE is open; since these are a decided minority, we simply keep zeros for those daily returns.

20 T-Statistics in Figure 5 are often significantly positive or negative over extended time periods, indicating that CTAs are not a market neutral strategy over time scale of several months. This time scale is relevant for investors, who must decide whether an allocation to CTAs makes sense for a market neutral portfolio. For example, all rolling 60-trading day periods ending between October 9, 2006 and January 31, 2008 have positive equity correlation, while all periods ending between February 1, 2008 and June 20, 2009 have negative equity correlation. Positive (negative) equity exposure would be valuable to a portfolio in rising (falling) markets, but carries potentially unwanted systematic risk.

21 Our focus remains on CTA attribution, but we include Macro indexes to illustrate the decomposition; more caution must be used in interpreting the Macro index results, since macro funds employ more selection than CTA funds, including single stocks, sectors emerging markets, and relative value trades. This selection may need to be disentangled from the market timing attribution.

22 Thus, even though our analysis of CTA and macro indexes only goes through June 30, 2009, we needed to use index data through July 3, 2009 to compute weekly sign factors.

23 Since quarterly and annual timing factors match (or are strictly opposite) index returns over long periods (whole quarters or years), several years of data may be needed to distinguish them from index returns.

[24] An alternative approach of adding daily absolute values of factor returns over, say, a month to create a sequence of monthly variables—then doing the same for weekly absolute returns—and running a monthly model with daily, weekly, and monthly effects is not sufficiently sensitive to capture high-frequency timing skill. Consider an example: A fund with four years (1,008 trading days) of history has a 0.125 correlation with absolute daily equity returns. The corresponding T-Statistics is a highly significant 4.0. If we sum the daily absolute equity returns over each month, then (ignoring compounding effects) the correlation of the monthly fund returns and monthly sum of absolute equity returns is the same as for daily returns—it might change if there was serial correlation, but that is not an issue for CTAs or the factors we use. The T-Statistics is now only 0.87 for monthly data; i.e., at a monthly time scale, daily timing ability is reduced to noise. Our approach still requires long time periods to distinguish quarterly and annual timing from directional (beta) exposure, but it is capable of extracting high-frequency timing skill.

[25] Even with daily data, if a fund does not have timing ability at daily and weekly frequencies, analysts may prefer to use a monthly scale attribution model, since there is no daily-to-monthly compounding error in this case.

[26] In the multiple time scale analysis, the GSCI timing factor was more significant at the monthly than at the weekly frequency (they were tied in the single time scale analysis), and the weekly $US timing factor was significant in the multi-time scale analysis, whereas it was only borderline significant in the single time scale analysis.

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