

Market Timing of CTAs: An Examination of Systematic CTAs vs. Discretionary CTAs¹

By

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Abstract

This paper uses a set of return-based factors to test for market (return and volatility) timing ability of Commodity Trading Advisors (CTAs). Unlike previous research, we use return-based factors that are related to the markets in which most CTAs trade. This leads to a higher explanatory power for our multifactor model. Our approach allows us to test for the presence of market timing in multiple markets, and, therefore, we are able to identify the markets in which CTAs have market timing ability. We find that systematic CTAs are in general better at market timing than discretionary CTAs, with the latter having slightly better overall risk-adjusted performance during our study period: Jan 1994 to Dec 2004. We suspect that this is caused by higher turnover of portfolios of discretionary CTAs leading to frequent changes in their factor exposures that cannot be captured through monthly observations. We show that CTAs display a negative relationship between market timing ability and security selection, and as a group CTAs generate their returns mainly from market timing, rather than security selection ability.

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1. Introduction

The term *managed futures* represents an industry comprised of professional money managers known as *commodity trading advisors* (CTAs) who manage client assets, using global futures and options markets as an investment medium. These managers are usually self-regulated and registered¹ and they are compensated through both management fees and incentive fees. Because of their similarities to hedge funds, CTAs are usually listed as a strategy of hedge funds with the style name managed futures. In the literature, CTAs are also known as “trend-followers”² since many CTAs utilize their proprietary trading models to capture trends in futures markets. Based on their trading strategies, there are mainly two sub-sets of CTAs: systematic CTAs, who base their trading on technical models and discretionary CTAs, who base their trading on managers’ discretions. The portfolio benefits of CTAs have been studied by Billingsley and Chance (1996), Liang (2004) and Kat (2004). They show that CTAs improve risk-return characteristics of equity and fixed income portfolios as they especially exhibit negative correlation with the overall securities market during extreme negative market returns.

A potential source of benefit provided by CTAs is that they can take long or short positions in low transaction cost investment vehicles (i.e., futures contracts) to benefit from trends in commodity prices, exchanges rates, interest rates and equity markets. Market timing is the ability of money managers to forecast the market trend and adjust risk exposures to the market accordingly. Previous research in the area of market timing has generally focused on mutual funds; these studies find no or negative timing ability using monthly return data (among others see Jensen (1972), Merton (1981), Henriksson and Merton (1981), Admati, Bhattacharya,

¹ CTAs with a domicile in US are usually registered with NFA or CFTC, those with a domicile in England are registered with FSA, and those with a domicile in Canada are registered with OSC, for example.

² Fung and Hsieh (1997) identify a principal component in hedge funds returns as from CTAs, while Fung and Hsieh (2001) study the return characteristics in trend-followers.

Pfleiderer and Ross (1986), Lehman and Modest (1987), Ferson and Schadt (1996), Becker, Ferson, Myers and Schill (1999)). More recently, research using high frequency return data or portfolio holdings data finds evidence supporting the presence of timing ability in mutual funds (Busse (1999), Bollen and Busse (2001), and Jiang, Yao, and Yu (2005)). Empirical evidence on timing ability for hedge funds is also mixed. For example, Fung, Xu and Yau (2002) find negative timing ability for a group of hedge fund managers who follow global macro strategy. Chen (2005) finds timing ability in some styles of hedge funds in their focus markets (mainly US and non-US bond markets and currency markets). Chen and Liang (2006) find significant return and volatility timing ability for hedge funds that claim to time the market.

This study investigates the market timing and volatility timing ability of CTAs, and examines whether there is a difference in market timing abilities of discretionary versus systematic CTAs. Due to the empirical similarities between market timers and trend-followers, anecdotal evidence indicates that trend following CTAs possess timing ability. The goal of this paper to test this hypothesis and to determine if non-diversified CTAs display market timing ability in those markets in which they focus. As previous studies have shown (e.g., Fung and Hsieh (2001)), the challenge is that traditional equity and fixed income indices have low explanatory power and therefore cannot be used to estimate the market timing abilities of CTAs. Besides, some of these traditional indices (e.g., see Fung and Hsieh (2001)) may exclude important risk factors such as various currencies, commodities or interest rates, and, therefore, may present an incomplete picture of CTAs risk exposures. In order to overcome this problem, we use a set of new risk factors that are based on returns from the most heavily traded futures contracts. Our proposed set of factors is found to possess much higher explanatory power for CTA returns.

Similar to previous market timing studies, we use Treynor and Mazuy (TM, 1966) and Henriksson and Merton (HM, 1981) models to detect market return timing ability. In testing for the presence of market return and volatility timing we use model proposed by Bollen and Busse (2001). Our tests are applied to both portfolios of CTAs and to individual CTAs. We construct CTA indices for a sample with 900 CTAs, both live and defunct, with at least three years of return history, and conduct timing tests with traditional factors as well as our proposed risk factors. The use of defunct funds reduces the impact of survivorship bias on our results.

We find that overall CTAs exhibit market return timing and volatility timing ability. More importantly, we find that CTAs are generally able to time the futures markets in which they claim to specialize. For example, currency CTA index is found to time the Euro and Japanese Yen futures market well, commodity CTA index is able to time the corn futures market, while diversified CTA index is found to time multiple markets. Commodity CTA index and stock index CTA index are found to exhibit negative timing ability in certain futures markets, though.³

We also find significant differences between discretionary and systematic CTAs. Even with the help of our unique set of futures return-based factors, we are generally able to explain less than 10% of the variation in discretionary CTAs returns, while the percentage for systematic CTAs is much higher (ranges between 40-50%).

Market timing and selection ability are believed to represent macro- and micro-forecasting abilities of funds managers. When Jensen's alpha is used as the measure for selection ability, however, it can assign negative performance to a market timer, as examples in Jensen (1972), Admati and Ross (1985), Dybvig and Ross (1985) show. Grinblatt and Titman (1989) suggest a positive period weighting measure that identifies informed investors as positive performers by

³ We notice that the explanatory power for commodity CTA index is very low (negative adjusted R-squared value) and that there are very few commodity CTAs and stock index CTAs in the live CTA universe. (Table 1, Panel A)

assuming independent timing and selectivity and a certain risk aversion. Mamaysky, Spiegel, and Zhang (2004) demonstrate that a fund's alpha can actually be decomposed into portions due to successful market timing as well as transaction cost. So as a fund's return is modeled by assuming market timing ability besides return from risk factors, the intercept (alpha) may drop if positive market timing ability exists. We confirm this with our CTA sample: as relevant factors are added to the modeling process and more of the variability in CTAs' returns is explained by positive market timing ability, we observe that the intercept (alpha) goes from significant positive to insignificant, and even to significant negative for our CTA indices. Systematic CTA indices are better explained with our risk factors and they are also found to present highly significant negative alphas. Our model displays poor explanatory power for discretionary CTA indices, and reports significant timing ability for this class of CTAs. On other hand, it is shown that discretionary CTA indices have significant positive alphas.

Since most CTAs do not invest in individual securities, the concept of security selection does not readily apply to them. The set of return based factors that we use in this study cover a significant part of the investment universe considered by CTAs. Therefore, security selection, as applied to mutual funds, should not be a significant source of return. While in the context of hedge funds and mutual funds the estimated value of alpha is typically assumed to be driven by security selection ability or lack of it, we speculate that in the context of CTAs is driven by other factors. For example, CTAs and especially discretionary CTAs may change their factor exposures more frequently than the monthly returns that can be found in public databases. This lack of synchronization between trading frequency and observation frequency could lead one to obtain a significant estimate for security selection ability or market timing ability when none exists (see Goetzmann et al. (2000)). The other potential reason for obtaining negative estimated

alphas is the presence of fees and transaction costs. We use net of fees returns and if market timing abilities of CTAs are not sufficient to cover both asset management fee and performance fee, the effect would appear as a negative value for our estimates of alpha. Also, as explained in the next section, our risk factors represent returns to rolling positions in futures contracts. In calculating the returns to these rolling strategies, we do not account for transaction costs. This should have very little impact on estimates of risk exposures and market timing ability, but will have an impact on estimates of alpha.

For robustness test, we run the same timing test for individual CTAs to gain a full picture of how CTAs generate return; we find similar results to those reported for CTA indices. Between one half and one third individual CTAs possess significant timing ability and it is almost always *positive* timing ability. On the other hand, most of these CTAs possess negative significant selection ability as measured by the negative alpha.

The paper is organized as follows: Section 2 describes the CTA return data and risk factors; Section 3 discusses our methodology; Section 4 presents empirical results from various market timing models with different factors; Section 5 conducts robustness tests and Section 6 concludes.

2. Data

2.1 CTA Data

Like many other alternative investment vehicles, hedge funds and funds of funds, for example, CTAs together with the managed futures industry have had a dramatic growth in the past fifteen years. From Figure 1, we see that the asset under management (thereafter AUM) for the managed futures industry has grown from less than US\$10 billion in 1990 to more than

US\$130 billion by the end of 2004. AUM for CTAs increases from US\$6 billion to close to US\$90 billion.

Our data for the study comes from CISDM database,⁴ with monthly, net-of-fees return, asset under management (AUM), as well as data on other fund characteristics, such as fund inception date, self-declared category the fund belongs to, as well as the management company. To minimize survivorship and backfilled biases, we include only CTAs that have return series between January 1994 and December 2004, since CISDM database did not start keeping record of both live and defunct funds until December 1993. We also exclude CTAs that do not have information on their self-claimed category/specialization market.⁵ Before applying the above filter, there are 1082 CTAs in CISDM database, with return series between December 1989 and December 2004. Among them, 681 funds had stopped reporting to CISDM by December 2004, hence are considered “defunct funds”. After applying the filter, our sample is left with 278 live and 622 defunct CTA funds. The oldest CTA in our sample has an inception date of May 31, 1973. The total AUM for our sample is over \$64 billion and accounts for 72.12% of the CTA universe. Panel A of Table 1 reports summary statistics for our sample.

[Table 1 about here]

Next, we construct equally weighted indices of discretionary and systematic CTAs and use these indices to study the market timing ability at aggregate level. Both live and defunct funds are included to minimize survivorship bias discussed in Fung and Hsieh (2000) and others. Fung and Hsieh (1997) points out those CTAs have option-like payoffs and perform well in extreme markets. We reproduce their plot of CTA returns in five states of world equity market in Figure 2

⁴ Formerly known as MAR, CISDM database is one of the major hedge funds databases and provides most comprehensive data for CTAs. Fung and Hsieh, Billingsley and Chance (1996) all use CISDM database for CTA studies.

⁵ There is a field in the database with self-reported information on the specialization market of each CTA.

and observe that systematic CTAs plot quite differently from discretionary CTAs against the five states: Discretionary CTAs are more positively correlated to equity market, while systematic CTAs are negatively related to market, performing the best in extreme states and below average in non-extreme states.

[Figure 2 about here]

Based on their self-declared specialization markets, there are mainly four different types of markets for CTAs: currencies, commodities (physicals), financials (interest rates), and equities. CTA managers may classify themselves to specialize in one of the above four markets, or if they may classify themselves as following a diversified strategy. Diversified CTAs dominate the CTA universe in terms of the number of funds and AUM. Financial and currency CTAs are next and commodity and equity CTAs are the smallest groups. Panel A of Table 1 presents the distribution of the five categories of live CTAs. The distribution of the five categories for all live discretionary and systematic CTA indices is provided in Panel B.

2.2 Factors

To explain fund returns, the most popular factor models are the single-factor (market model), Fama-French three-factor, and Carhart (1997) four-factor models. However, none of these models seem to explain CTA returns well.⁶ We augment the above traditional factors with term premium, credit risk premium, convertible premium, as well as an emerging market premium to form an augmented eight-factor model. This model has slightly higher explanatory power.

⁶ Fung and Hsieh (2001) point out that the explanatory power of traditional asset index factors for CTAs is quite low, with adjusted R^2 's no higher than in the teens and can even go below zero. The ineffectiveness is in contrast to other work on market timing of other money managers. For example, regression on HFR market timing hedge fund index using Carhart four-factor model yields an adjusted R-squared of higher than 0,50 in Chen and Liang (2006). This implies that traditional factors are not appropriate for explaining CTA returns.

Fung and Hsieh (2001) propose a set of Primitive Trend-Following Strategy (PTFS) factors and use them to explain CTA returns. The PTFS factors⁷ represent returns from investing in a portfolio of look-back straddles written in futures contracts in interest rate, currency, commodity and stock markets. Fung and Hsieh (2001) show that the PTFS factors together with equity and bond market factors can increase the explanatory power for trend-following funds returns significantly.

Inspired by Fung and Hsieh (2001), we propose using factors based on returns from investing in the most popular futures contracts⁸ to explain CTA returns and to detect their timing ability. There are several advantages to using returns from futures contracts as risk factors:

- Using a model that can detect market timing in multiple markets, we are able to see the markets in which a CTA has timing ability.
- Our proposed risk factors are heavily traded futures contracts and are highly liquid. Hence we can avoid the problem that holding illiquid assets may lead one to obtain estimates of market timing when there is none (see Chen, Ferson, and Peters (2005)).

Panel C through E of Table 1 report the summary statistics of traditional factors, augmented factors, PTFS factors, as well as our proposed futures contracts-based factors. Panel F gives the correlation matrix for our proposed risk factors that are based on returns from the fourteen futures contracts. With exception of the correlation between the two stock index futures, FTSE100 and S&P 500, other estimates of correlations are not too high to lead to multicollinearity

⁷ For details about how the five PTFS factors are constructed, please refer to Fung and Hsieh (2001) Appendix.

⁸ We use return from investing in the most heavily traded fourteen futures contracts. They are, currency futures (futures of Euro, Japanese Yen, and British Pound), interest rate futures (futures of US Treasury Bill, German government bond, and Eurodollar), commodity futures (futures of gold, copper, natural gas, crude oil and corn), and stock index futures (futures of S&P 500, FTSE 100, and NIKKEI225).

Table 2 reports the explanatory power of traditional factor, augmented factor, as well as PTFS factor models for indices of discretionary CTAs versus systematic CTAs. The augmented PTFS factor model provides the highest explanatory power for both and we notice that all factor models are better at explaining return variations in systematic CTAs than discretionary CTAs. The difference is quite significant as well, for example, 0.052 versus 0.447 in adjusted R-squared values with augmented PTFS models.

3. Methodology

Since CTA managers usually follow their declared strategies closely, we use risk factors constructed from relevant futures contracts to analyze each style of CTAs. For example, we use risk factors constructed from currency futures for currency CTAs, those constructed from commodities futures for commodity CTAs, and so on. For about half of the CTA universe (i.e., those who claim to be diversified CTAs) we use a step-wise regression to select relevant risk factors. This factor-selection process ensures inclusion of relevant factors and helps build a parsimonious model.

3.1 Apply Market Timing Models to CTAs

A. Multi-Market Timing in Returns

Treynor and Mazuy (TM) (1966) and Henriksson and Merton (1981) are the most widely used models in the empirical literature of market timing. In TM model, managers with timing ability adjust their risk exposure to the overall market according to their forecast of the market return, so that there is a convex relationship between the manager's return and the market return. Admati et al. (1986) develops an empirical test based on TM model by assuming a CAPM framework. HM model, however, does not need the assumption that CAPM holds. Merton (1981) and the test developed in Henriksson and Merton (1981) model the economic value of

timing as the payoff from a call option. A manager with timing ability chooses whether to invest in the market or hold cash based on his/her forecast of the excess market return being positive or negative.

Our study tests for market timing ability in CTAs with both TM and HM models, and expand them to accommodate multiple markets since CTAs usually trade in multiple futures markets. In our model the cross-product terms are not included. These terms can only be ignored if returns from different futures contract are independent from each other.⁹ The advantage of ignoring the cross-products is that we arrive at a parsimonious model. Aragon (2007) develops a multi-market timing version of HM model with two alternative specifications and applies them to mutual funds. His first specification assumes that managers choose markets with positive excess returns¹⁰ and is consistent with our equations (1) and (2) with $S_{j,t+1} = \max(F_{j,t+1}, 0)$. His second specification, however, states that the manager is able to detect the best-performing market (with positive excess returns) and maximize his/her risk exposure to it. Consistent with this specification, the timing signal should be written as $S_{j,t+1} = \max(\max(F_{1,t+1}, F_{2,t+1}, \dots), 0)$. We adopt both specifications in our study and conduct the same exercise for funds at aggregate level and individual fund level to investigate whether CTAs are able to time the best-performing market.

Let's consider that the return of a CTA fund (r_p) is generated by a multi-factor model with factors denoted by F_j . In our set-up, the factors are buy-hold-roll returns from futures contracts as described in section 3 and the CTA manager adjusts his/her exposure to these factor based on

⁹ We are cautious about this assumption here, especially for the application in TM model, as currencies and physicals could assume independent return pattern, but stock indices or many financials may not. So we focus on discussing results in applicable cases. For HM model, however, it should be of less concern to assume the independency.

¹⁰ Returns that are excess of risk-free rate.

signal S_j . The signal S_j is $S_{j,t+1} = F_{j,t+1}$ for the TM model and $S_{j,t+1} = \max(F_{j,t+1}, 0)$ or $S_{j,t+1} = \max(\max(F_{1,t+1}, F_{2,t+1}, \dots), 0)$ for the HM model. The following equations are the bases of our empirical tests:

$$\beta_j = \beta_{0,j} + \gamma_{j,t} S_{j,t+1} + v_{t+1} \quad (1)$$

$$r_{p,t+1} = \alpha + \sum_{j=1}^K \beta_{jt} F_{j,t+1} + \omega_{t+1} \quad (2)$$

Equation (1) describes how a manager determines his/her exposure, β_j , to factor returns while equation (2) describes the return to the CTA's portfolio. The above expressions describe a multi-market timing scenario for the CTA manager, where coefficient γ evaluates the market timing ability of the manager: If the manager is able to increase exposure to factors with positive market risk premium and decrease exposure if the opposite is true, he/she is said to possess market return timing ability and the estimated γ should be positive. No matter which model we use (TM or HM), for a successful market-timing CTA, the estimated coefficient γ should be positive, showing more convexity to the factor than non-timers.

B. Volatility Timing

Hedge funds and CTAs are usually cited as being “long” or “short” market volatility. Fung and Hsieh (2001) show that the payoffs from trend-followers¹¹ can be replicated with a look-back straddle and present evidence for volatility timing in CTAs. Busse (1999) analytically shows that a fund manager who is able to time the market volatility reduces market exposure when he/she forecasts an increase in market volatility. Busse (1999) is the first one to test for

¹¹ A lot of these trend-followers are actually CTAs.

volatility timing ability in money managers and he applies the following model to a group of mutual fund managers:

$$r_{p,t+1} = \alpha + \sum_{j=1}^K \beta_j F_{j,t+1} + \lambda r_{m,t+1} (\sigma_{m,t+1} - \bar{\sigma}_m) + \varepsilon_{t+1} \quad (3)$$

In equation (3), F_j are risk factors and $\sigma_{m,t+1}$ is market volatility. Busse (1999) estimates $\sigma_{m,t+1}$ with conditional volatility models (EGARCH) and finds that mutual fund managers have volatility timing ability. Chen and Liang (2006) use two proxies for market volatility, namely the implied volatility (VIX) and the realized market volatility and find significant evidence for “market timing” hedge funds to time the stock market volatility, especially in bear markets. The model they use can be written as:

$$r_{p,t} = \alpha + \sum_{i=1}^k \beta_i R_{i,t} + \lambda r_{m,t} (\sigma_{m,t} - \bar{\sigma}_m) + \varepsilon_t, \quad (4)$$

where $\sigma_{m,t}$ are end-of-month VIX and $\bar{\sigma}_m$ is the overall mean for time series of VIX.

Since the risk factors we use in this study are constructed with returns from relevant futures contracts, the first question we need to address is which market volatility benchmark we should use when testing for volatility timing in CTAs? Should it be the volatility in various futures markets or a proxy for the equity market volatility (VIX)?

Stock market volatility is often used as a proxy for volatility in financial markets. On the other hand, as managers trade various futures contracts, it seems reasonable that volatility in these futures markets be used as benchmark for timing. So we investigate this issue empirically. To detect volatility timing ability in the specialization markets, we use the following specification:

$$r_{i,t} = \alpha + \sum_{j=1}^k \beta_j r_{j,t} + \sum_{l=1}^n \gamma_l r_{l,t} (\sigma_{l,t} - \bar{\sigma}_l) + \varepsilon_t \quad (5)$$

The volatility measures used in equations (4) and (5) are end-of-month VIX for as proxy for overall market volatility and realized return volatility calculated from returns of relevant futures contracts. If CTAs are able to time the volatility, be it equity market volatility or volatility of specific markets, we expect to see negative significant coefficients for γ .

No significant γ 's were found when equation (5) is used. That is, no volatility timing ability with regards to the relevant futures markets were detected for CTAs. However, the estimated value of γ in specification (4) turns out to be significantly negative, indicating volatility timing with respect to the market overall volatility. Based on this finding, we use an augmented version of (4) combined with timing models and report results on volatility timing with respect to overall market volatility in section 4.

C. Combine Return and Volatility Timing

Chen and Liang (2006) examine combined timing ability in hedge funds and find evidence for both return and volatility timing. Following Busse (1999), we use models (6), (7) and (8) to detect combined return and volatility timing for CTAs. Equation (6) is TM model while equations (7) and (8) are HM specifications (I) and (II).

$$r_{p,t} = \alpha + \sum_{j=1}^k \beta_j r_{j,t} + \sum_{i=1}^n \lambda_i r_{i,t}^2 + \delta r_{m,t} (\sigma_{m,t} - \bar{\sigma}_m) + \varepsilon_t \quad (6)$$

$$r_{p,t} = \alpha + \sum_{j=1}^k \beta_j r_{j,t} + \sum_{i=1}^n D_i \max(r_{i,t}, 0) + \delta r_{m,t} (\sigma_{m,t} - \bar{\sigma}_m) + \varepsilon_t \quad (7)$$

$$r_{p,t} = \alpha + \sum_{j=1}^k \beta_j r_{j,t} + \sum_{i=1}^n D_i \max(r_{i-t}, 0) + \delta r_{m,t} (\sigma_{m,t} - \bar{\sigma}_m) + \varepsilon_t \quad (8)$$

Where $r_{j,t}$ represents excess return on a futures contract and $\sigma_{m,t}$ represents market return volatility, measured by end-of-month VIX. If CTAs have both return and volatility timing ability, we expect to see positive significant coefficients for λ and D , negative significant coefficients for δ .

4. Empirical Results

4.1 Detect Market Timing with PTFS Factors

As shown in Fung and Hsieh (2001), empirically one cannot distinguish between successful trend followers and successful market timers. Returns for successful market timers resemble return from a standard straddle where the timer enters the straddle based on his/her forecast. Returns for successful trend-followers resemble return from a look-back straddle where the trend-follower buys at the bottom and sells at the peak. As time horizon of holding period shrinks, return from a standard straddle approaches that from a look-back straddle with same terms. Based on this analogy, we use PTFS factors to detect CTA timing abilities. If a CTA is able to time a certain market, he/she should show positive loadings on the PFTS factor constructed based on the return from a look-back straddle invested in that market. The results in Table 2 show that regression of CTA return on PFTS factors for systematic CTAs do have significant timing ability in the fixed income, currency, commodity and equity markets. However, discretionary CTAs do not display significant timing ability in any of these markets.

[Table 2 about here]

4.2 Detect Market Timing with Futures Return-Based Factors

HM model specification (II) provides another overall test of CTAs' market timing ability and the results are reported in Table 3. As we noted in the previous section, specification (II) of

HM assumes that managers can time the best-performing markets in each of the specialization markets; hence with this specification we can come up with a parsimonious model without losing any explanatory power.

All of the timing coefficient estimates are positive for both discretionary and systematic CTA indices. The explanatory power are 0.106 and 0.292, respectively, which is significantly higher than those based on traditional factors, especially for discretionary CTAs. Discretionary CTAs show ability in timing the best performing markets among physicals futures, including corn, crude oil, natural gas, and gold, at aggregate level. Systematic CTAs, on the other hand, show ability in timing the best performing markets among currency futures (represented by Euro, Japanese Yen, and British Pounds) and physicals futures.

[Table 3 about here]

Table 4 reports return timing results for CTA indices by category. Based on their self-reported classification, we have five different CTA indices built from equally weighting all CTAs in categories of currency, financial, commodity, stock index, and diversified, where diversified CTAs may be involved in all futures markets.¹² We see that all market timing regressions have higher explanatory power for systematic CTAs than for discretionary CTAs. The difference in adjusted R^2 is actually significant except that for the diversified category.

Panel A reports timing coefficients estimated from TM model and Panel B reports those from the first specification of HM model. Conclusion on the timing ability from the two models is consistent to a large extent. For example, systematic currency CTAs are found to have strong timing ability in Euro, Japanese Yen markets while discretionary ones are able to time the British pound market. Diversified CTAs are found to be able to time Euro, Germany government bond futures markets, etc. It is interesting to see that stock index CTAs actually possess negative

¹² A stepwise regression is used to find effective factors for diversified CTAs to achieve parsimony.

return timing ability for FTSE and SP500. The HM specification (I) actually locates significant timing ability for discretionary diversified CTAs in Euro, British Pound, corn markets as well.

Another interesting finding in Panel A and Panel B is that CTAs identified with significant return timing ability (positive significant β) have negative significant abnormal performance (negative significant α). This is consistent with findings in Spiegel, Mamaysky, and Zhang (2004) and others that there is a negative relationship between α and β due to estimation process. On the other hand, this also reflects the fact that after the portion of return explained by timing ability, the leftover in performance is usually significantly negative, indicating that selection ability is almost non-existent in CTAs and the negative α represents fees and other charges.

[Table 4 about here]

4.3 Combine Return Timing and Volatility Timing

Table 5 shows the abnormal performance (α) and volatility timing results from applying volatility timing model (4). Following Chen and Liang (2006), we use the end-of-month implied volatility from VIX series as we find that volatility in individual futures markets does not seem to play a role in explaining CTA returns. Again, the volatility timing model does a better job explaining return of systematic CTAs. At aggregate level, the estimated coefficients are negative for both discretionary and systematic CTAs, while it is highly significant that for systematic CTAs. Most categories of CTAs, whether they are discretionary or systematic, also exhibit significant volatility timing ability. However, we notice that currency CTAs are an exception in that market volatility does not seem to play a role in affecting their returns, leaving a significant amount of unexplained performance in the intercept estimate (α).

[Table 5 about here]

Table 6 reports results from the combined return and volatility timing models (6), (7), (8). Based on the previous results, we pick the futures markets in which CTAs are found to be able to time and use them only in the model to achieve parsimony. With this complete model, we see that the explanatory power improves for both at aggregate level and categorical level. With a TM model, we find in Panel A that discretionary CTAs successfully time corn, German bond futures markets and that systematic CTAs successfully time Euro futures market and VIX. The futures factor models work well for discretionary diversified CTAs, who are found to time Euro markets successfully. Systematic diversified CTAs, however, time Euro, corn, Germany government bond futures markets, and VIX successfully. Panel B shows results from a HM model specification (I); the results are similar to those from a TM model. From Table 6 we notice that the stock index CTAs seem to behave differently from the majority, where they present negative timing ability as well as positive significant abnormal performance.

[Table 6 about here]

We also use a 36-month window rolling regression to estimate return and volatility timing coefficients for our CTA categorical indices to examine the time variation of timing coefficients. The results are plotted in Figure 3 together with the *t*-statistics of those coefficients. Consistent with our full-period regression, CTAs show both return and volatility timing ability during January 1994 and December 2004. This is most pronounced for currency, financial, and commodity CTAs, while stock index CTAs is the only group that seems to present negative return timing.

[Figure 3 about here]

5. Robustness

Our findings so far point to positive market return and volatility timing ability in most CTA managers. However, multiple reasons can lead to finding pseudo-timing in a sample. First, as suggested by Jagannathan and Korajczyk (1986), option payoffs have a convex relationship with the market return, which may be interpreted as timing ability even if the fund manager just holds some options and does not time the market at all. Second, illiquid asset holdings are likely to lead to pseudo-timing. Third, Ferson and Schadt (1996), Ferson and Christopherson (1998) emphasize the possible impact of not considering public information in performance evaluation. Finally, as Goetzmann, et al. (2000) and Ferson and Khang (2002) state, the high frequency at which a fund manager trades combined with the low frequency at which the returns are reported may also lead to spurious results that the manager possesses market timing ability.

We carry out robustness checks to address the above concerns. Since CTAs trade mainly liquid futures contracts, the concern regarding liquidity is not likely to affect our study. To address the third concern, we exclude CTAs that trade options from our sample and run the same analysis to see whether they exhibit timing ability to address the option-trading concern. Since we do not have higher frequency return data, it is not possible for us to address the last concern.

Table 7 reports the regression results on all CTA indices from a combined timing model using various models. There are altogether 740 CTAs which indicate to the database that they do not trade options. We run the timing test on the equally weighted average index of all these 740 CTAs based on TM, HM specifications. The explanatory power is reasonable, taking into consideration the poor explanatory power from traditional factors, and we again find significant return and volatility timing ability for this group. Currency markets stay the most popular area

for CTAs that exhibit return timing ability. So our concern about pseudo-timing due to option trading is alleviated to a large extent.

[Table 7 about here]

To further check the robustness of our results, we investigate the timing ability at individual fund level. We report a number of significant timing ability for individual CTAs. The results are reported in Table 8 for CTA categories that are identified to exhibit significant timing ability at index level only, including currency CTAs, financial CTAs and diversified CTAs. We require each individual CTA to have at least 36 months of return history to be included for study so that we have a reasonably long time series for timing test against multiple factors. This restriction reduces the number of qualified funds: The number of currency CTAs is reduced from 44 to 32, that of financial CTAs is reduced from 154 to 113 and that of diversified CTAs is reduced from 452 to 337. We observe that the timing ability in different markets (currency CTAs to currency futures markets, financial CTAs to currency and bond/interest rate futures markets, diversified CTAs to all the futures markets) are significant for more than half of the individual CTAs. We further observe that if a CTA does exhibit significant timing ability, it is highly probable that (>95%) that he/she displays positive market timing ability. On the other hand, most of these CTAs exhibit negative significant abnormal performance.

[Table 8 about here]

This finding that CTA funds have a combination of positive significant timing ability and negative significant securities selection ability similar results reported by Kon (1983), Henriksson (1984) and Mamaysky, Spiegel and Zhang (2004), and others with regard to mutual funds

In tests that are not reported here, we also detect significant timing ability for some individual funds in the category of physicals CTAs and stock index CTAs. Even though no significant timing ability is found for these categories at index level, individual funds are able to time the markets. The findings are in general consistent with what have been reported in Table 8 and discussed above.

6. Conclusion

This paper makes several contributions to literature of CTA performance. First, it is the first study to examine the return and volatility timing ability for CTAs as a separate group. Second, with risk factors based on returns from several futures contracts, we are able to present multi-factor models with increased explanatory power to test for the presence of market timing ability. Third, using the multi-market model of market timing, we are able to estimate market timing ability of CTAs in markets that are focus of their trading strategies. Fourth, we document that discretionary CTAs behave differently from systematic CTAs, having higher alpha (measuring selection ability) and less market timing ability. Fifth, from our tests on individual CTAs, we find evidence that CTAs generate their returns mostly from successful market timing and confirm the negative relationship between market timing and selection.

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Figure 1: Asset under management for managed futures industry and CTAs, 1990-2004. Data are from *Benefits of Managed Futures, 2005 Update*, Published by CISDM, 2005

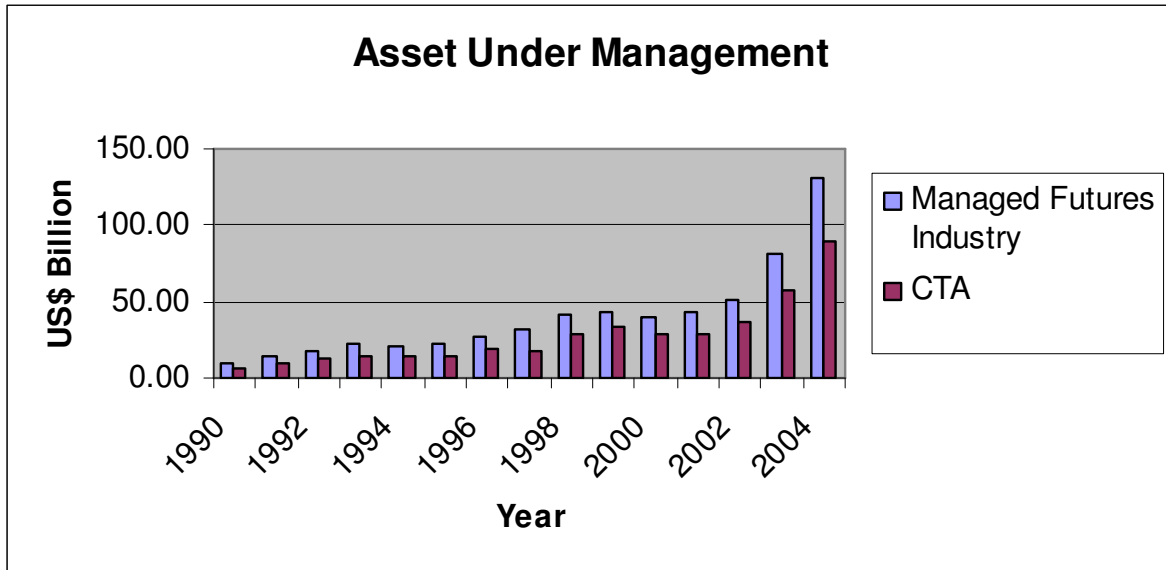


Figure 2: plots the average return of 36 months in states 1-5. State 1 is the worst performing 36 months for MSCI World equity index, state 5 is the best performing 36 months for MSCI World equity index. State 2 is the second worst performing 36 months for MSCI World, state 4 is the second best performing 36 months for MSCI World and state 3 is the rest 36 months.

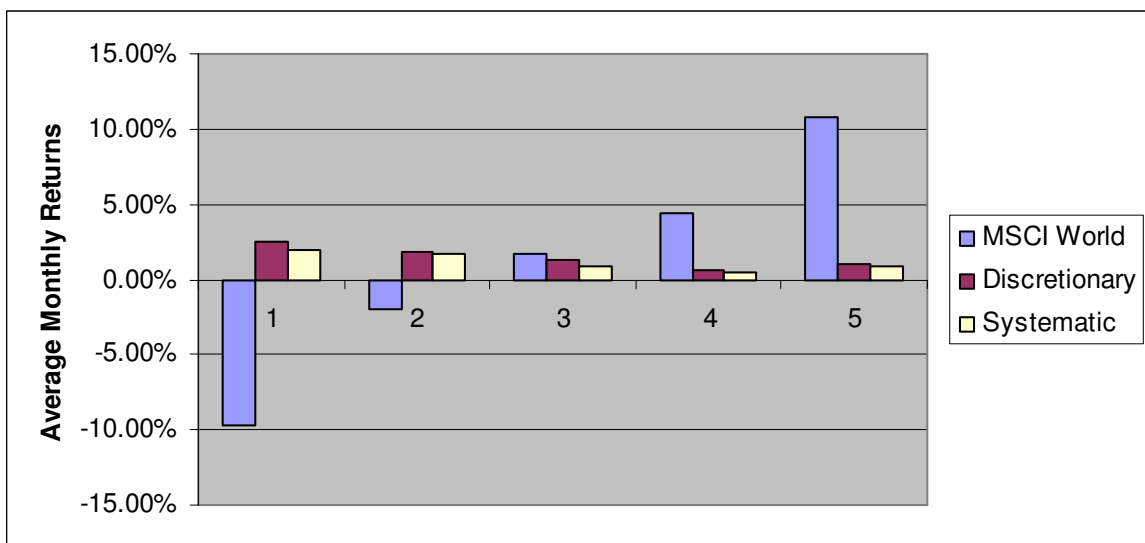


Figure 3 Time variation of timing coefficient. Timing variation in timing coefficient for the futures markets that CTAs exhibit return timing ability are plotted. The timing coefficients are estimated from the combined return and volatility timing HM model specification (II) as in (8). The Figures display market timing with respect to currencies, interest rate rates, commodity prices, stock indices and volatility. The plots of t -statistics are also presented. DIS represents the equally weighted portfolio of all discretionary CTAs, and SYS represents the equally weighted portfolio of systematic CTAs, in each category. CUR, COM, FIN, STK represent currency, physicals, financials, and stock indices futures markets, respectively. The rolling regression window is 36 months. The sample period is from January 1994 to December 2004.

Figure 3, Panel A. Time variation of timing coefficient to currency futures markets

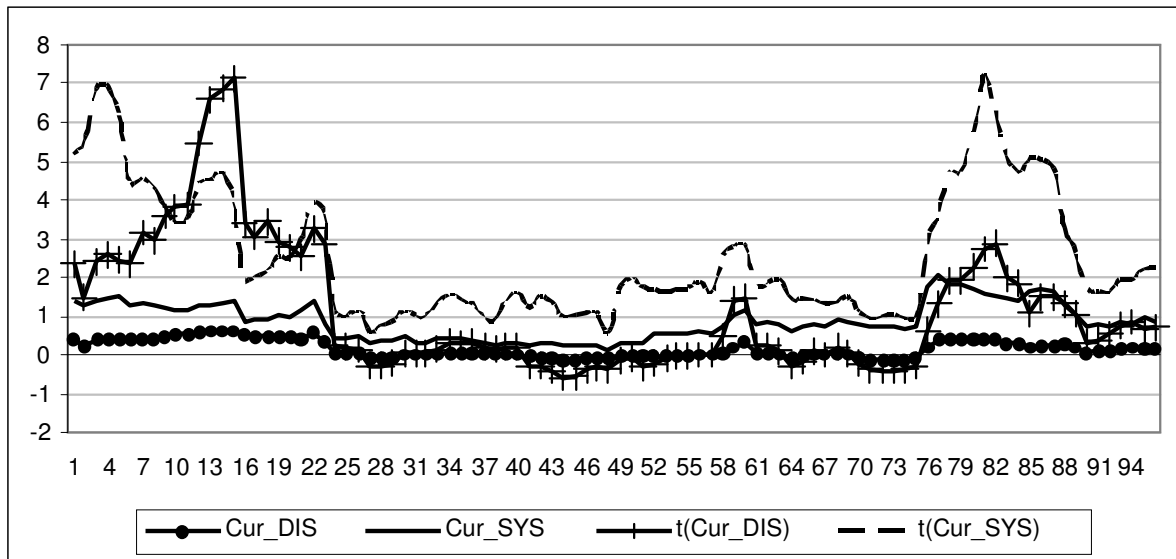


Figure 3, Panel B. Time variation of timing coefficient to bond/interest rate futures markets

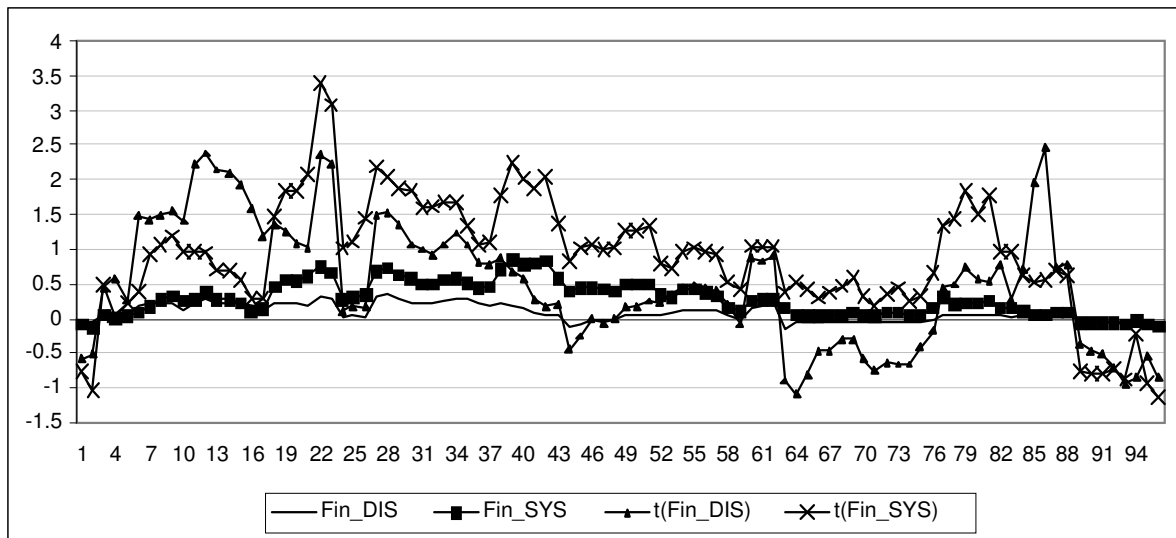


Figure 3, Panel C. Time variation of timing coefficient to commodity futures markets

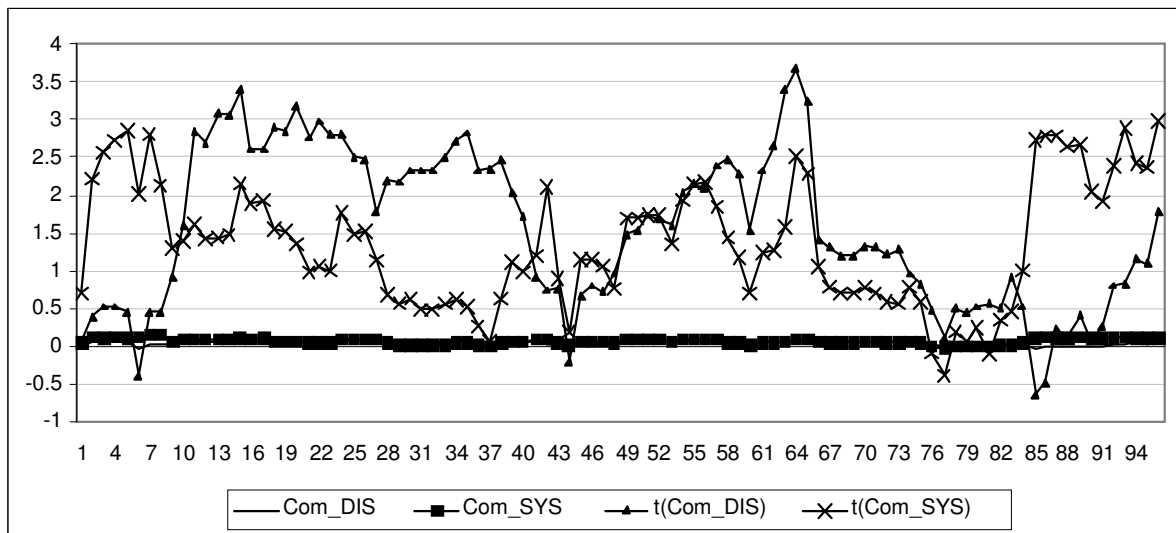


Figure 3, Panel D. Time variation of timing coefficient to stock index futures markets

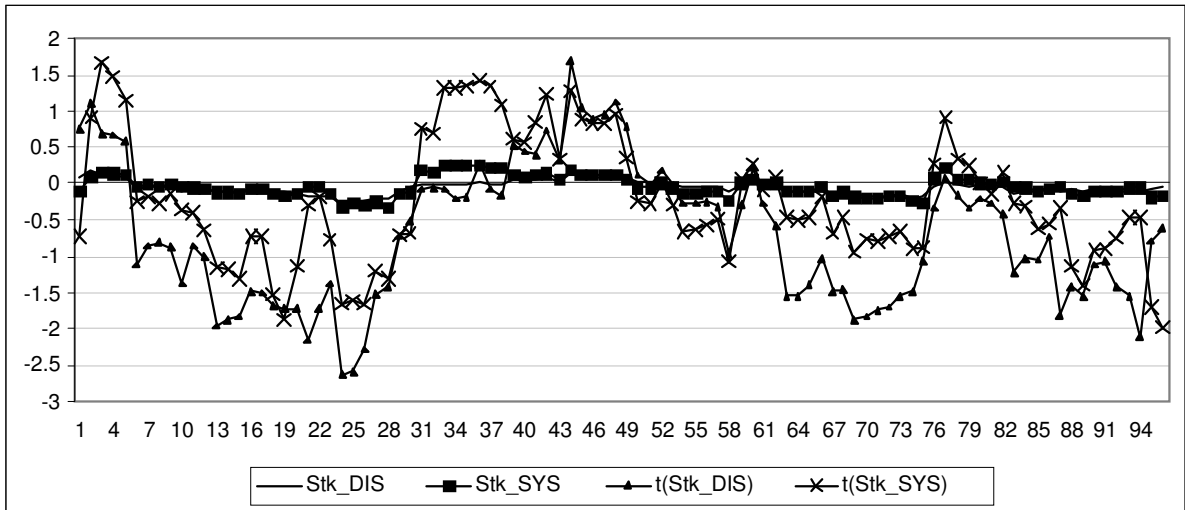


Figure 3, Panel E. Time variation of timing coefficient to market volatility (VIX)

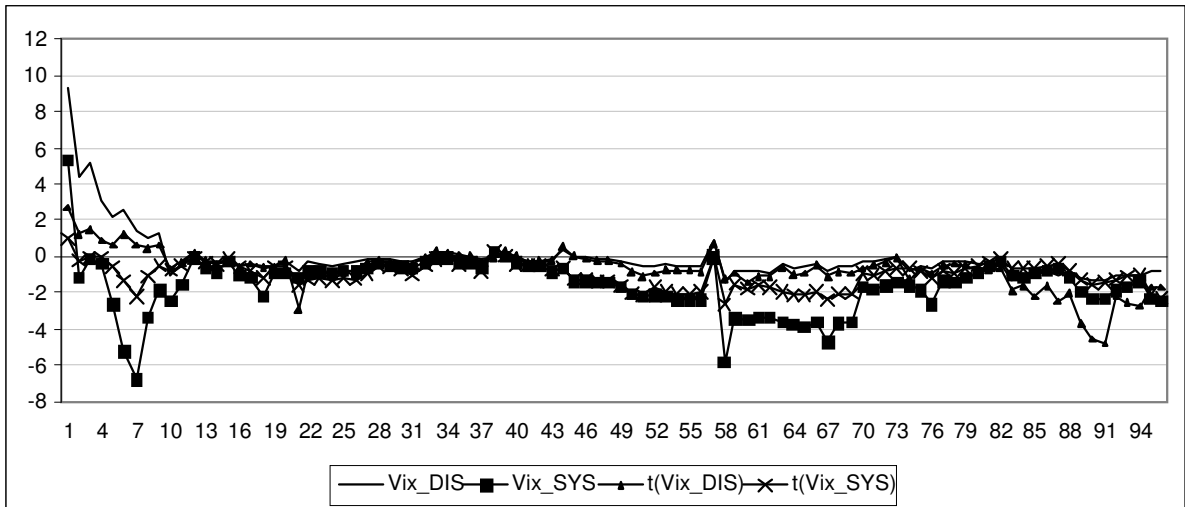


Table 1 Summary statistics

Panel A. AUM and Age (Live CTAs by the end of 2004 only)

	Number	Total AUM (US\$ million)	Average AUM (US\$ million)	Average Age (month)
All CTAs	278	61376.60	221.60	85
Commodity CTAs	16	1389.80	86.90	56
Currency CTAs	45	9199.80	204.40	87
Diversified CTAs	150	36753.00	245.00	93
Financial CTAs	45	13447.00	298.80	66
Stock Index CTAs	22	671.60	30.50	68

Panel B. Summary Statistics of CTA Indices

	Mean (%)	Stdev (%)	Min (%)	Max (%)	ρ
All - Discretionary	1.190	1.544	-1.812	9.859	0.101
All- Systematic	0.993	2.810	-4.527	9.376	-0.009
Currency -Discretionary	0.898	1.320	-2.990	4.618	0.318
Currency - Systematic	0.747	2.466	-3.166	12.018	0.065
Financial - Discretionary	0.900	1.413	-4.536	5.443	-0.071
Financial - Systematic	0.892	3.013	-6.715	9.683	0.101
Commodity - Discretionary	1.350	3.961	-6.697	27.950	0.015
Commodity - Systematic	2.787	11.256	-31.955	60.240	-0.287
Stock Index - Discretionary	1.371	2.515	-9.957	12.475	-0.080
Stock Index - Systematic	0.840	1.903	-5.409	5.723	-0.036
Diversified - Discretionary	1.070	2.552	-5.309	9.729	0.161
Diversified - Systematic	1.011	3.620	-6.533	10.180	-0.036

Panel C, D, E: Summary Statistics of Factors

	Mean (%)	Stdev (%)	Min (%)	Max (%)	ρ
Panel C: Futures Return					
JPY	-0.250	3.675	-9.813	16.817	0.002
EURO	0.070	2.803	-6.295	7.518	0.144
IBP	0.296	2.127	-6.674	5.682	-0.100
US Interest	0.323	2.665	-10.224	7.357	0.075
German Gov. Bond	0.299	1.501	-3.782	3.622	0.078
Eurodollar	-1.718	6.765	-29.701	21.108	0.280
Gold	-0.206	3.640	-9.693	15.642	-0.115
Copper	0.542	6.524	-18.200	19.710	-0.121
Natural Gas	0.531	14.306	-29.473	46.995	0.065
Crude Oil	1.653	9.075	-23.130	34.166	0.011
Corn	-0.825	5.742	-15.445	12.351	0.081
FTSE100	0.013	4.245	-13.718	8.812	-0.014
NIKKEI225	-0.322	6.085	-14.493	14.149	-0.038
S&P 500	0.455	4.499	-15.638	8.618	0.003
Panel D: PTFS Factors					
PTFSBD	0.796	15.994	-24.215	66.224	0.143
PTFSFX	-0.123	19.231	-29.975	90.267	0.038
PTFSCOM	-0.514	12.484	-22.935	64.996	-0.123
PTFSIR	-0.242	18.852	-24.645	98.698	0.040
PTFSSTK	-5.696	13.287	-30.192	46.149	0.200
Panel E: Traditional Factors					
TBill	0.329	0.150	0.071	0.532	0.993
Exmkt	0.631	4.534	-15.990	8.160	0.045
SMB	0.292	3.719	-11.600	14.620	-0.030
HML	0.201	4.472	-20.790	14.920	0.111
UML	0.823	5.528	-25.000	18.380	-0.071
Emerging Market	0.410	6.715	-28.914	13.770	0.166
Convertible	0.818	3.628	-12.542	12.686	0.091
Term Premium	0.653	2.538	-8.875	7.732	0.099
High Yield	0.596	2.066	-7.372	7.492	0.147
End-of-month VIX	6.032	1.880	3.069	12.783	0.235

Panel F. Correlation Matrix: correlation between the returns of fourteen most heavily traded futures.

	JPY	EURO	Sterling	US T-bond	German Bond	Eurodollar	Gold	Copper	Natural Gas	Crude Oil	Corn	FTSE 100	Nikkee	S&P500
JPY	1.000													
EURO	0.438	1.000												
Sterling	0.266	0.633	1.000											
US T-bond	0.013	0.133	0.168	1.000										
German Bond	-0.033	0.026	0.049	0.718	1.000									
Eurodollar	-0.074	-0.174	-0.202	-0.571	-0.420	1.000								
Gold	0.255	0.358	0.238	0.099	0.077	-0.156	1.000							
Copper	0.134	0.095	0.100	-0.155	-0.080	0.153	0.196	1.000						
Natural Gas	-0.007	0.221	0.156	0.205	0.126	0.008	0.139	0.029	1.000					
Crude Oil	0.076	0.048	0.014	0.011	-0.065	0.069	0.149	0.154	0.365	1.000				
Corn	0.040	-0.017	0.028	0.108	-0.013	0.000	0.021	0.026	0.132	-0.024	1.000			
FTSE100	0.085	-0.151	-0.257	-0.116	-0.028	0.268	-0.086	0.227	0.000	-0.047	0.008	1.000		
Nikkee1225	0.005	-0.220	-0.116	-0.050	-0.017	0.157	0.120	0.237	0.157	0.193	0.055	0.378	1.000	
S&P500	0.144	-0.097	-0.064	-0.063	-0.057	0.215	-0.032	0.311	0.032	-0.040	0.106	0.783	0.457	1.000

In bold, significant values (except diagonal) at the level of significance $\alpha=0.050$ (two-tailed test)

Table 2 Explanatory power of various factor models

Single- and multi- factor models with traditional factors and Fung and Hsieh (2001) PTFS factors. Mkt, SMB, HML, UMD are Fama-French (1993) three factors and Carhart (1997) momentum factor. Emer, LT, HY, CV are augmented factors representing returns from MSCI emerging market index, term premium, credit risk premium, convertible bond premium index. BD, FX, COM, IR, STK represent Fung and Hsieh (2001) PTFS factors: PTFSBD, PTFSFX, PTFSCOM, PTFSIR and PTFSSTK, respectively.

Model	Single Factor		Carhart 4-factor		Augmented 8-factor		FS PTFS Factor		Augmented PTFS	
	DIS	SYS	DIS	SYS	DIS	SYS	DIS	SYS	DIS	SYS
A	0.008 *** (6.281)	0.007 *** (3.112)	0.009 *** (6.031)	0.006 ** (2.316)	0.009 *** (5.788)	0.005 ** (2.255)	0.008 *** (5.735)	0.009 *** (4.050)	0.009 *** (5.117)	0.007 *** (2.919)
β (Mkt)	0.004 -0.187	-0.085 (-1.292)	-0.004 (-0.129)	-0.045 (-0.506)	-0.058 (-1.392)	-0.178 *(-1.890)			-0.036 (-0.885)	-0.07 (-0.919)
β (SMB)			-0.044 (-1.386)	0.003 -0.043	-0.049 (-1.176)	-0.006 (-0.068)			-0.049 (-1.236)	0.006 -0.105
β (HML)			-0.036 (-0.761)	0.063 -0.659	-0.054 (-0.927)	0.109 -1.022			-0.065 (-1.161)	0.094 -1.054
β (UMD)			-0.018 (-0.604)	0.081 -1.129	-0.031 (-1.030)	0.032 -0.401			-0.037 (-1.147)	0.046 -0.738
β (Emer)					0.082 *** (2.990)	0.093 * (1.856)			0.084 *** (2.742)	0.134 *** (3.357)
β (LT)					0.139 ** (2.523)	0.424 *** (4.108)			0.129 ** (2.582)	0.306 *** (3.657)
β (HY)					-0.081 (-1.050)	-0.343 ** (-2.174)			-0.048 (-0.697)	-0.146 (-1.172)
β (CV)					-0.026 (-0.413)	0.211 * (1.766)			-0.067 (-1.042)	0.017 -0.185
β (BD)							0.01 -1.358	0.031 *** (2.626)	0.007 -0.79	0.032 *** (2.672)
β (FX)							0.014 -1.572	0.06 *** (6.275)	0.016 *(1.767)	0.057 *** (5.290)
β (COM)							0.01 -0.879	0.049 *(1.968)	0.012 -1.014	0.049 ** (2.032)
β (IR)							-0.006 (-1.145)	-0.003 (-0.266)	-0.003 (-0.576)	0.004 -0.391
β (STK)							-0.004 (-0.474)	0.034 ** (2.388)	-0.006 (-0.716)	0.027 * (1.939)
<i>R-square</i>	-0.008	0.011	-0.022	-0.001	0.029	0.123	0.02	0.379	0.052	0.447

*, **, and *** mean statistically significant at 10%, 5%, and 1%, respectively.

Table 3 Return Timing: All CTA Indices, HM Model Specification (II)

This table shows the return timing results for each category of CTAs in their specialization markets using HM model specification (II), where managers are assumed to time the best-performing futures market(s), hence the timing signal is $\max(\max(F_{1,t+1}, F_{2,t+1}, \dots), 0)$. DIS represents the equally weighted portfolio of all discretionary CTAs, and SYS represents the equally weighted portfolio of systematic CTAs, in each category. CUR, COM, FIN, STK represent currency, physicals, financials, and stock indices futures markets, respectively. D (*) are estimated coefficients for return timing ability in these markets under HM Model specification (II).

*, **, and *** mean statistically significant at 10%, 5%, and 1%, respectively.

$$\beta_j = \beta_{0,j} + \gamma_{j,t} S_{j,t+1} + v_{t+1} \quad (1)$$

$$r_{p,t+1} = \alpha + \sum_{j=1}^K \beta_{jt} F_{j,t+1} + \omega_{t+1} \quad (2)$$

All CTAs	alpha	D(CUR)	D(COM)	D(FIN)	D(STK)	\bar{R}^2
DIS	0.002 (0.674)	0.151 (1.616)	0.027 **(2.523)	0.003 (0.064)	0.028 (0.409)	0.106
SYS	-0.014 **(-2.310)	0.645 *** (2.955)	0.053 ** (2.436)	0.057 (0.705)	0.001 (0.012)	0.292

Table 4 Return timing: Category CTA indices

This table shows the return timing results for each category of CTAs in their specialization markets using TM model, HM model specification (I). DIS represents the equally weighted portfolio of all discretionary CTAs, and SYS represents the equally weighted portfolio of systematic CTAs, in each category. Euro, JPY, IBP, corn, Tbond, Ger, Eurodollar, gold, copper, gas, oil, FTSE, NIKKEI, SP are Euro, Japanese Yen, British Pound, corn, US T-bond, German Government Bond, Eurodollar, gold, copper, natural gas, crude oil, FTSE 100, NIKKEI 225 and S&P 500 futures markets for TM model and HM specification (I). γ , D are return timing coefficients for TM model and HM model respectively. *, **, and *** mean statistically significant at 10%, 5%, and 1%, respectively.

Panel A. TM Model

Currency CTAs	alpha	γ (Euro)	γ (JPY)	γ (IBP)				\bar{R}^2
DIS	0.002 (1.402)	0.427 (0.253)	0.529 (1.480)	4.129 **(2.104)				0.055
SYS	-0.01 ***(-5.728)	11.814 *** (3.837)	2.679 *** (4.249)	2.086 (0.472)				0.454
Financial CTAs	alpha	γ (Euro)	γ (JPY)	γ (IBP)	γ (US Tbond)	γ (Ger)	γ (Eudollar)	\bar{R}^2
DIS	0.002 (0.811)	1.171 (0.836)	0.252 (0.557)	0.140 (0.067)	-0.339 (-0.356)	12.023 *(1.664)	-0.038 (-0.295)	0.021
SYS	-0.016 ***(-4.319)	11.328 *** (3.416)	1.111 *(1.804)	-0.733 (-0.126)	-0.910 (-0.434)	28.000 *** (3.918)	0.062 (0.285)	0.424
Commodity CTAs	alpha	γ (gold)	γ (copper)	γ (gas)	γ (oil)	γ (corn)	\bar{R}^2	
DIS	0.0086 (0.862)	-0.4177 (-1.270)	0.1917 (1.346)	0.0087 (0.097)	-0.1662 (-1.175)	0.3616 *(1.886)	-0.012	
SYS	0.0086 (0.920)	-0.3610 (-1.205)	0.1618 (1.111)	0.0057 (0.0647)	-0.1407 (-0.954)	0.3233 *(1.752)	-0.043	
Stock Index CTAs	alpha	γ (FTSE)	γ (NIKKEI)	γ (SP)				\bar{R}^2
DIS	0.018 *** (5.210)	-2.37 *** (-2.744)	0.281 (0.319)	-1.183 ** (-2.274)				0.082
SYS	0.003 (1.494)	0.057 (0.130)	-0.058 (-0.120)	-0.127 (-0.404)				0.326
Diversified CTAs	alpha	γ (Euro)	γ (JPY)	γ (IBP)	γ (corn)	γ (Ger)	γ (FTSE)	\bar{R}^2
DIS	-0.003 (-1.021)	7.179 *** (4.157)	0.386 (0.822)	2.952 (0.880)	0.366 (1.559)	10.726 (1.557)	-0.176 (-0.194)	0.313
SYS	-0.015 *** (-3.201)	10.516 *** (2.952)	0.725 (0.750)	6.042 (0.992)	0.808 *(1.815)	21.322 ** (2.111)	1.711 (1.498)	0.332

Panel B. HM Model Specification (I)

Currency CTAs	alpha	D(Euro)	D(JPY)	D(IBP)				\bar{R}^2
DIS	-0.001 (-0.422)	0.026 -0.132 (1.036)	0.139 (1.422)	0.435 **(2.226)				0.055
SYS	-0.024 ***(-8.229)	1.226 *** (3.829)	0.671 *** (3.817)	0.616 (1.437)				0.461
Financial CTAs	alpha	D(Euro)	D(JPY)	D(IBP)	D(Tbond)	D(Ger)	D(Eu\$)	\bar{R}^2
DIS	-0.002 (-0.481)	0.167 (1.036)	0.078 (0.763)	-0.013 (-0.057)	0.188 (0.971)	0.545 (1.306)	-0.052 (-0.990)	0.019
SYS	-0.031 ***(-4.634)	1.113 *** (3.222)	0.329 ** (1.987)	0.462 (0.979)	0.096 (0.219)	1.219 ** (2.172)	0.026 (0.239)	0.398
Commodity CTAs	alpha	D(gold)	D(copper)	D(gas)	D(oil)	D(corn)	\bar{R}^2	
DIS	0.014 (1.488)	-0.444 (-1.400)	0.240 (1.101)	0.005 (0.060)	-0.177 (-1.527)	0.135 (0.565)	-0.012	
SYS	0.039 (1.611)	0.275 (0.290)	-0.784 ** (-2.281)	0.254 (1.373)	-0.455 (-1.058)	0.031 (0.061)	-0.033	
Stock Index CTAs	alpha	D(FTSE)	D(NIKKEI)	D(SP)				\bar{R}^2
DIS	0.015 *** (4.459)	-0.234 * (-1.943)	-0.109 (-0.729)	-0.055 (-1.002)				0.04
SYS	0.005 ** (1.974)	-0.031 (-0.322)	-0.093 (-1.029)	0.026 (0.715)				0.335
Diversified CTAs	alpha	D(Euro)	D(JPY)	D(IBP)	D(corn)	D(Ger)	D(FTSE)	\bar{R}^2
DIS	-0.016 *** (-3.453)	0.566 *** (2.648)	0.191 (1.295)	0.664 ** (2.040)	0.188 ** (2.237)	0.531 (1.068)	0.153 (0.953)	0.291
SYS	-0.038 *** (-4.922)	0.896 ** (2.129)	0.315 (1.398)	1.245 ** (2.123)	0.342 ** (2.567)	1.043 * (1.860)	0.388 ** (2.087)	0.348

Table 5 Volatility Timing

Table 5 shows the abnormal performance (alpha) and volatility timing results as in volatility timing model (7). VIX is the end-of-month implied volatility from CBOE VIX series. δ is volatility timing coefficient. *, **, and *** mean statistically significant at 10%, 5%, and 1%, respectively.

		alpha	$\delta(\text{VIX})$	\bar{R}^2
All CTAs	DIS	0.008 ***(5.307)	-0.237 (-0.939)	0.032
	SYS	0.004 *(1.944)	-1.509 **(-2.475)	0.153
Currency CTAs	DIS	0.005 *** (3.370)	-0.164 (-0.750)	-0.006
	SYS	0.005 ** (2.225)	0.423 (0.784)	-0.006
Financial CTAs	DIS	0.006 *** (4.021)	0.484 (1.253)	-0.005
	SYS	0.003 (1.265)	-1.488 ** (-2.249)	0.187
Commodity CTAs	DIS	0.010 *** (2.712)	-0.937 (-1.438)	-0.018
	SYS	0.022 *** (2.765)	-3.192 * (-1.780)	-0.004
Stock Index CTAs	DIS	0.012 *** (5.701)	1.735 *** (2.719)	0.085
	SYS	0.003 * (1.963)	-0.239 (-0.704)	0.339
Diversified CTAs	DIS	0.006 ** (2.608)	-0.734 (-1.250)	0.123
	SYS	0.004 (1.441)	-2.136 *** (-2.787)	0.166

Table 6 Combine return and volatility timing

This table shows the combined return and volatility timing results for TM model, HM model specification (I) and (II) in equations (6), (7) and (8). DIS represents the equally weighted portfolio of all discretionary CTAs, and SYS represents the equally weighted portfolio of systematic CTAs, in each category. Euro, JPY, IBP, corn, Tbond, Ger, Eurodollar, gold, copper, gas, oil, FTSE, NIKKEI, SP are Euro, Japanese Yen, British Pound, corn, US T-bond, German Government Bond, Eurodollar, gold, copper, natural gas, crude oil, FTSE 100, NIKKEI 225 and S&P 500 futures markets for TM model and HM specification (I). Cur, Com, Fin and Stk are currency, commodity, bond/interest rate and stock index futures markets. VIX is the end-of-month implied volatility from CBOE VIX series. γ , D are return timing coefficients and δ is volatility timing coefficient. *, **, and *** mean statistically significant at 10%, 5%, and 1%, respectively.

Pane A. TM model

All CTAs	alpha	γ (Euro)	γ (JPY)	γ (IBP)	γ (corn)	γ (Ger)	γ (FTSE)	δ (VIX)	\bar{R}^2
DIS	0.003 (-1.489)	2.379 (1.599)	0.167 (0.368)	2.031 (1.011)	0.441 **(2.576)	10.127 **(2.080)	-0.164 (-0.402)	-0.299 (-1.203)	0.143
SYS	-0.01 ***(-3.107)	10.595 *** (3.311)	1.113 (1.576)	2.211 (0.429)	0.447 (1.396)	11.118 (1.502)	0.369 (0.525)	-1.516 **(-2.263)	0.408
Currency	alpha	γ (Euro)	γ (JPY)	γ (IBP)				δ (VIX)	\bar{R}^2
DIS	0.002 (1.127)	0.553 (0.329)	0.624 *(1.764)	3.798 *(1.925)				-0.489 *(-1.678)	0.059
SYS	-0.010 ***(-6.236)	11.932 *** (3.766)	2.768 *** (4.132)	1.775 (0.383)				-0.458 (-0.613)	0.452
Financial	alpha	γ (Euro)	γ (JPY)	γ (IBP)	γ (Tbond)	γ (Ger)	γ (Eudollar)	δ (VIX)	\bar{R}^2
DIS	0.001 (0.716)	0.949 (0.712)	0.055 (0.111)	0.744 (0.361)	-0.542 (-0.580)	13.737 *(1.887)	0.041 (0.308)	1.112 *(1.739)	0.062
SYS	-0.016 ***(-4.195)	11.697 *** (3.517)	1.441 ** (2.311)	-1.740 (-0.305)	-0.573 (-0.287)	25.141 *** (3.555)	-0.069 (-0.342)	-1.855 **(-1.991)	0.448
Commodity	alpha	γ (gold)	γ (copper)	γ (gas)	γ (oil)	γ (corn)		δ (VIX)	\bar{R}^2
DIS	0.008 (1.340)	-1.124 (-0.886)	0.465 (0.647)	0.075 (0.784)	-0.506 ***(-3.158)	1.114 (1.462)		-0.900 (-1.363)	-0.013
SYS	0.030 ** (2.363)	0.230 (0.091)	-2.367 **(-2.217)	0.163 (0.773)	-0.903 (-1.609)	0.671 (0.483)		-3.870 *(-1.837)	-0.036
Stock Index	alpha	γ (FTSE)	γ (NIKKEI)	γ (SP)				δ (VIX)	\bar{R}^2
DIS	0.017 *** (5.190)	-1.841 **(-2.213)	0.707 (0.722)	-1.078 **(-2.131)				2.406 *** (2.942)	0.147
SYS	0.003 (1.573)	-0.051 (-0.110)	-0.145 (-0.288)	-0.148 (-0.468)				-0.490 (-0.993)	0.326
Diversified	alpha	γ (Euro)	γ (JPY)	γ (IBP)	γ (corn)	γ (Ger)	γ (FTSE)	δ (VIX)	\bar{R}^2
DIS	-0.003 (-1.132)	6.600 *** (3.778)	0.606 (1.307)	3.398 (1.043)	0.361 (1.485)	12.428 (1.616)	0.322 (0.441)	-0.453 (-0.605)	0.301
SYS	-0.014 ***(-3.418)	11.161 *** (3.136)	1.225 (1.521)	4.265 (0.720)	0.834 ** (2.017)	18.863 *(1.950)	0.929 (0.949)	-2.513 **(-2.536)	0.375

Panel B. HM Specification (I)

All CTAs	alpha	D(Euro)	D(JPY)	D(IBP)	D(corn)	D(Ger)	D(FTSE)	$\delta(VIX)$	\bar{R}^2
DIS	-0.003 (-1.118)	0.180 (0.927)	0.102 (0.814)	0.308 (1.400)	0.141 **(2.372)	0.533 *(1.659)	-0.007 (-0.070)	-0.347 (-1.438)	0.134
SYS	-0.027 ***(-4.877)	0.996 *** (2.706)	0.382 ** (2.341)	0.759 (1.512)	0.201 ** (2.040)	0.453 (1.121)	0.128 (0.950)	-1.678 ** (-2.618)	0.417
Currency	alpha	D(Euro)	D(JPY)	D(IBP)				$\delta(VIX)$	\bar{R}^2
DIS	-0.001 (-0.658)	0.043 (0.222)	0.164 *(1.687)	0.395 *(1.946)				-0.508 *(-1.768)	0.060
SYS	-0.025 ***(-8.090)	1.245 *** (3.712)	0.697 *** (3.577)	0.575 (1.242)				-0.527 (-0.678)	0.460
Financial	alpha	D(Euro)	D(JPY)	D(IBP)	D(Tbond)	D(Ger)	D(Eudollar)	$\delta(VIX)$	\bar{R}^2
DIS	-0.002 (-0.456)	0.131 (0.819)	0.063 (0.600)	0.030 (0.130)	0.179 (0.895)	0.624 (1.334)	-0.051 (-0.910)	0.447 (1.034)	0.023
SYS	-0.031 ***(-4.804)	1.230 *** (3.313)	0.376 ** (2.324)	0.324 (0.655)	0.125 (0.297)	0.964 *(1.844)	0.020 (0.193)	-1.439 ** (-2.123)	0.420
Commodity	alpha	D(gold)	D(copper)	D(gas)	D(oil)	D(corn)		$\delta(VIX)$	\bar{R}^2
DIS	0.014 (1.497)	-0.432 (-1.355)	0.221 (1.020)	-0.001 (-0.014)	-0.186 (-1.583)	0.127 (0.527)		-0.886 (-1.244)	-0.014
SYS	0.040 *(1.710)	0.331 (0.348)	-0.872 ** (-2.454)	0.228 (1.156)	-0.494 (-1.169)	-0.008 (-0.015)		-4.013 ** (-1.984)	-0.024
Stock Index	alpha	D(FTSE)	D(NIKKEI)	D(SP)				$\delta(VIX)$	\bar{R}^2
DIS	0.023 *** (4.447)	-0.330 *(-1.975)	-0.264 ** (-2.090)	0.029 (0.158)				2.490 *** (3.150)	0.152
SYS	0.004 *(1.715)	0.003 (0.025)	-0.013 (-0.164)	-0.127 (-1.049)				-0.527 (-1.108)	0.332
Diversified	alpha	D(Euro)	D(JPY)	D(IBP)	D(corn)	D(Ger)	D(FTSE)	$\delta(VIX)$	\bar{R}^2
DIS	-0.016 *** (-3.440)	0.585 *** (2.691)	0.216 (1.473)	0.622 *(1.850)	0.189 ** (2.284)	0.502 (1.003)	0.129 (0.819)	-0.574 (-0.779)	0.289
SYS	-0.038 *** (-5.295)	0.987 ** (2.346)	0.435 ** (2.199)	1.049 *(1.769)	0.348 *** (2.723)	0.908 (1.651)	0.277 (1.509)	-2.699 ** (-2.615)	0.387

Table 7 Robustness test: CTAs indices as equally weighted average of all non-opiton trading CTAs

This table shows the timing ability of 740 CTAs that do not trade options using TM model, HM specification (I) and (II). DIS represents the equally weighted portfolio of all discretionary CTAs that do not trade options, and SYS represents the equally weighted portfolio of all systematic CTAs that do not trade options. Euro, JPY, IBP, corn, Ger, FTSE are Euro, Japanese Yen, British Pound, corn, German Government Bond and FTSE 100 futures markets for TM model and HM specification (I). Cur, Com, Fin and Stk are currency, commodity, bond/interest rate and stock index futures markets. VIX is the end-of-month implied volatility from CBOE VIX series. γ , D are return timing coefficients and δ is volatility timing coefficient. *, **, and *** mean statistically significant at 10%, 5%, and 1%, respectively.

Panel A: TM Model

	alpha	γ (Euro)	γ (JPY)	γ (IBP)	γ (corn)	γ (Ger)	γ (FTSE)	δ (VIX)	\bar{R}^2
DIS	0.000 (-0.126)	5.133 **(2.165)	1.675 **(2.340)	0.566 (0.169)	0.190 (0.710)	15.649 *(1.960)	0.215 (0.348)	-0.688 (-1.509)	0.148
SYS	-0.012 ***(-3.323)	11.508 *** (3.374)	1.277 *(1.697)	2.287 (0.409)	0.516 (1.526)	11.359 (1.463)	0.431 (0.564)	-1.614 **(-2.258)	0.419

Panel B: HM Model Specification (I)

	alpha	D(Euro)	D(JPY)	D(IBP)	D(corn)	D(Ger)	D(FTSE)	δ (VIX)	\bar{R}^2
DIS	-0.01 *(-1.832)	0.336 (1.163)	0.481 **(2.292)	0.275 (0.852)	0.069 (0.721)	0.689 (1.270)	0.156 (0.961)	-0.780 (-1.638)	0.134
SYS	-0.03 ***(-4.945)	1.087 *** (2.783)	0.429 **(2.477)	0.794 (1.472)	0.222 ** (2.102)	0.441 (1.046)	0.146 (1.015)	-1.797 ***(-2.625)	0.428

Panel C: HM Model Specification (II)

	alpha	D(CUR)	D(COM)	D(FIN)	D(STK)	δ (VIX)	\bar{R}^2
DIS	-0.003 (-0.487)	0.479 *** (3.452)	0.011 (0.585)	-0.043 (-0.739)	0.104 (0.783)	-0.897 *(-1.872)	0.119
SYS	-0.015 ***(-2.506)	0.753 *** (3.361)	0.054 ** (2.276)	0.034 (0.432)	-0.059 (-0.738)	-1.871 ***(-3.107)	0.341

Table 8 Individual Funds Timing

This table reports the number of CTAs that belong to the categories in which market timing has been detected at index level (either successful or unsuccessful). The qualified CTAs have at least 36 months of return history. $t(\alpha)$ is t-statistic for abnormal performance (α), $t(\gamma\text{-cur})$ is t-statistic for timing coefficients on the three currency futures markets (Euro, Japanese Yen, and British Pound), $t(\gamma\text{-fin})$ is t-statistic for timing coefficients on the three interest rate futures (US T-bond, German government bond, Eurodollar), $t(\gamma\text{-com})$ is t-statistic for timing coefficients on the five physicals futures (Gold, Copper, Natural gas, Crude oil, and Corn), and $t(\gamma\text{-stk})$ is t-statistic for timing coefficients on the three stock index futures (FTSE100, Nikkei 1225, and S&P 500).

	All	Live (ALL)	Defunct (ALL)	Live (DIS)	Live (SYS)	Defunct (DIS)	Defunct (SYS)
Currency CTAs							
# CTAs	131	44	87	9	35	21	66
# Qualified	89	32	58	8	24	14	44
$lt(\alpha)>1.65$	46	17	29	1	16	3	26
$T(\alpha)>1.65$	6	3	3	1	2	1	2
$lt(\gamma\text{-cur})>1.65$	47	17	30	1	16	3	27
$T(\gamma\text{-cur})>1.65$	47	17	30	1	16	3	27
Financial CTAs							
# CTAs	154	42	112	6	36	20	92
# Qualified	113	39	74	5	34	16	58
$lt(\alpha)>1.65$	45	23	22	2	21	2	20
$T(\alpha)>1.65$	2	0	2	0	0	0	2
$lt(\gamma\text{-cur})>1.65$	42	21	21	0	21	3	18
$T(\gamma\text{-cur})>1.65$	41	21	20	0	21	3	17
$lt(\gamma\text{-fin})>1.65$	7	0	7	0	0	1	6
$T(\gamma\text{-fin})>1.65$	6	0	6	0	0	0	6
Diversified CTAs							
# CTAs	452	150	302	11	139	49	253
# Qualified	337	134	203	11	123	35	168
$lt(\alpha)>1.65$	130	61	69	1	60	5	64
$T(\alpha)>1.65$	2	1	1	0	1	0	1
$lt(\gamma\text{-cur})>1.65$	136	64	72	7	57	10	62
$T(\gamma\text{-cur})>1.65$	132	63	69	7	56	9	60
$lt(\gamma\text{-fin})>1.65$	84	33	51	2	31	4	47
$T(\gamma\text{-fin})>1.65$	75	28	47	1	27	4	43
$lt(\gamma\text{-com})>1.65$	60	40	20	2	38	1	19
$T(\gamma\text{-com})>1.65$	57	40	17	2	38	1	16
$lt(\gamma\text{-stk})>1.65$	22	8	14	1	7	2	12
$T(\gamma\text{-stk})>1.65$	12	3	9	1	2	0	9