CSIRO-Monash Superannuation Research Cluster

WORKING PAPER SERIES

FACTORS AFFECTING THE BIRTH OF AND FUND FLOWS INTO CTAs

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31 August 2014
CSIRO-MONASH WORKING PAPER NO 2014-03
CLUSTER PROJECT 4: FUND INDEXING, STYLE AND HEDGE FUNDS

ABSTRACT

Our paper investigates the timing of commodity trading advisors (CTAs) inception and the relationship between their fund flows and performance. Our results show that the CTA industry performance has over the long run (short run), a positive (negative) effect on new CTAs. The flow–performance relationship is strongly evidenced, though its functional form differs across CTA subcategories. Also, we do not observe a 'smart money' effect, indicating that investors are generally unsuccessful in choosing subsequent well-performing CTAs.

JEL Classification: G12, G20, and G29

Keywords: Commodity trading advisors, fund flows, flow–performance relation, smart money effect.

ACKNOWLEDGEMENTS: THIS RESEARCH WAS SUPPORTED BY THE CSIRO-MONASH SUPERANNUATION RESEARCH CLUSTER, A COLLABORATION BETWEEN CSIRO, MONASH UNIVERSITY, GRIFFITH UNIVERSITY, THE UNIVERSITY OF WESTERN AUSTRALIA, THE UNIVERSITY OF WARWICK, AND STAKEHOLDERS OF THE RETIREMENT SYSTEM IN THE INTEREST OF BETTER OUTCOMES FOR ALL.

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THE UNIVERSITY OF WESTERN AUSTRALIA
THE UNIVERSITY OF WARWICK
AUSTRALIAN CENTRE FOR FINANCIAL STUDIES

1. INTRODUCTION

A commodity trading advisor (CTA) can be defined as any individual or firm that receives compensation for giving investors advice on options, futures, and the actual trading of managed futures accounts.[1] In the US, CTAs are required to register with the Commodity Futures Trading Commission. They invest in equity, commodities, options, futures, and currencies globally. From the time of the first CTAs in 1949, the industry has experienced rapid growth in both the number of funds and assets under management (AUM). The total AUM have grown from approximately USD 300 million at the beginning of the 1980s to approximately USD 300 billion as at the end of 2012.[2] Despite this astounding growth, little is known about the factors affecting the birth of new CTAs and the associated fund flow patterns.

Our paper examines the lifecycle of CTAs. While a number of studies investigate the flow-performance relation and life cycle of mutual funds, hedge funds and private equity funds, the related literature specific to CTAs is scarce. Very little is known about what causes CTA funds to be born, about why some CTAs grow and prosper, and about why others disappear very early in their life. An understanding of the CTA lifecycle is important investors and the market generally. Our findings provide interesting insights about the formation of capital in the CTA industry. We also contribute to the CTA literature by being the first study to examine the factors affecting birth and fund flows of different CTA groups over a longer time period that includes the recent financial crisis. In addition, our results provide further supporting evidence for the flow-performance relationship and suggest strong competition among CTAs to attract fund flows. We also show that a naive strategy of chasing past winners does not appear to work for CTAs.

We find that that there is a positive long-term trend and negative short-term effect associated with past CTA performance. The number of new CTAs and the amount of new

[1] This definition is used by the U.S. Commodity Futures Trading Commission.

[2] Historical data on CTA AUM are from BarclayHedge web-site: http://www.barclayhedge.com/research/indices/cta/mum/CTA_Fund_Industry.html

funds being raised increases after a period of long-term (one year) good performance. We argue that this is because strong industry performance helps to create positive sentiment among investors towards the CTA industry as a whole and can help new CTAs attract new funds from other hedge fund categories or asset classes. However, we also find that the number of new CTAs and the amount of new funds being raised increases after a period of poor short-term (one to three months) performance. Competition among CTAs for funds means that CTAs which start when others are not doing well may have a better chance of attracting funds to survive and grow. Therefore, our results suggest that new CTAs often enter the market when CTAs outperform other hedge fund strategies or asset classes over the long-term, but have a poor track record over the last several months.

We also study the relationship between past performance and other characteristics of individual CTAs and fund flows into CTAs. All CTAs are classified based on their approach to investment decision making, i.e. systematic versus discretionary. The results show that systematic funds exhibit a positive and linear flow-performance relation, while this relationship is concave among discretionary funds. We also find that during the recent financial crisis, when many hedge funds suffered large losses due to negative tail risk, higher order moments can become important factors explain the behavior of these funds.

Finally, we examine the potential 'smart money' effect of CTAs. That is we examine whether investors make smart choices in selecting funds. For systematic CTAs we do not find any evidence of 'smart money' at quarterly horizons, while there is limited evidence of 'hot hands' among discretionary CTA investors. At annual horizons no evidence of 'smart money' effect is found for either group of funds. Overall, we conclude that CTA investors chasing past performance do not earn higher subsequent returns.

Our paper is organized as follows. Section 2 provides a brief background of CTAs and outlines their key differences from other hedge funds. Section 3 discusses the relevant literature. Section 4 describes the data and potential biases. Section 5 outlines the research method. Section 6 discusses our empirical results. Finally, Section 7 concludes.

2. CTA BACKGROUND

CTAs represent a particular subset of the hedge fund universe which is commonly referred to as the managed futures style. From hedge funds, CTAs inherit many characteristics and regulatory features, such as absolute return targets, high managerial fees, quick turnaround and voluntary disclosure. However, there are significant differences between the managed futures style and other hedge fund styles. Most of the CTAs are trend followers exercising momentum strategies (Billingsley & Chance, 1996; Fung & Hsieh, 2001). They build computer models to back-test trading rules using historical data. Because of high-frequency trading and the ability to capitalize on both growing and falling trends by taking long and short positions, CTA returns have low correlation with other asset classes.

Figure 1 shows the returns of CTAs against US stocks and bonds during up and down markets. From this figure it is quite clear that CTAs have a low correlation with US equity stock returns. This is important as one rationale for the use of CTAs is to provide protection during bear markets. Barclays' reports on hedge funds and CTA indices show that during the 12-month period leading up to December 2008, all but one hedge fund strategy reported negative returns with the overall average return of negative 21.63%.[3] At the same time the average CTA fund reported positive returns with an overall average of 14.09%. Therefore, during this period it can be seen that CTAs are more successful than other hedge fund strategies. The correlation of CTA returns with returns of other hedge fund strategies is also low and does not exceed 0.2 for all styles except for the Global Macro style with correlation of around 0.4 (Lhabitant, 2006).

Besides providing diversification for stock and bond portfolios CTAs also have lower negative tail risk. Tail risk is important for investors to consider because it has been associated with high failure rates and led to poor performance of hedge funds during the Global Financial Crisis (Liang & Park, 2010). Most of the hedge fund strategies are known to have fat-tailed, negatively skewed and leptokurtic return distributions (Lo, 2001; Malkiel &

[3] Historical data on hedge funds and CTAs performance are from BarclayHedge web-site: http://www.barclayhedge.com/research/indices.html

Saha, 2005). In contrast, CTAs tend to have positively skewed return distributions (Dori, Krieger, & Schubiger, 2013; Fung & Hsieh, 2001; Kat, 2004). Kat (2004) and Rollinger (2012) show that adding managed futures funds to a portfolio of stocks and bonds reduces portfolio's standard deviation more and speedier than hedge funds do, and without undesirable side effects on skewness and kurtosis.

Another difference between CTAs and other hedge funds is related to liquidity. Unlike hedge funds, CTAs primarily trade highly-liquid exchange-listed futures and in deep, cash-forward markets. The high liquidity of futures markets has several important implications for CTAs. First, there is almost no "stale" pricing, in contrast to hedge funds trading illiquid distressed securities or emerging market debt and equity (Asness, Krail, & Liew, 2001; Getmansky, Lo, & Makarov, 2004). Second, CTAs trading in liquid markets face less capacity constraints. Gregoriou (2006) reports that CTA size has a relatively weak impact on its performance. Lamponi (2013) compares the performance of small and large CTAs and concludes that large CTA funds appear to cope well with their size. Liquidity and scalability of trading strategies are especially important for large institutional investors.

Although CTAs represent one style of the hedge fund universe there are two distinct subcategories of CTAs using different strategies to make investment decisions. The systematic subcategory of CTAs use computerized trading systems that generate trading signals. The role of a fund manager is to develop trading algorithm and periodically review it. In contrast, discretionary subcategory of CTAs rely primarily on manager's judgment and evaluation of market indicators and fundamental information to make investment decisions. Discretionary CTA strategies include: top-down macro, fundamental analysis, market-neutral strategies. BarclayHedge, one of the leading providers of data and research on alternative investments, defines a systematic CTA as a fund with at least 95% of the decision-making process is rules-based, whereas in discretionary funds at least 65% of the decision-making process should be based on trader's judgment. A recent article in the Financial Times compares the benefits and drawbacks of systematic and discretionary approaches.[4] Although CTA classification by trading style is common, it is not universal.[5] Nevertheless, since it is a clear and commonly used approach among practitioners we follow it in this study.

Despite the potentially attractive features of CTAs, institutional allocations to managed futures style have been relatively low. According to a recent survey,[6] 50% of institutional investors surveyed have minimal exposure (i.e., only between 0 to 10%) of their current hedge fund portfolio to CTA strategies. Comparative fund flows to CTAs have also been low: from 1997 to 2007 CTA AUM increased five-fold while the increase to hedge funds overall was seventeen-fold. However, after the recent financial crisis the situation reversed slightly: AUM grew by 60% for CTAs and by 23% for all hedge funds in the period from 2008 to 2012.[7] Remarkably, the increase of fund flows coincided with poor CTA performance relative to the rest of the hedge fund sector.

Concluding this section we argue that due to the significant differences between CTAs and other hedge fund styles, investors likely view them distinctly from the rest of hedge funds and that can lead to enhanced competition between CTAs and other styles. For this reason we argue that CTAs deserve a separate study on birth, fund flows and performance.

[4] See http://www.ft.com/cms/s/0/f37adf8e-aeeb-11e1-a4e0-00144feabdc0.htmlaxzz1xPRQ74tf

[5] For example, Fung and Hsieh (1997) identify only one dominant style among CTA funds, “trend following”. Similarly, Billingsley and Chance (1996), Brown et al. (2001), Molyboga, Seungho and Bolson (2013) have all studied CTAs as a single group. Spurgin (1999) and Lajbcygier (2008) acknowledge the existence of subcategories within the managed futures style, but choose to focus only on one subcategory, systematic diversified funds. At the other extreme are studies by Gregoriou, Hübner, Papageorgiou, and Rouah (2005) and Gregoriou, Hübner, and Kooli (2010) who consider seven different CTA subcategories from the Barclays database.

[6] Barclays Capital “Trending Forward: CTAs/Managed Futures.” Hedge Fund Pulse, February 2012.

[7] The figures are authors’ calculations based on the data from BarclayHedge website: http://www.barclayhedge.com

3. LITERATURE REVIEW

The first part of this paper investigates the impact of past performance of the CTA industry on the number and fund flows of new CTAs entering the market. To our knowledge none of the prior studies have addressed this issue before in the context of CTAs. Based on the recent hedge fund literature (Getmansky, 2012; Horst & Salganik, 2014) we hypothesize that past CTA performance drives two competing forces which can affect new entrants. These forces are related to style investing and intra-style competition. When CTAs perform better than other hedge fund strategies, investors are likely to increase allocations to the sector. This is because in large and heterogeneous investment classes, such as stocks, mutual funds or hedge funds, investors often make portfolio allocations by selecting among investment styles, rather than by selecting among individual assets or fund managers (Barberis & Shleifer, 2003; Horst & Salganik, 2014). The style investing hypothesis (Barberis & Shleifer, 2003) asserts that investors categorize risky assets into styles and subsequently allocate money to each style according to its relative performance. Pomorski (2004) finds evidence of style chasing behavior in mutual funds and Horst and Salganik (2014) document similar investors' behavior in the hedge funds industry. Therefore, when overall CTA performance is strong, the inflow of money into CTA styles increases and it becomes easier for new CTAs to enter the market and raise funds. Conversely, the growth of the CTA style inevitably increases the intra-style competition for investors' capital. It becomes harder for new CTAs to attract investors because they do not have a track record. As a result, strong CTA performance will influence investors to move into existing CTAs with strong track records.

Getmansky (2012) describes a similar tension between style investing and intra-style competition in the context of hedge fund performance and survival. When investors chase a hedge fund strategy that has performed well, the probability of a hedge fund liquidating in that category increases. This is because as competition among hedge funds within the style category increases, marginal performing funds are more likely to be liquidated than funds that deliver superior risk-adjusted returns. However, investors chasing individual fund performance, increase fund flows and decrease probabilities of hedge funds liquidating. Perhaps, investors engage in both strategies, i.e. they chase best performing hedge fund category and pick winning funds too (Horst & Salganik, 2014). Therefore, Getmansky (2012) concludes that hedge fund managers should dynamically weight the risks of being in a particular category at any time.

We conjecture that the effects of investors' style chasing behavior and intra-style competition on new CTAs are concentrated at different time horizons. Specifically, style chasing dominates in the long-run, while intra-style competition dominates in the short-run. As such, aggregate long-run CTA performance would be positive for new CTAs as they attract new funds from other hedge fund styles (or asset classes) towards CTAs. However, in the short-run, high performance among existing CTAs create pressure and competition for funds among CTAs and make it more difficult for new CTAs to attract new funds to survive and grow. Therefore, a favorable time to start a new CTA could be during a prolonged period of good aggregate CTA performance, but relatively poor short-term performance.

Although style performance is an important factor for fund flows, since it determines whether CTA funds are favorably positioned against funds from other hedge fund styles, individual fund performance also plays an important role. To this end, we investigate the importance of individual fund performance and other fund-specific factors for fund flows. The literature on flow-performance at the fund level is rich, but not in the context of CTAs. Ippolito (1992), Chevalier and Ellison (1997), Goetzmann and Peles (1997), Gruber (1996), Sirri and Tufano (1998) and Zheng (1999) examine the determinants of money flows in mutual funds and find a positive and convex flow-performance relationship. In hedge fund studies there is much less agreement about the shape of the flow-performance function. Agarwal, Daniel and Naik (2004) find a positive convex flow-performance relation, similar to that documented for mutual funds. In contrast, Goetzmann, Ingersoll and Ross (2003) document a concave flow-performance relation, while Baquero and Verbeek (2009) find a linear relation. In a recent study Ding, Getmansky, Liang and Wermers (2009) show that different levels of flow restrictions among the samples and time-periods used by these papers explain differences in flow-performance relationship.[8]

In the context of CTAs Brown, Goetzmann and Park (2001) and Lajbcygier (2008) are the only papers that have studied the flow-performance relation. Lajbcygier (2008) finds a linear relation between fund flows and performance. However, in Lajbcygier (2008) it is not absolute performance, but relative performance that drives fund flows. Brown et al. (2001) report both absolute and relative performance measures to be important factors determining subsequent fund flows of CTAs.

Our study extends CTA flow-performance literature. Specifically, we treat systematic and discretionary CTA substrategies separately. Discretionary CTAs mostly rely on manager judgment, while systematic CTA strategies are mechanistic and driven by prespecified trading algorithms. The purpose is to explore whether the investment trading style has any impact on the fund-flow performance relationship. To date there is no literature examining in detail these two subcategories of CTAs. For example, no one has considered the differences in share restrictions or liquidity of the systematic versus discretionary CTA strategies. Lajbcygier (2008) studied the flow-performance relation only for systematic diversified[9] CTAs from the Barclays database, while Brown et al. (2001) used CTAs as a single group. Also, our study incorporates a broad range of performance characteristics, which cover aspects of risk and return beyond the conventional first two moments of the return distribution.

Finally, this study examines how 'smart' are the money flows into CTAs. Gruber (1996) and Zheng (1999) find selection ability of mutual fund investors. However, Sapp and Tiwari (2004) shows that the 'smart money' effect is likely to be caused by stock return momentum. Frazzini and Lamont (2008) even introduce the idea of the 'dumb money' effect

[8] Ding, Getmansky, Liang and Wermers (2009) consider the following flow restrictions at the individual fund level: share restrictions including lockup periods, redemption periods, advance notice periods, subscription periods, closure to new investment, certain onshore fund statutory restrictions as well as implicit restrictions driven by capacity constraints of fund's strategy and illiquidity in the assets held by the fund.

[9] The definition of systematic diversified subcategory in the Barclays database might be less broad than the definition of systematic subcategory used in this study. Lajbcygier (2008) mentions systematic discretionary subcategory among 55 other self-reported styles in the Barclays database.

where investors allocate funds in the stocks that perform poorly over time. Baquero and Verbeek (2009) analyze the 'smart money' effect for hedge funds and find little evidence to support the hypothesis. The authors suggest that investors fail to predict future fund returns, however, they are relatively successful in their divestment strategies, responding quickly and appropriately by de-allocating from the persistent losers.

Fung, Hsieh, Naik and Ramadorai (2008) use a comprehensive set of fund-of-hedge funds and find significant difference between money flows to have-alpha funds and beta-only funds. Funds that generate abnormal return (alpha) in the seven-factor model of Fung and Hsieh (2004), receive far greater inflows of capital and the inflows are steady and do not significantly respond to recent past returns. In contrast, beta-only funds, funds that only provide investors with compensation for taking systematic risk (beta), receive much less capital inflow and their fund flows are characterized by return-chasing investors' behavior. Although this suggests selection ability among some investors, the authors also show that capital inflows adversely affect the ability of alpha producers to deliver alpha in the future. Our study adds to the literature by examining the 'smart money' effect in the context of CTAs. Moreover, we investigate if there are differences between the two CTA subcategories. Both short-term and long-term effects are considered.

4. DATA DESCRIPTION

Our study uses a dataset of 587 active and 1823 liquidated CTAs, sourced from TASS 'Live' and 'Graveyard' databases, spanning the period from January 1994 to September 2010. TASS provides one of the largest databases on hedge funds and CTAs currently available. Active funds represent CTAs which are in operation as at the end of the sample period and liquidated funds are CTAs which have closed, liquidated or stopped reporting for any reason by September 2010.

Since CTAs (like other hedge funds) report voluntarily to the data vendors, CTA data are prone to various biases extensively discussed in the hedge fund literature. These biases include survivorship bias, instant history or backfilling bias, self-selection bias and return smoothing bias (see, among others, (Baquero, Horst, & Verbeek, 2005; S. Brown, Goetzmann, Ibbotson, & Ross, 1992; Fung & Hsieh, 1997, 2000, 2002; Getmansky et al., 2004; Liang, 2000; Park, 1995)). Survivorship bias occurs when funds that no longer exist are excluded from the database. TASS maintains the history of defunct funds from 1994. Therefore, in an effort to mitigate potential survivorship bias in the data we select 1994 as the starting point of our sample, though the data on live CTAs are available in TASS database from 1973.

Instant history bias usually arises due to the funds which choose to report to the database after a trial period with earlier returns backfilled. This practice may create a problem for performance analysis, because only successful funds tend to be included in the database. Our study does not set performance evaluation as a sole goal. For the first question related to the number and fund flows of new CTAs, individual fund performance data are not required. The critical data are funds' inception dates and time-series of monthly AUMs. While funds have incentive to manipulate performance data, we do not expect a systematic bias in inception dates or AUMs. For the second and third questions focusing on flow-performance relation we do need funds' returns and they are likely to suffer from backfill bias. We estimate that backfilled data account for around 10% of the total data sample. We perform all empirical analysis using both corrected and the original dataset and find very similar results.[10] Accordingly, to maintain consistency with the first research question, all the results are presented based on the original dataset not corrected for backfilling.

Self-selection bias may arise if only funds with good performance choose to be included in a database. This can lead to an upward bias in the reported historical performance of hedge funds. However, this upward bias is limited, as funds with good performance can sometimes chose not to publish their performance e.g. when they have reached their goal in terms of AUM or their target size and thus, do not wish to attract more investors. Fung and Hsieh (2000) investigate the issue and conclude that this bias is

[10] These results are available from the authors upon request.

negligible based on such reasoning. Accordingly, no corrections are made for self-selection bias.

Finally, the literature shows that hedge fund returns exhibit serial correlation (Getmansky et al., 2004). Stale prices (Asness et al., 2001) or trading illiquid securities lacking readily available prices are one of the reasons. This can lead to the effect of return smoothing. Lo (2002) demonstrates that smoothed returns result in overestimation of Sharpe ratios and information ratios. Fortunately, as mentioned above, CTAs trade mostly liquid securities. Getmansky (2004) estimates first-order correlation for managed futures styles of -0.1%, which is much smaller than for other hedge fund styles. Therefore, CTA returns are unlikely to be smoothed. Accordingly, no corrections are performed for serial correlation.

After correcting for the biases we apply several filters to the dataset. Specifically, we eliminate CTAs which: (i) do not report net-of-fee returns; (ii) report returns in currencies other than US dollars; (iii) report returns less frequently than monthly; (iv) do not provide assets under management or only provide estimates; and (v) have fewer than 12 monthly returns. The final sample consists of 1818 CTAs, of which 311 are active and 1507 are liquidated.

In contrast to other databases, such as the one maintained by BarclayHedge, TASS does not provide information on CTA subcategory. Instead, there are details on each fund's investment approach, with the total of 18 different approaches.[11] A fund in the TASS database is permitted to follow any number of investment approaches. The analysis of the dataset shows that over 52% of the funds follow a systematic only trading style, 18% follow a discretionary approach only, 9% follow both strategies while 21% of CTAs follow neither. Such classification leaves us 4 CTA subcategories: Systematic, Discretionary, Systematic & Discretionary and Other CTAs. Ours is not the first study to classify CTAs based on the

[11] TASS investment approaches are: arbitrage, bottom-up, contrarian, directional, discretionary, diversified, fundamental, long bias, market-neutral, non-directional, opportunistic, other, relative value, short bias, systematic quant, technical, top-down-macro, and trend-follower.

trading style. Arnold (2012), Arnold, Kosowski and Zaffaroni (2012) and Kazemi and Li (2009) have studied systematic and discretionary CTAs separately.

There are three time series in the dataset: the monthly rate of return (ROR) for each CTA, the monthly assets under management (AUM) ($US000), and the value-added monthly index (VAMI). The VAMI shows the return of a hypothetical investment of $1000 in a particular CTA. The aggregate total AUM for the active CTAs exceeds US$72 billion as of September 2010. We use S&P 500 total return index as the proxy for equity market and Goldman Sachs Commodity Index (GSCI) total return (Jensen, Johnson, & Mercer, 2002) as the proxy for commodity market.

Figure 2 presents the evolving number of CTAs through the period 1973-2009. The first CTA from TASS database was established in 1973 and then the number of CTAs increased gradually to about 100 in 1984. Since 1985, there has been a dramatic increase in the number of CTAs - it peaked in late 1994 with around 700 CTAs, then declined to 550 funds and bounced back to 676 in 2005. As of September 2010 there were 613 active CTAs in our sample.

Table 1 shows annual entry, exit, and attrition rates of the CTAs in our sample. The average entry and attrition rates over the period 1994-2009 are 0.142 and 0.137 respectively. Figure 3 highlights the differences in entry and attrition rates across CTA subcategories. Overall, the attrition rate is more volatile than the entry rate. The disparities in entry rates between the subcategories are not very significant, ignoring one outlier point for the ‘other’ subcategory in 2004. Conversely, the attrition rate for discretionary funds has been consistently higher than for systematic funds except for the GFC period. The latter result conforms with the higher median survival rate for systematic CTAs found by Arnold (2012). It is important to note that, although the attrition rate is correlated with the failure rate, it is unavoidably biased upwards, because not all defunct funds cease to exist, they might leave TASS database due to other reasons mentioned above.

It is well known that hedge funds often alter their portfolios and adjust risk loadings in response to market events (Fung et al., 2008). Time-varying risk exposures can lead to heteroscedasticity in returns. The issue is likely to be present in our data, since the long period employed spans almost 17 years and covers various market conditions. Prior literature generally agrees on two structural breaks in the hedge fund data between 1994 and 2007. These breakpoints are linked to LTCM collapse in the late 1998 and technology bubble in the early 2000s (Fung & Hsieh, 2004; Fung et al., 2008; Kosowski, Naik, & Teo, 2007; Meligkotsidou & Vrontos, 2008). After 2007 due to the short time period since the recent financial crisis few studies have been published dealing with structural breaks. Edelman et al. (2012) documents two breaks, one in June 2007 and another in April 2009, while Arnold (2012) finds only one break in July 2007. We have tested three breakpoints identified in the most relevant study on CTAs by Arnold (2012) and in a recent hedge fund study by Bali et al. (2011). For all research questions we find qualitatively different results only in the two subperiods: before and after the start of the subprime crisis. Therefore, all the further analysis will be based on two subperiods: January 1994 – July 2007 and August 2007 – September 2010.

5. RESEARCH METHOD

5.1. The Birth of New CTAs

Following, Kaplan and Schoar (2005), we test the relation between the number of new CTAs and market performance using the following regressions:

$$NEWCTA_t = \alpha_0 + \beta_1 EMR_t + \beta_2 EMR_{t-1} + \beta_3 EMR_{t-6} + \beta_4 EMR_{t-12} + \beta_5 NEWCTA_{t-1} + ISJAN_t + \varepsilon_t \qquad (1a)$$

$$NEWCTA_t = \alpha_0 + \beta_1 CMR_t + \beta_2 CMR_{t-1} + \beta_3 CMR_{t-6} + \beta_4 CMR_{t-12} + \beta_5 NEWCTA_{t-1} + ISJAN_t + \varepsilon_t \qquad (2a)$$

$$NEWCTA_t = \alpha_0 + \beta_1 CTAR_t + \beta_2 CTAR_{t-1} + \beta_3 CTAR_{t-6} + \beta_4 CTAR_{t-12} + \beta_5 NEWCTA_{t-1} + ISJAN_t + \varepsilon_t \qquad (3a)$$

where $NEWCTA_t$ is the natural log of the number of new CTAs entering the market at month t, EMR_t, CMR_t, $CTAR_t$ are the equity market return, commodity market return, and CTA industry return at month t, respectively and $ISJAN_t$ is the dummy variable which equals 1 if CTA enters the market in January of any year and 0 otherwise. This dummy variable captures the potential seasonal effect related to the beginning of new calendar year. The CTA industry returns are the returns of the TASS asset-weighted CTA index. Similar variables for one-month, six-month, and 12-month lags are denoted by *t-1, t-6*, and *t-12*, respectively. The 6-month and 12-month lagged variables are moving average returns. Negative (positive) β_2, β_3, and β_4 in the regressions provide evidence that the past performance of existing CTAs has a negative (positive) impact on the number of new CTAs.

We also test for the amount of capital raised by new funds and the returns of different markets. The regressions are as follows:

$$NEWCTA\$_t = \alpha_0 + \beta_1 EMR_t + \beta_2 EMR_{t-1} + \beta_3 EMR_{t-6} + \beta_4 EMR_{t-12} + \beta_5 NEWCTA\$_{t-1} + ISJAN_t + \varepsilon_t \quad (1b)$$

$$NEWCTA\$_t = \alpha_0 + \beta_1 CMR_t + \beta_2 CMR_{t-1} + \beta_3 CMR_{t-6} + \beta_4 CMR_{t-12} + \beta_5 NEWCTA\$_{t-1} + ISJAN_t + \varepsilon_t \quad (2b)$$

$$NEWCTA\$_t = \alpha_0 + \beta_1 CTAR_t + \beta_2 CTAR_{t-1} + \beta_3 CTAR_{t-6} + \beta_4 CTAR_{t-12} + \beta_5 NEWCTA\$_{t-1} + ISJAN_t + \varepsilon_t \quad (3b)$$

where $NEWCTA\$_t$ is the natural log of the total amount of capital raised by new CTAs at month *t*. Past performance is measured with one-month, six-month, and 12-month lagged moving average returns. Negative (positive) β_2, β_3, and β_4 in the regressions indicate that the past performance of existing CTAs has a negative (positive) impact on the amount of funds raised by new CTAs.

5.2. Fund flow and performance

This section outlines our setup for assessing the relationship between monthly fund flow of CTAs and CTA own characteristics, including absolute and relative performance, downside risk, long-term performance persistence, higher-order moments and other CTA variables. Performance is measured by the Sharpe ratio.[12, 13] To examine the flow-performance relationship we estimate a piecewise linear regression with current flow as the dependent variable and past performance as the main independent variable.

[12] We define the Sharpe ratio as the ratio of the monthly average return to the monthly standard deviation (versus the original definition in which the numerator is the standard deviation of return in excess of the risk-free rate).

[13] To date there is no universally accepted hedge fund pricing model. The hedge fund literature abounds with examples of multi-factor models, including the seven-factor model of Fung and Hsieh (2004) and the six-factor model of Hasanhodzic and Lo (2007), to name just two. On the other hand, traditional asset pricing models such as the CAPM (Sharpe, 1964) and the Fama-French model (1993) are not applicable to CTAs because CTAs have low correlation with the equity market. In the context of hedge fund pricing, the true set of risk factors is virtually unknown (Vrontos, Vrontos, & Giamouridis, 2008). Hence, since the veracity of CTA alpha is open to serious concern we avoid such a measure in our analysis.

$$FLOW_{i,t} = \alpha_i + \sum_{j=1}^{4} \beta_j SHARPE_{i,t-1}^{j} + \beta_5 PW_{i,t-1} + \beta_6 SD_{i,t-1} + \beta_7 TUW_{i,t-1} + \beta_8 SKEW_{i,t-1} + \beta_9 KURT_{i,t-1} + \beta_{10} AUM_{i,t-1} + \beta_{11} AGE_{i,t-1} + \beta_{12} FLOW_{i,t-1} + \beta_{13} INCFEE_i + \beta_{14} MGTFEE_i + \beta_{15} MINACC_i + \beta_{16} PRIVATE_i + \beta_{17} ACTIVE_i + \varepsilon_{i,t} \quad (4)$$

We also examine the role of other performance and non-performance related factors:

$$FLOW_{i,t} = \alpha_i + \beta_1 SHARPE_{i,t-1} + \beta_2 RANKSHRP_{i,t-1} + \beta_3 PW_{i,t-1} + \beta_4 SD_{i,t-1} + \beta_5 TUW_{i,t-1} + \beta_6 SKEW_{i,t-1} + \beta_7 KURT_{i,t-1} + \beta_8 AUM_{i,t-1} + \beta_9 AGE_{i,t-1} + \beta_{10} FLOW_{i,t-1} + \beta_{11} INCEFEE_i + \beta_{12} MGTFEE_i + \beta_{13} MINACC_i + \beta_{14} PRIVATE_i + \beta_{15} ACTIVE_i + \varepsilon_{i,t} \quad (5)$$

The dependent variable is monthly fund flow into the CTA, calculated as follows:

$$FLOW_{i,t} = [AUM_{i,t} - AUM_{i,t-1} * (1+ROR_{i,t})] / AUM_{i,t-1}$$

The test Variables are outlined below.

- **Absolute performance** - $SHARPE_{i,t-1}^{j}$ is the moving average Sharpe ratio from month *t-12* to *t-1* of CTA *i* if the Sharpe ratio is in quartile *j* and 0 otherwise. Coefficients $\beta_j, j = 1,..,4$ capture variations in the flow-performance relation between bottom- and top-performing funds. Absolute past performance is expected to have a strong positive relation with fund flow; a positive (negative) difference between β_4 and β_1 will indicate convex (concave) relation.
- **Relative performance** - $RANKSHRP_{i,t-1}$is the moving average rank of CTA *i* based on this fund's Sharpe ratio from month *t-12* to *t-1*. A positive coefficient is predicted.
- **Long-term performance persistence -** $PW_{i,t-1}$ is the percentage of "wins", which equals the number of months with a positive return for CTA *i* until month t-1 divided by *the number of assessed months*. A positive coefficient in these regressions supports the view that CTAs with more persistence in performance attract higher fund flow.
- **Risk -** $SD_{i,t-1}$ is the standard deviation of the returns for CTA *i* until month *t-1*. Higher risk is expected to have a significant negative effect on fund flow - therefore, a negative coefficient is predicted.

- **Time under water -** Time under water, $TUW_{i,t-1}$, is a measure of downside risk. It is defined as the number of months in a drawdown until month *t-1* divided by *the number of assessed months*. A drawdown begins when the VAMI starts to decrease from a local peak and ends when it goes back to that local peak value. Due to the high correlation between drawdown and time under water, only *TUW* is included to avoid multicollinearity. A negative coefficient is expected as investors seek to avoid funds with downside risk.
- **Higher moments -** $SKEW_{i,t-1}$ and $KURT_{i,t-1}$ is the skewness and kurtosis of the returns of CTA *i* until month *t*-1. A positive coefficient for skewness and negative coefficient for kurtosis are expected since such a combination will result in lower left tail risk.

The control variables are outlined below.

- **Fund size** - $AUM_{i,t-1}$ is the fund size of CTA *i* at time *t-1*. It is measured as the natural log of AUM.
- **Fund age** - $AGE_{i,t}$ is the age of CTA *i* and is defined as number of months from inception till time *t*.
- **Performance incentives** - $INCFEE_i$ is the incentive fee that managers receive for achieving returns above the high-water mark of CTA *i*, measured as a percentage.
- **Management fee** - $MGTFEE_i$ is the fee (measured as a percentage) charged by CTA *i* for managing funds.
- **Minimum investment** - $MINACC_i$ is the minimum investment amount required by CTA *i*. It is measured by taking the natural log of the minimum investment amount in dollar terms.
- **Private CTA** - $PRIVATE_i$ is a dummy variable that takes on a value of 1 if the CTA is private and 0 otherwise. A CTA is considered private when it is not open for public investment.

- **Active CTA** – is a dummy variable that equals 1 if CTA *i* is in operation as at September 2010 and 0 otherwise.

We use the Fama and MacBeth (1973) method to estimate the regressions in Equations (4) and (5).[14] Cross-sectional regressions are run month by month, the time series of the estimated coefficients are averaged and t-statistics computed. Since the coefficients obtained from this technique are likely to be correlated across time, Cochrane (2005) suggests that improper control of this correlation can greatly affect the result. Therefore, the t-statistics are scaled by the adjustment factor $\sqrt{1+p}\,/\sqrt{1-p}$, where *p* is the first-order autocorrelation of the coefficient. The adjusted t-statistics provide a more conservative significance level for the observed coefficients.

5.3. The 'smart money' effect in CTAs

We perform both short-term (one to three months) and long-term (one year) analysis of the 'smart money' effect, using the Fama and MacBeth (1973) method. In the short-term analysis the two main performance measures used are absolute and relative raw performance and the models are as follows:

$$ROR_{i,t} = \alpha_i + \beta_1 FLOW_{i,t-1} + \beta_2 FLOW_{i,t-2} + \beta_3 FLOW_{i,t-3} + \beta_4 ROR_{i,t-1} + \beta_5 SD_{i,t-1} + \beta_6 AGE_{i,t-1} + \beta_7 AUM_{i,t-1} + \beta_8 INCFEE_i + \beta_9\, MGTFEE_i + \beta_{10} MINACC_i + \beta_{11} PRIVATE_i + \beta_{12} ACTIVE_i + \varepsilon_{i,t} \qquad (6)$$

$$RANK_{i,t} = \alpha_i + \beta_1 FLOW_{i,t-1} + \beta_2 FLOW_{i,t-2} + \beta_3 FLOW_{i,t-3} + \beta_4 ROR_{i,t-1} + \beta_5 SD_{i,t-1} + \beta_6 AGE_{i,t-1} + \beta_7 AUM_{i,t-1} + \beta_8 INCFEE_i + \beta_9\, MGTFEE_i + \beta_{10} MINACC_i + \beta_{11} PRIVATE_i + \beta_{12} ACTIVE_i + \varepsilon_{i,t} \qquad (7)$$

where $ROR_{i,t}$ is return and $RANK_{i,t}$ is the rank of CTA *i* at time *t*.

[14] Each CTA-month is treated as one independent observation period and each group is treated as a pool. However, as Sirri and Tufano (1998) point out, this technique can underestimate the standard error and overestimate the t statistic if the independence assumption is violated.

In the long-term analysis, we assess the one year horizon, i.e. we examine the absolute and relative risk-adjusted performance in the next year after fund flow into CTAs:

$$SHARPE_{i,t} = \alpha_i + \beta_1 FLOWANN_{i,t-12} + \beta_3 AGE_{i,t-12} + \beta_4 AUM_{i,t-12} + \beta_5 INCFEE_i + \beta_6 MGTFEE_i + \beta_7 MINACC_i + \beta_8 PRIVATE_i + \beta_9 ACTIVE_i + \varepsilon_{i,t} \quad (8)$$

$$RANKSHRP_{i,t} = \alpha_i + \beta_1 FLOWANN_{i,t-12} + \beta_3 AGE_{i,t-12} + \beta_4 AUM_{i,t-12} + \beta_5 INCFEE_i + \beta_6 MGTFEE_i + \beta_7 MINACC_i + \beta_8 PRIVATE_i + \beta_9 ACTIVE_i + \varepsilon_{i,t} \quad (9)$$

where $SHARPE_{i,t}$ is current year annual Sharpe ratio, $RANKSHRP_{i,t}$ is current year CTA rank based on Sharpe ratio and $FLOWANN_{i,t-12}$ is the previous year annual fund flow, calculated as follows:

$$FLOWANN_{i,t} = \frac{AUM_{i,t} - AUM_{i,t-12} * \prod_{j=0}^{11}(1 + ROR_{i,t-j})}{AUM_{i,t-12}}$$

In equations (6) and (7) the variables are calculated monthly, while in equations (9) and (10) the variables are calculated annually for non-overlapping 12-month periods to reduce serial correlation between coefficients' estimates. T-statistics are scaled by the adjustment factor $\sqrt{1+p}\,/\sqrt{1-p}$ to further control for autocorrelation. The variables of interest are one-, two-, three-month and one-year lagged fund flows. Positive and significant coefficients β_1, β_2, or β_3 in equations (6) and (7) and β_1 in equations (8) and (9) will provide evidence of the 'smart money' effect among CTAs.

6. EMPIRICAL RESULTS

6.1. The Birth of New CTAs

Table 2 reports the results testing the effect of the performance of equity, commodity and CTA markets on the number of new CTAs starting up and the amount of funds they raise. The dependent variable in equations (1a)-(3a) ((1b)-(3b)) is the number of new CTAs (the amount of funds raised by new CTAs). The results for regressions (1a) and (2b) show that past equity market performance do not affect number of new CTAs and past commodity market performance also have little effect on the amount of funds raised by new CTAs. However, the amount of funds raised by new CTAs seems to be related to previous month equity market return, as seen from the results for the equation (1b). Prior to the crisis the coefficient is positive and highly significant, indicating that more funds flow to new CTAs after a good month in equity market. During and after the GFC the relation becomes insignificant, pointing to the possible role of CTAs as an alternative asset during the crisis period. Overall the results of models (1a)-(2b) are in line with earlier comments about the low correlation of CTA returns with equity and commodity market returns.

In equations (3a) and (3b), the number and fund flow of new CTAs are regressed against current month return, the 1-month, 6-month, and 12-month lagged moving average returns of the CTA industry. Before the financial crisis the coefficients for current month and 1-month and 6-month return are negative. In equation (3a) the prior month return coefficient is significant at the 5% level, while in equation (3b) the current month and prior month coefficients are significant at the 1% level and 6-month lagged return coefficient is significant at the 10% level. In contrast, the 12-month coefficient is positive in both models and significant at the 5% level. After July 2007 qualitatively the results are similar but statistically weaker. Current and last month returns have negative coefficients, while 6-month and 12-month returns have positive coefficients with one of them in equation (3b) being statistically significant at the 10% level.

Generally, these results confirm that style chasing has a long-term effect on new CTAs, while intra-style competition is predominantly a short-term effect. Over the long-run, performance has a positive effect on future birth and fund flows of new CTAs. However, in the short-term CTAs have to compete with each other making it harder for new CTAs to enter the market. These two trends suggest that an appropriate time for a manager to start a new CTA would be during a period of consistently good CTA industry performance over at least one year (i.e. longer term), but when CTAs have a bad recent track record over the last several months (i.e. shorter term).

The final comment regarding Table 2 relates to the dummy variable *ISJAN* which captures a seasonal variation in the number of new entries and fund flows due to the January effect. The estimated coefficients are positive and significant in most of the regressions, particularly in the earlier period before July 2007. This suggests that fund managers tend to start up their business at the beginning of a given calendar year. The January effect perhaps can be attributed to the annual structure of employment and compensation contracts at previous jobs of new CTA managers. Hedge fund managers often come from proprietary desks of investment banks and mutual funds where bonuses are linked to employees' annual performance. Notably, not only more CTAs enter the market in January, but they are able to attract more funds.

*6.2. **Fund flows and performance***

This section presents the results that establish the factors affecting fund flows over the entire life of a CTA. The descriptive statistics for the important variables are reported in Table 3. The average fund flow into CTAs is 0.022 per month. This means that, on average, the size of CTA increases by 2.2% per month, adjusted for each fund's returns.[15] The average monthly return is 0.8% per month, while the median return is much lower at 0.4% per month. The average standard deviation of returns is 6.8%. The average Sharpe ratio, is 0.367,

[15] The top and bottom 0.1% of flows are winsorized to minimize the effect of outliers and ensure meaningful results. Ding et. al (2006) exclude the top 1% from their hedge fund flow analysis. However, 1% in this case might exclude those months when CTAs perform very well and hence create a bias. Thus we adopt a 0.1% cut-off point.

which is very similar to all hedge funds of 0.343.[16] The average time under water is 0.668, indicating that on average every year a CTA spends around 8 months in a drawdown situation. In terms of the long-term persistence of performance, the average percentage of wins coefficient is 0.584 (58.4%). It means that positive returns occur a little bit more frequently than negative ones. The average skewness coefficient is 0.575, while the average and median values of kurtosis are 5.451 and 4.031. The sign and magnitude of higher order moments are in accordance with the recent literature (Arnold, 2012), Positive excess kurtosis (i.e. kurtosis value over 3) indicates leptokurtic return distribution. The average age of CTAs is 82 months and the median age is 65 months. The average CTA size is over $US101 million, while the median size is only $US13.296 million. This big divergence between the average and median sizes shows that assets are concentrated in few large funds.

Given the evidence from prior studies on individual fund's performance being an important factor for fund flows, first we examine the flow-performance relation using piecewise linear regression given by equation (4). The results for the flow–performance relation of four CTA subcategories during the period from January 1994 to July 2007 are presented in Table 4 Panel A. The post-crisis period is omitted because there is not enough data to perform piecewise regression analysis for all CTA subcategories. Overall, we confirm that past CTA performance is found to be a significant factor determining current fund flows. However, there are differences across subcategories in terms of the functional form of the flow-performance relation.

In systematic CTAs the relation is linear. The four performance coefficients are highly significant, but the difference between the coefficients in the first and fourth quartiles is not significant. In contrast, the flow-performance relationship in discretionary CTA group is clearly concave. The performance has significantly less effect on fund flows among top-performing discretionary funds than among funds from the lowest quartile. The difference between the coefficients in low and top quartiles is 0.133 and significant at the 5% level.

[16] It is measured as the Sharpe ratio of TASS hedge fund composite index for the same period.

We conjecture that trading strategies of discretionary funds requiring manager judgment and analysis might be more capacity constrained than computer-driven systematic CTA strategies with most of the trading concentrated in liquid markets. Due to capacity constraints, top-performing discretionary CTAs might be reluctant to accept new funds and that induces a concave relationship. Also, the difference in share restrictions of CTAs from the two subcategories might be important. The systematic & discretionary subcategory exhibits a linear flow-performance relation. Based on the previous results, this implies that there might be more of these CTAs following a systematic approach than employing the discretionary approach. In the 'other' subcategory comprising a diverse range of funds, the dependence between past performance and subsequent fund flow is pronounced only among the top 50% of CTAs.

The divergent results above highlight the importance of accounting for differences between CTA subcategories. Getmansky et al. (2004) analyze serial correlation and liquidity of hedge fund categories and finds the managed futures style to be liquid and that its returns exhibit a very low level of serial correlation. Based on this finding Ding at al. (2009) describes the managed futures style as a style without significant capacity constraints. Further, from the logic proposed by Ding et al. (2009) and Getmansky (2012) (i.e., that the functional form of flow-performance relation depends on capacity constraints and share restrictions), it follows that managed futures funds should not exhibit a concave relationship, but instead a linear or even a convex one. Nevertheless, Getmansky (2012) documents concave relationships for all hedge fund styles, including the managed futures style. Our findings suggest that this inconsistency might be attributed to differences between systematic and discretionary CTAs, which were not taken into account by Getmansky (2012).

Next, we investigate the role of other performance characteristics of CTA fund flows. Equation (5) includes measures of relative performance, downside risk, long-term performance persistence and higher order moments. The results for the two sub-periods are summarized in Table 4, Panels B and C.

Prior to the beginning of the crisis, lagged relative performance ($RANKSHRP_{i,t-1}$) shows a positive and significant coefficient at the 1% level in the systematic CTA subcategory as well as in the 'other' subcategory. The importance of relative performance confirms the existence of intra-style competition between CTAs and provides support for the hypothesis that competition affects the birth and fund flow of new CTAs. However, relative performance is not statistically significant for the discretionary and systematic & discretionary subcategories. This difference could be due to more the complex flow-performance relationship in these subcategories found in the previous section.

Remarkably, the percentage of wins variable, a characteristic of fund's ability to persistently deliver absolute returns in the long-run, is not significant for systematic and discretionary funds. As Lajbcygier (2008) notes, to attract funds it is more important for a fund manager to win "big" than to win often, i.e. the magnitude of performance results is more important than consistency. A number of control variables also have an effect on fund flows. Consistent with other studies fund size negatively affects fund flows (Getmansky, 2012). Minimum investment amount, in contrast, has a significant positive effect on fund flows. Incentive fee is also positively related to fund flows of systematic funds, though academic evidence suggests that incentive fee per se does not explain and cannot predict future fund's performance (Agarwal, Daniel, & Naik, 2009).

As evident from the Panel C the financial crisis has affected investors' preferences. In the systematic subcategory the coefficient for skewness is positive and statistically significant at the 5% level and coefficient for kurtosis is negative and highly significant at the 1% level. It means that systematic CTA investors seem to realize that risk and return are not the only important performance characteristics. Higher order moments started to play an important role during this period of extreme market volatility. Investors were prudently selecting funds with less tail risk. The negative kurtosis coefficient is also statistically significant at the 10% level in the systematic & discretionary subcategory. For discretionary funds the only factor found to be important during the crisis is relative performance.

6.3. The 'smart money' effect in CTAs

The previous section examines the determinants of the flow-performance relationship for CTAs. It provides evidence that CTA investors chase past performance. This section presents and discusses the results of analysing the consequences of such investors' behavior. Now, we seek to answer the follow-on question: Do CTAs exhibit a 'smart money' effect? In other words, do past-performance-chasing investors receive subsequent high returns?

To this end we test the effect of fund flows on subsequent fund's short-term and long-term performance. For the short-term analysis absolute and relative returns are used as dependent variables in equations (6) and (7) and are regressed against one-, two-, and three-month lagged fund flows and other control variables. Table 5 shows the results of OLS regressions for four subcategories of CTAs before and after the beginning of the financial crisis. As seen from Panels A and B, systematic and discretionary funds reveal different patterns of fund-flow performance. Evidence of the 'smart money' effect among discretionary CTAs is mixed. At the quarterly horizon in equation (6) for raw returns the coefficient of three-month lagged flows is positive and significant at the 5% level and in equation (7) for relative performance it is positive and significant at the 1% level. However, in both equations one- and two-month lagged flow coefficients are not significant. Therefore, we are cautious to claim that discretionary CTA investors have an ability to predict future returns. In contrast, in the systematic subcategory not only is there an absence of evidence of 'smart money', but CTAs that receive high flows in one period exhibit significantly poorer performance in the next two or three months compared to other CTAs. In equation (6) the coefficients for two- and three-month lagged flows are negative and significant at the 1% and 10% levels. In equation (7) the two-month fund-flow coefficient is negative and significant at the 10% level.

There is at least one potential reason which can explain the difference in results between systematic and discretionary CTAs. Since in both CTA subcategories, investors are chasing winner funds, subsequent performance of funds depends on persistence of funds' performance. From this point of view, the limited evidence of the 'smart money' effect in discretionary funds and the lack of such evidence in systematic funds can be due to stronger performance persistence of discretionary funds. The literature on CTAs provides some support for this argument. In a recent study Arnold (2012) performs an out-of-sample test of CTA performance persistence. The author finds that equally-weighted portfolios of discretionary CTAs have a much larger spread between returns of funds in the top and bottom quintiles than portfolios of systematic CTAs. Accordingly, performance persistence might be more pronounced among discretionary CTAs.

A number of other control variables also prove to have an effect on CTAs' absolute and relative performance. Age, incentive fee, and management fee have positive and significant coefficients for systematic CTA performance. Lagged raw return, standard deviation and minimum investment account have positive and significant coefficients, while fund size has negative coefficient in discretionary funds.

Next, Panels C and D present the results of the same analysis for the period after the beginning of the subprime crisis. Clearly, the turmoil in the markets has had an impact on CTAs. Fund-flow coefficients are no longer statistically significant and their signs are mixed.

While short-term analysis of investors' fund selection skill is important, it is necessary to examine the predictive ability of fund selection in the long-run, because investors might not be able to reallocate funds between CTAs quickly due to search costs and fund lock-up rules. Also, long-term analysis permits examining risk-adjusted performance: risk adjustments should take into account investors' preferences for higher order moments in return distribution, particularly after the financial crisis of 2008. However, in view of the lack of data after the financial crisis we examine the long-term 'smart money' effect during the whole period 1994-2009[17] adjusting returns only for volatility using the Sharpe ratio.

As seen from Table 6 the coefficients for lagged one-year fund flows in systematic and discretionary funds are not statistically significant. This means that CTAs received higher fund flows due to good performance last year have neutral performance in the

[17] Annual fund flows and Sharpe ratios are calculated here on annual calendar basis. Accordingly, we ignore the partial data available for 2010.

following year (either in absolute nor relative terms). This is consistent with the large volume of literature which finds no long-term persistence of performance of hedge funds (Agarwal & Naik, 2000; Barès, Gibson, & Gyger, 2003; Capocci & Hubner, 2004; Malkiel & Saha, 2005). The result is even stronger for the funds from the 'other ' subcategory: lagged one year fund flow coefficients are negative and significant at the 10% level in the model for absolute performance and at the 1% level in the model for relative performance.

Overall, the results confirm that chasing past performance does not work for CTA investing. The likely reasons are two-fold. First, performance persistence is primarily a short-term effect as documented widely in the hedge fund literature (Agarwal & Naik, 2000; Baquero et al., 2005; S. Brown, Goetzmann, & Ibbotson, 1999). Second, due to the search costs, investors are too slow to take advantage of short-term performance persistence (Baquero & Verbeek, 2009). Earlier studies come to similar conclusions for mutual funds (Sapp & Tiwari, 2004), hedge funds (Baquero & Verbeek, 2009) and common stocks (Frazzini & Lamont, 2008).

7. CONCLUSIONS

The CTA industry is a unique and important part of alternative investments, one that has grown tremendously over the last two decades, both in size and scope. Prior studies have mainly focused on traditional questions of performance and persistence in performance. Our study expands this research scope by addressing three questions.

First, we investigate the impact of existing CTAs' performance on the number and fund flows of new CTAs. We argue that CTA performance in the long run positively affects fund flow to the industry. However, in the short-term it makes the competition between CTAs tougher and harder for new CTAs to enter the market. Long-term and short-term effects can be explained by style chasing investor' behavior and intra-style competition. Our findings show that managers appear to have a strategy in timing the inception of their new CTAs when the aggregate long-run performance is good but short-run performance is poor.

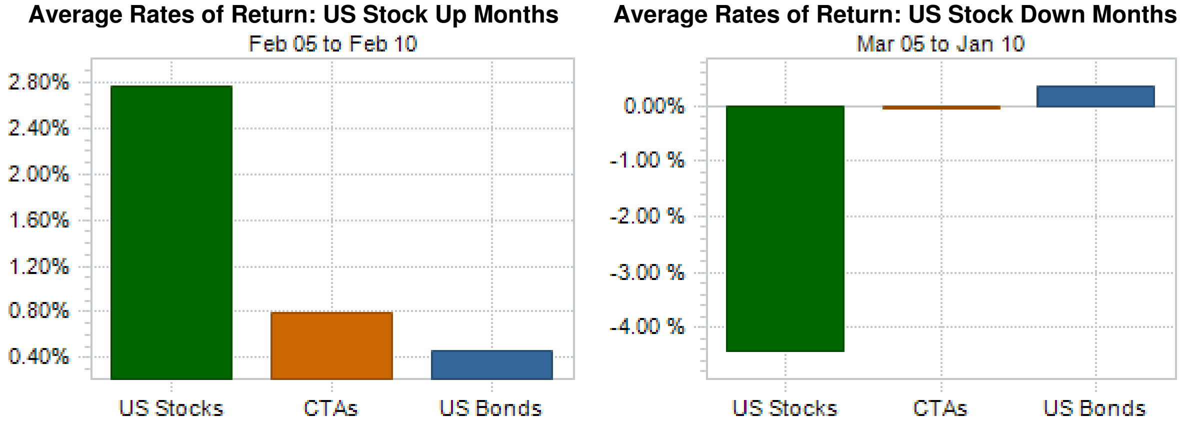
Second, we investigate the importance of performance and other fund-specific factors to fund flows throughout the entire life of CTAs. There are noticeable differences in the flow-performance relation among CTA subcategories. Systematic CTAs have linear, positive flow-performance functions, while discretionary CTAs exhibit concave patterns. It points to possibly higher capacity constraints or more share restrictions among discretionary CTAs. In general we confirm that past absolute and relative performance are one of the main drivers of fund flows for both subcategories. After the crisis, the evidence also suggests that higher order moments have become important for investors of systematic CTAs.

Finally, our study tests the selection ability of CTAs' investors by examining the performance of new flows to the CTAs. We observe that systematic CTAs with high flows have statistically poorer performance compared to others in the next two or three months. The evidence of 'smart money' among discretionary funds at horizons up to one quarter is inconclusive. At a yearly horizon both subcategories do not reveal any evidence of 'smart money'.

In conclusion, we suggest that more research is needed focusing on the differences between systematic and discretionary CTAs. As our results show the two subcategories often demonstrate divergent behaviour. A deeper insight into capacity constraints, share restrictions and liquidity of systematic and discretionary CTAs could provide valuable information for a better understanding of fund flows and performance of CTAs.

FIGURE 1

CTAs' Returns versus Equity and Bonds Returns



Source: www.managedfutures.com

FIGURE 2

Number of Active CTAs May 1973 – September 2010

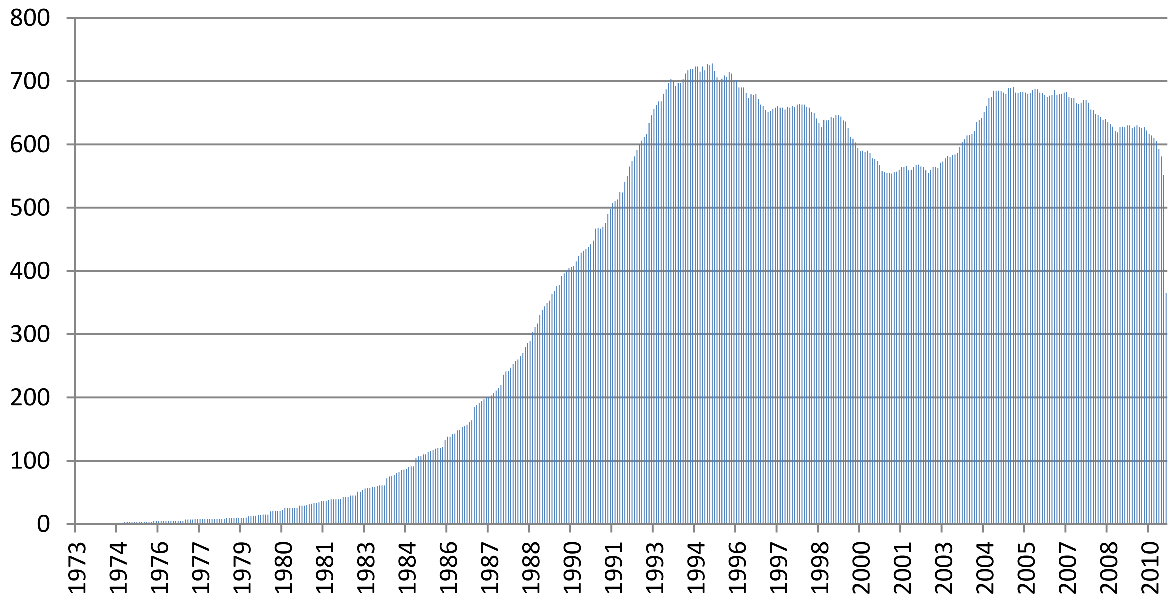


TABLE 1
Entry, exit, and attrition rates of CTAs

Table 1 presents the number of CTAs entering and exiting the dataset on a yearly basis. The attrition rate is calculated as the number of exiting CTAs in a year divided by the number of CTAs at the beginning of the same year.

Year	Year start	Entry	Exit	Year end	Attrition rate
1973	0	1	0	1	
1974	1	1	0	2	0.0000
1975	2	1	0	3	0.0000
1976	3	2	0	5	0.0000
1977	5	3	0	8	0.0000
1978	8	1	0	9	0.0000
1979	9	6	0	15	0.0000
1980	15	10	0	25	0.0000
1981	25	11	0	36	0.0000
1982	36	9	0	45	0.0000
1983	45	16	0	61	0.0000
1984	61	30	0	91	0.0000
1985	91	31	0	122	0.0000
1986	122	43	1	164	0.0082
1987	164	57	3	218	0.0183
1988	218	74	5	287	0.0229
1989	287	97	13	371	0.0453
1990	371	101	49	423	0.1321
1991	423	148	64	507	0.1513
1992	507	165	69	603	0.1361
1993	603	170	96	677	0.1592
1994	677	143	123	697	0.1817
1995	697	126	142	681	0.2037
1996	681	106	146	641	0.2144
1997	641	90	84	647	0.1310
1998	647	70	100	617	0.1546
1999	617	85	100	602	0.1621
2000	602	44	98	548	0.1628
2001	548	63	62	549	0.1131
2002	549	68	57	560	0.1038
2003	560	97	56	601	0.1000
2004	601	131	59	673	0.0982
2005	673	86	83	676	0.1233
2006	676	85	95	666	0.1405
2007	666	77	82	661	0.1231
2008	661	54	100	615	0.1513
2009	615	63	65	613	0.1057

FIGURE 3

Entry and attrition rates of CTA subcategories

Figure 3a: Entry rate

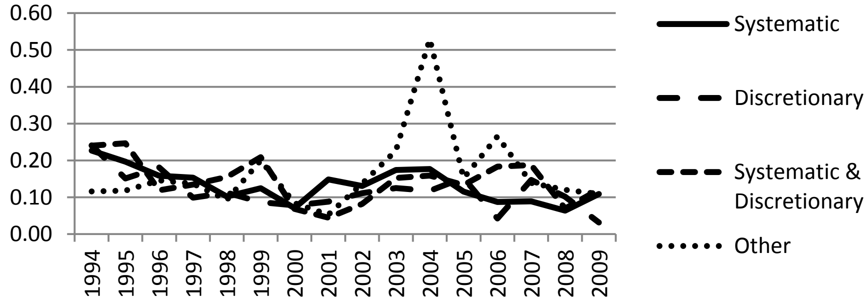


Figure 3b: Attrition rate

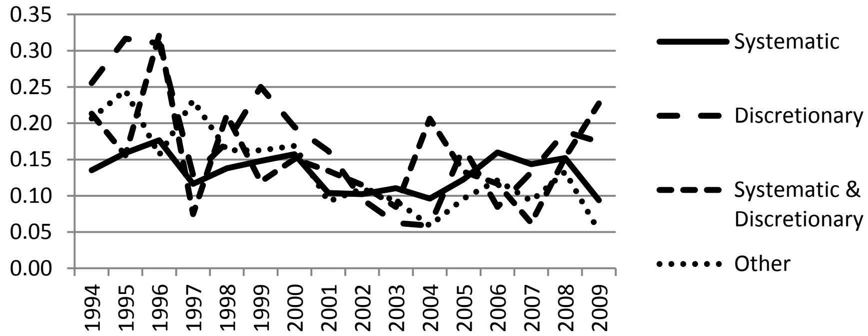


TABLE 2

Number of new CTAs entering the market and funds raised by new CTAs

Table 2 presents the results from the ordinary least squares regressions using the number of new CTAs (*NEWCTA*) as the dependent variable in Equations 1a-3a and the amount of funds raised by new CTAs (*NEWCTA$*) as the dependent variable in Equations 1b-3b during the two periods before and after the start of the Global Financial Crisis. Equations 1a and 1b use equity market returns (EMR_t) and its one-month, six-month, and 12-month lagged moving average; Equation 1a uses the one-month lag of the number of new CTAs ($NEWCTA_{t-1}$) while Equation 1b uses the one-month lag of the amount of funds raised by new CTAs ($NEWCTA\$_{t-1}$) as independent variables. Equations 2a and 2b use commodity market returns (CMR_t) and its one-month, six-month, and 12-month lagged moving average; Equation 2a uses the one-month lag of the number of new CTAs ($NEWCTA_{t-1}$) while Equation 2b uses the one-month lag of the amount of funds raised by new CTAs ($NEWCTA\$_{t-1}$) as independent variables. Equations 3a and 3b use equally weighted CTA industry returns ($CTAR_t$) and its one-month, six-month, and 12-month lagged moving average; Equation 3a uses the one-month lag of the number of new CTAs ($NEWCTA_{t-1}$) while Equation 3b uses the one-month lag of the amount of funds raised by new CTAs ($NEWCTA\$_{t-1}$) as independent variables. A dummy variable *ISJAN* used in all Equations 1a-3b equals 1 if CTA enters the market in January of any year and 0 otherwise. Entries marked with *, **, and *** are significant at the 10, 5, and 1% levels, respectively. The t-statistics presented are adjusted for heteroskedasticity.

Panel A

	Jan-1994 - Jul-2007				Aug-2007 - Sep-2010			
	Equation 1a		Equation 1b		Equation 1a		Equation 1b	
Variable	Coefficient	t-Stat	Coefficient	t-Stat	Coefficient	t-Stat	Coefficient	t-Stat
Intercept	0.928***	7.424	13.606***	10.649	0.386***	2.913	9.149***	3.927
EMR_t	-0.104	-0.078	-2.68	-0.438	-0.348	-0.191	-1.38	-0.062
EMR_{t-1}	-0.374	-0.283	14.68**	2.434	-1.336	-0.632	-23.819	-0.922
EMR_{t-6}	5.011	0.940	19.536	0.797	2.157	0.381	2.925	0.043
EMR_{t-12}	-0.067	-0.011	-1.158	-0.041	-3.246	-0.536	-89.513	-1.194
$\log(NEWCTA_{t-1})$	0.28***	3.730			0.115	0.665		
$\log(NEWCTA\$_{t-1})$			0.118	1.503			0.199	1.181
ISJAN	0.959***	5.530	1.318*	1.703	0.608	1.690	4.791	1.094
$Adj.R^2$	0.186		0.069		-0.043		0.118	

Panel B

	Jan-1994 - Jul-2007				Aug-2007 - Sep-2010			
	Equation 2a		Equation 2b		Equation 2a		Equation 2b	
Variable	Coefficient	t-Stat	Coefficient	t-Stat	Coefficient	t-Stat	Coefficient	t-Stat
Intercept	0.941***	7.506	13.512***	10.420	0.408***	3.060	8.026***	3.291
CMR_t	0.021	0.021	-0.083	-0.018	0.671	0.568	0.6	0.039
CMR_{t-1}	0.279	0.294	3.714	0.841	0.044	0.032	-1.06	-0.059
CMR_{t-6}	1.282	0.337	-15.849	-0.895	-0.801	-0.260	-15.447	-0.386
CMR_{t-12}	-2.541	-0.602	21.159	1.074	1.935	0.536	16.165	0.348
$\log(NEWCTA_{t-1})$	0.303***	4.093			0.111	0.642		
$\log(NEWCTA\$_{t-1})$			0.138*	1.732			0.326*	1.950
ISJAN	0.988***	5.679	1.493*	1.871	0.589	1.679	4.063	0.891
$Adj.R^2$	0.177		0.011		-0.046		-0.01	

Panel C

	Jan-1994 - Jul-2007				Aug-2007 - Sep-2010			
	Equation 3a		Equation 3b		Equation 3a		Equation 3b	
Variable	**Coefficient**	**t-Stat**	**Coefficient**	**t-Stat**	**Coefficient**	**t-Stat**	**Coefficient**	**t-Stat**
Intercept	0.921***	6.811	15.206***	11.447	0.266*	1.710	6.642***	2.881
$CTAR_t$	-2.724	-1.345	-31.219***	-3.467	-1.785	-0.361	-20.131	-0.321
$CTAR_{t-1}$	-4.874**	-2.408	-29.112***	-3.178	-0.994	-0.210	-9.76	-0.162
$CTAR_{t-6}$	-9.435	-1.248	-62.701*	-1.846	24.128	1.136	69.894	0.288
$CTAR_{t-12}$	27.624**	2.373	115.596**	2.273	9.126	0.424	476.322*	1.716
$\log(NEWCTA_{t-1})$	0.252***	3.376			-0.06	-0.329		
$\log(NEWCTA\$_{t-1})$			0.037	0.465			0.117	0.668
ISJAN	0.994***	5.913	1.529**	2.090	0.557*	1.717	4.488	1.081
Adj.R^2	0.232		0.163		0.105		0.169	

TABLE 3

Descriptive statistics of CTAs

Table 3 presents the descriptive statistics over the entire life of CTAs from January 1994 to September 2010. *FLOW* is the relative fund flow of CTAs; *ROR* is the raw monthly return; *SHARPE* is the annualized Sharpe ratio, *PW* is the percentage of wins; *SD* is standard deviation of returns, *TUW* is the percentage time under water, *SKEW* and *KURT* are skewness and kurtosis, respectively, calculated on *ROR*; *AGE* is the age of CTAs in months; and *AUM* are assets under management (in thousands of U.S. dollars).

	FLOW	ROR	SHARPE	PW	SD	TUW	SKEW	KURT	AGE	AUM
Mean	0.022	0.008	0.367	0.584	0.068	0.668	0.575	5.451	82	101,642
Median	0.000	0.004	0.493	0.574	0.058	0.696	0.462	4.031	65	13,296
Maximum	5.513	2.808	10.774	1.000	0.564	0.985	7.352	108.655	402	10,978,258
Minimum	-1.589	-0.952	-32.028	0.000	0.001	0.000	-10.153	1.093	11	0
Std.dev.	0.286	0.073	1.329	0.092	0.045	0.159	1.002	5.329	61	409,566
Skewness	11.403	3.831	-14.016	0.783	2.588	-1.052	0.771	6.541	1.43	12.67
Kurtosis	192.159	102.941	345.473	5.401	16.584	4.628	11.231	73.672	5.30	229.01

TABLE 4

The relation between CTA fund flow and performance

Table 4, Panel A presents the results of the ordinary least squares (Fama-MacBeth) piecewise linear regressions given by equation (4) using monthly relative fund flow ($FLOW_{i,t}$) as the dependent variable for the period January 1994 – July 2007. The key independent variable is rolling annual Sharpe ratio ($SHARPE_{i,t-1}$) across four quartiles. $SHARPE_{i,t-1}^{1-4}$ is the difference between the coefficients in the first and fourth quartiles. Panels B and C present the results of linear (Fama-MacBeth) regressions given by equation (5) with monthly relative fund flow as the dependent variable for the two subperiods January 1994 – July 2007 and August 2007 – September 2010 respectively. Independent variables in focus are risk-adjusted performance ($SHARPE_{i,t-1}$), relative risk-adjusted performance ($RANKSHRP_{i,t-1}$), lagged percentage of wins ($PW_{i,t-1}$), lagged standard deviation ($SD_{i,t-1}$), lagged time under water ($TUW_{i,t-1}$), lagged skewness ($SKEW_{i,t-1}$) and lagged kurtosis ($KURT_{i,t-1}$). Other independent control variables include lagged fund size ($AUM_{i,t-1}$), lagged fund age ($AGE_{i,t-1}$), lagged fund flows ($FLOW_{i,t-1}$), incentive fee ($INCFEE_i$), management fee ($MGTFEE_i$), minimum investment account ($MINACC_i$), a dummy variable for private CTAs ($PRIVATE_i$) which equals 1 if CTA *i* is private and 0 otherwise, a dummy variable for active CTAs ($ACTIVE_i$) which equals 1 if CTA *i* is in operation by September 2010 and 0 otherwise. Entries marked with *, **, and *** are significant at the 10, 5, and 1% levels, respectively. The t statistics presented are adjusted for heteroskedasticity.

Panel A: Equation 4, January 1994 – July 2007

	Systematic		Discretionary		Systematic & Discretionary		Other	
Variable	**Coefficient**	**t-Stat**	**Coefficient**	**t-Stat**	**Coefficient**	**t-Stat**	**Coefficient**	**t-Stat**
Intercept	0.219***	4.901	0.428***	3.183	0.378**	2.515	-0.061	-0.661
$\mathrm{SHARPE}_{i,t-1}^{1}$	0.097***	7.636	0.171***	2.764	0.097**	2.373	0.044	0.652
$\mathrm{SHARPE}_{i,t-1}^{2}$	0.068**	2.115	0.1	1.254	0.148	1.588	0.072	0.934
$\mathrm{SHARPE}_{i,t-1}^{3}$	0.073***	3.729	0.029	0.75	-0.007	-0.144	0.163**	2.299
$\mathrm{SHARPE}_{i,t-1}^{4}$	0.076***	8.648	0.037***	3.874	0.066***	4.102	0.053**	2.152
$\mathrm{SHARPE}_{i,t-1}^{1-4}$	0.021	1.278	0.133**	2.125	0.030	0.605	-0.009	-0.117
$PW_{i,t-1}$	-0.022	-0.601	-0.04	-0.375	-0.136	-1.096	0.232**	2.173
$SD_{i,t-1}$	-0.033	-0.897	-0.035	-0.391	-0.079	-0.696	0.07	0.415
$TUW_{i,t-1}$	-0.111***	-4.824	-0.094	-1.461	-0.162**	-2.101	0.069	1.174
$SKEW_{i,t-1}$	-0.002	-0.716	-0.003	-0.455	-0.013	-1.002	0.01	1.643
$KURT_{i,t-1}$	0	0.072	0.001	0.674	0.002	1.118	-0.001	-1.23
$AUM_{i,t-1}$	-0.011***	-8.598	-0.025***	-5.359	-0.014***	-4.677	-0.016***	-4.223
$AGE_{i,t-1}$	0	-0.438	0	-1.206	0	0.062	0	-1.655
$FLOW_{i,t-1}$	0.026**	2.016	-0.024	-0.496	0.084*	1.712	0.019	0.306
$INCFEE_i$	0.113***	2.966	0.007	0.082	-0.174	-1.389	-0.119	-1.497
$MGTFEE_i$	0.193*	1.676	0.143	0.354	-0.09	-0.239	0.223	0.434
$MINACC_i$	0.003***	4.229	0.01***	3.151	0.005	1.499	0.015***	3.464
$PRIVATE_i$	0.001	0.196	-0.072***	-2.733	0.01	0.417	-0.024	-1.08
$ACTIVE_i$	0.006**	2.471	0.013	1.106	0.008	0.931	-0.004	-0.279
Adj R^2	0.043		0.097		0.141		0.114	

Panel B: Equation 5, January 1994 – July 2007

	Systematic		Discretionary		Systematic & Discretionary		Other	
Variable	Coefficient	t-Stat	Coefficient	t-Stat	Coefficient	t-Stat	Coefficient	t-Stat
Intercept	0.185***	4.142	0.327***	2.765	0.348**	2.417	-0.102	-1.182
$SHARPE_{i,t-1}$	0.033**	2.154	0.04**	2.272	0.077**	2	-0.055	-1.577
$RANKSHRP_{i,t-1}$	0.074***	5.363	0.038	1.331	0.035	0.829	0.137***	3.582
$PW_{i,t-1}$	-0.033	-0.915	0.002	0.016	-0.146	-1.2	0.227**	2.375
$SD_{i,t-1}$	-0.028	-0.75	-0.017	-0.158	-0.061	-0.563	0.086	0.546
$TUW_{i,t-1}$	-0.098***	-4.251	-0.047	-0.792	-0.145*	-1.881	0.057	1.036
$SKEW_{i,t-1}$	-0.003	-1.12	0	0.014	-0.016	-1.313	0.016***	2.982
$KURT_{i,t-1}$	0	0.128	0	0.122	0.003	1.505	-0.001	-1.626
$AUM_{i,t-1}$	-0.011***	-8.92	-0.023***	-5.543	-0.015***	-5.116	-0.017***	-4.5
$AGE_{i,t-1}$	0	-0.541	0	-1.021	0	0.511	0	-1.572
$FLOW_{i,t-1}$	0.023*	1.733	-0.014	-0.287	0.089**	2.136	0.022	0.394
$INCFEE_i$	0.099**	2.548	-0.049	-0.774	-0.143	-1.277	-0.109	-1.426
$MGTFEE_i$	0.191*	1.683	0.355	1.142	-0.011	-0.032	0.268	0.719
$MINACC_i$	0.003***	4.36	0.01***	3.295	0.007**	2.115	0.016***	3.93
$PRIVATE_i$	0.002	0.454	-0.063***	-2.756	-0.003	-0.137	-0.017	-0.765
$ACTIVE_i$	0.005**	2.097	0.012	0.959	0.008	1.305	-0.008	-0.681
Adj R^2	0.048		0.089		0.147		0.095	

Panel C: Equation 5, August 2007 – September 2010

	Systematic		Discretionary		Systematic & Discretionary		Other	
Variable	Coefficient	t-Stat	Coefficient	t-Stat	Coefficient	t-Stat	Coefficient	t-Stat
Intercept	0.008	0.101	0.343	0.479	0.289	0.605	0.681**	2.357
$SHARPE_{i,t-1}$	-0.033	-1.065	-0.032	-0.737	-0.045	-0.468	0.023	0.245
$RANKSHRP_{i,t-1}$	0.089**	2.543	0.131*	1.82	0.068	0.669	0.137	1.225
$PW_{i,t-1}$	0.124	1.163	-0.086	-0.166	-0.227	-0.544	-0.267	-1.199
$SD_{i,t-1}$	-0.156	-0.973	0.482	0.407	0.456	1.145	-0.197	-0.766
$TUW_{i,t-1}$	0.005	0.097	-0.144	-0.313	-0.145	-0.634	-0.322**	-2.12
$SKEW_{i,t-1}$	0.02**	2.367	0	-0.016	0.02	0.787	-0.004	-0.161
$KURT_{i,t-1}$	-0.004***	-3.566	0.001	0.615	-0.007*	-1.712	-0.001	-0.129
$AUM_{i,t-1}$	-0.01***	-3.516	-0.017	-1.406	0.003	0.355	-0.013	-1.495
$AGE_{i,t-1}$	0	-1.247	0	-0.367	0	-0.759	0	0.158
$FLOW_{i,t-1}$	0.007	0.294	0.002	0.009	-0.436	-1.267	-0.027	-0.217
$INCFEE_i$	0.035	0.498	-0.129	-0.282	-0.227	-0.503	0.092	0.843
$MGTFEE_i$	0.144	0.404	3.158	1.084	0.439	0.569	0.067	0.098
$MINACC_i$	0.004	0.901	-0.002	-0.356	-0.006	-0.847	-0.012**	-2.615
$PRIVATE_i$	-0.012	-1.057	0.068	0.359	-0.004	-0.134	-0.008	-0.246
$ACTIVE_i$	0.052***	3.212	0.024	0.93	0.019	0.567	0.02	0.707
Adj R^2	0.058		0.166		0.276		0.042	

TABLE 5
Estimation results for testing short-term 'smart money' effect in CTAs

Table 5 presents the results from the OLS (monthly Fama-MacBeth) regressions using absolute and relative return of CTAs as the dependent variable during two periods: Janurary 1994 – July 2007 and August 2007 – September 2010. Equation 6 uses absolute performance ($ROR_{i,t}$), while equation 7 uses relative performance ($RANK_{i,t}$) as the dependent variable. The key independent variables are 1-month, 2-month and 3-month lagged fund flows ($FLOW_{i,t-1}$, $FLOW_{i,t-2}$ and $FLOW_{i,t-3}$). Other independent control variables include lagged absolute return ($ROR_{i,t-1}$), lagged standard deviation ($SD_{i,t-1}$), lagged fund age ($Age_{i,t-1}$), lagged fund size ($AUM_{i,t-1}$), incentive fee ($INCFEE_i$), management fee ($MGTFEE_i$), minimum investment account ($MINACC_i$), a dummy variable for a private CTA ($PRIVATE_i$) that is equal to 1 if CTA i is private and 0 otherwise, a dummy variable for active CTA ($ACTIVE_i$) that is equal to 1 if CTA i was in operation by September 2010 and 0 otherwise. Figures marked with *, **, and *** are significant at the 10%, 5%, and 1% level, respectively. The t-statistics presented are adjusted for heteroskedasticity.

Panel A: Equation 6, January 1994 – July 2007

	Systematic		Discretionary		Systematic & Discretionary		Other	
Variable	Coefficient	t-Stat	Coefficient	t-Stat	Coefficient	t-Stat	Coefficient	t-Stat
Intercept	0	0.105	-0.015	-1.279	0.008	0.59	0.005	0.446
$FLOW_{i,t-1}$	-0.002	-1.251	-0.01	-1.353	-0.015**	-2.034	0.006	0.604
$FLOW_{i,t-2}$	-0.005***	-2.829	-0.002	-0.252	-0.003	-0.355	0.025*	1.761
$FLOW_{i,t-3}$	-0.003*	-1.661	0.016**	2.095	-0.005	-0.775	-0.01	-0.956
$ROR_{i,t-1}$	0.01	0.457	0.06	1.617	0.065**	2.118	-0.048	-1.001
$SD_{i,t-1}$	0.041	1.455	0.134***	3.378	0.002	0.042	0.074***	2.76
$AUM_{i,t-1}$	0	-0.948	-0.001**	-2.107	-0.001*	-1.86	-0.001*	-1.871
$AGE_{i,t-1}$	0***	-2.985	0	-1.635	0	-1.072	0***	-2.725
$INCFEE_i$	0.032***	2.649	0.03	1.027	0.071	1.653	-0.033	-1.335
$MGTFEE_i$	0.065*	1.74	0.013	0.135	-0.124	-0.885	0.035	0.446
$MINACC_i$	0	0.754	0.002***	3.562	0.001**	2.063	0.002**	2.181
$PRIVATE_i$	-0.002	-1.592	-0.001	-0.221	-0.009*	-1.835	-0.001	-0.367
$ACTIVE_i$	0.004***	6.051	-0.001	-0.263	0.001	0.412	0.006**	2.209
Adj R^2	0.114		0.268		0.294		0.26	

Panel B: Equation 7, January 1994 – July 2007

	Systematic		Discretionary		Systematic & Discretionary		Other	
Variable	Coefficient	t-Stat	Coefficient	t-Stat	Coefficient	t-Stat	Coefficient	t-Stat
Intercept	0.487***	20.899	0.411***	8.232	0.543***	7.568	0.495***	9.676
$FLOW_{i,t-1}$	-0.003	-0.426	-0.011	-0.302	-0.044	-1.178	0.078*	1.833
$FLOW_{i,t-2}$	-0.018*	-1.838	-0.006	-0.289	-0.024	-0.626	0.026	0.493
$FLOW_{i,t-3}$	-0.008	-0.998	0.075***	2.867	0.006	0.129	-0.083	-1.603
$ROR_{i,t-1}$	0.064	0.627	0.264***	3.048	0.287**	1.992	0.016	0.104
$SD_{i,t-1}$	-0.011	-0.087	0.298***	2.901	-0.105	-0.553	0.167	1.566
$AUM_{i,t-1}$	-0.001	-0.934	-0.001	-0.649	-0.005*	-1.738	-0.001	-0.316
$AGE_{i,t-1}$	0**	-1.993	0**	-2.485	0**	-2.125	0**	-2.512
$INCFEE_i$	0.112*	1.798	0.15	1.3	0.25	1.453	-0.133	-1.22
$MGTFEE_i$	0.285	1.481	-0.604	-1.622	-0.901*	-1.729	0.03	0.076
$MINACC_i$	0	0.097	0.008***	3.015	0.004	1.548	0.003	0.888
$PRIVATE_i$	-0.007	-1.287	-0.021	-1.047	-0.035	-1.577	0.011	0.625
$ACTIVE_i$	0.025***	6.706	0.006	0.611	-0.002	-0.176	0.039***	3.047
Adj R^2	0.105		0.161		0.203		0.174	

Panel C: Equation 6, August 2007 – September 2010

	Systematic		Discretionary		Systematic & Discretionary		Other	
Variable	**Coefficient**	**t-Stat**	**Coefficient**	**t-Stat**	**Coefficient**	**t-Stat**	**Coefficient**	**t-Stat**
Intercept	0.012	0.993	-0.061***	-3.574	0.033	1.062	0.021	0.643
FLOW $_{i,t-1}$	0.008	1.538	-0.086	-0.851	-0.012	-0.324	-0.033	-1.558
FLOW $_{i,t-2}$	0.001	0.132	0	0.016	-0.015	-0.233	-0.059	-1.302
FLOW $_{i,t-3}$	0	0.104	-0.034	-1.414	0.036	0.815	-0.005	-0.188
ROR $_{i,t-1}$	-0.026	-0.404	-0.155	-0.956	0.163	0.998	0.012	0.159
SD $_{i,t-1}$	0.114	1.272	0.17*	1.717	0.161	1.138	0.262	1.325
AUM $_{i,t-1}$	-0.001	-1.463	0.002*	1.908	0.002	0.667	-0.001	-0.394
AGE $_{i,t-1}$	0	-0.221	0	-1.173	0	1.144	0	0.962
INCFEE$_i$	0.001	0.032	-0.014	-0.351	-0.139	-0.971	0.006	0.086
MGTFEE$_i$	-0.148**	-2.065	-0.205	-0.836	-0.209	-0.569	0.106	0.265
MINACC$_i$	0	0.621	0.002**	2.065	-0.003	-1.163	-0.001	-0.489
PRIVATE$_i$	-0.001	-0.384	0.002	0.5	-0.004	-0.33	0.002	0.372
ACTIVE$_i$	0.006***	3.382	0.001	0.186	-0.005	-0.923	-0.006	-0.783
Adj R-sq	0.193		0.472		0.557		0.305	

Panel D: Equation 7, August 2007 – September 2010

	Systematic		Discretionary		Systematic & Discretionary		Other	
Variable	**Coefficient**	**t-Stat**	**Coefficient**	**t-Stat**	**Coefficient**	**t-Stat**	**Coefficient**	**t-Stat**
Intercept	0.45***	6.049	0.146	0.998	0.516***	5.214	0.605**	2.193
FLOW $_{i,t-1}$	0.03	0.705	-1.118	-0.99	-0.112	-0.726	-0.305*	-2.007
FLOW $_{i,t-2}$	-0.005	-0.183	0.003	0.018	-0.067	-0.242	-0.257	-0.735
FLOW $_{i,t-3}$	-0.016	-0.439	-0.195	-1.307	0.027	0.156	0.089	0.459
ROR $_{i,t-1}$	-0.076	-0.254	-0.694	-0.531	0.473	0.878	-0.24	-0.547
SD $_{i,t-1}$	0.488	1.227	0.63	1.202	0.854*	1.798	1.704*	1.796
AUM $_{i,t-1}$	-0.002	-0.597	0.009	1.013	0.017	1.661	-0.008	-0.318
AGE $_{i,t-1}$	0*	-1.716	0	-1.61	0.001**	2.323	0	1.326
INCFEE$_i$	-0.031	-0.232	-0.259	-0.929	-1.124**	-2.415	0.085	0.151
MGTFEE$_i$	-0.714	-1.594	-0.94	-0.579	-0.849	-0.642	0.29	0.096
MINACC$_i$	0.005	1.51	0.014**	2.039	-0.01	-1.111	-0.007	-0.639
PRIVATE$_i$	-0.013	-0.775	0.052*	1.84	-0.081	-1.61	0.026	0.919
ACTIVE$_i$	0.044***	3.527	0.052*	2.02	0.023	0.807	-0.067	-1.257
Adj R-sq	0.174		0.364		0.429		0.265	

TABLE 6
Estimation results for long-term 'smart money' effect in CTAs

Table 6 presents the results from the annual Fama-MacBeth cross-sectional regressions using absolute (Panle A) and relative (Panel B) risk-adjusted performance measures of CTAs as the dependent variable during the period from January 1994 to December 2009. Equation 8 uses annual Sharpe ratio (*$SHARPE_{i,t}$*), while equation 9 uses rank of CTA based on Sharpe ratio (*$RANKSHRP_{i,t}$*) as the dependent variable. The key independent variables is previous year annual fund flow (*$FLOWANN_{i,t-12}$*). Other independent control variables include lagged fund age (*$Age_{i,t-12}$*), lagged fund size (*$AUM_{i,t-12}$*), incentive fee (*$INCFEE_i$*), management fee (*$MGTFEE_i$*), minimum investment account (*$MINACC_i$*), a dummy variable for a private CTA (*$PRIVATE_i$*) that is equal to 1 if CTA i is private and 0 otherwise, a dummy variable for active CTA (*$ACTIVE_i$*) that is equal to 1 if CTA i was in operation by September 2010 and 0 otherwise. Figures marked with *, **, and *** are significant at the 10%, 5%, and 1% level, respectively. The t-statistics presented are adjusted for heteroskedasticity.

Panel A: Equation 8, January 1994 – December 2009

	Systematic		Discretionary		Systematic & Discretionary		Other	
Variable	Coefficient	t-Stat	Coefficient	t-Stat	Coefficient	t-Stat	Coefficient	t-Stat
Intercept	0.374***	4.256	-1.701**	-2.927	0.285	0.563	-0.142	-0.648
$FLOWANN_{i,t-12}$	-0.002	-0.362	-0.02	-0.584	0.009	0.504	-0.029*	-1.826
$AUM_{i,t-12}$	-0.025***	-4.191	0.245***	5.657	-0.021*	-1.866	0.008	0.403
$AGE_{i,t-12}$	0*	1.824	-0.006***	-3.159	-0.001	-1.307	0	-1.214
$INCFEE_i$	0.672	1.577	6.228*	1.766	1.606*	1.948	0.305	0.807
$MGTFEE_i$	-0.167	-0.127	-66.554	-1.502	-4.851	-1.174	-1.985	-1.284
$MINACC_i$	0.006	1.541	-0.18***	-4.626	0.015	1.013	0.02	1.014
$PRIVATE_i$	-0.037**	-2.268	0.782***	3.905	-0.152	-1.035	-0.029	-0.464
$ACTIVE_i$	0.039	1.352	1.144***	3.751	-0.226	-1.235	0.109**	2.545
Adj R^2	0.047		0.071		0.037		0.052	

Panel B: Equation 9, January 1994 – December 2009

	Systematic		Discretionary		Systematic & Discretionary		Other	
Variable	Coefficient	t-Stat	Coefficient	t-Stat	Coefficient	t-Stat	Coefficient	t-Stat
Intercept	0.474***	7.802	0.226*	1.975	0.313	0.892	0.256	1.338
$FLOWANN_{i,t-12}$	-0.002	-0.649	-0.011	-0.875	0.001	0.043	-0.034***	-3.237
$AUM_{i,t-12}$	-0.006	-1.653	0.008*	1.848	0.002	0.179	0	-0.004
$AGE_{i,t-12}$	0	-1.66	-0.001***	-3.058	-0.001**	-2.525	-0.001**	-2.492
$INCFEE_i$	0.342**	2.421	-0.111	-0.472	0.807	1.256	0.221	0.648
$MGTFEE_i$	-0.17	-0.261	-1.673	-0.931	-3.318	-0.94	0.106	0.065
$MINACC_i$	0.005**	2.92	0.021***	3.771	0.016	1.681	0.016	1.076
$PRIVATE_i$	-0.033*	-2.069	-0.009	-0.165	-0.087	-0.853	-0.029	-0.576
$ACTIVE_i$	0.079***	3.271	0.056*	2.072	-0.059*	-2.1	0.143***	3.727
Adj R^2	0.043		0.12		0.078		0.094	

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