Performance, Persistence, and Pay: A New Perspective on CTAs

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Abstract

Using a large and representative dataset of commodity trading advisors (CTAs), we provide compelling evidence that CTAs generate significant net excess returns of at least 4.1% annually; that approximately 64% of the funds have positively skewed returns; and that there is considerable heterogeneity among CTAs, with systematic trend followers doing significantly better than other subcategories. More importantly, we find that CTAs not only beat passive, normative benchmarks, with a yearly gross alpha of at least 5.3% but also generate significant, incremental crisis alpha during periods of equity market turmoil. Finally, we show that cross-sectional differences in the performance of CTAs are persistent up to three years and that managerial compensation predicts fund performance. Our results are consistent with a rational market where investors compete to invest with successful CTA managers who use fees to signal their skills to investors.

JEL Classification: G11, G12, G14, G23
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1 Introduction

A growing academic literature examines why investors continue to allocate their capital to seemingly unsuccessful active managers. While numerous studies focus on the performance of actively managed mutual funds (e.g. Gruber 1996; Cremers and Petajisto 2009; Berk and Green 2004) and hedge funds (e.g. Ackermann et al. 1999; Agarwal et al. 2009; Stulz 2007), performance of commodity trading advisors (CTAs) has received less attention.[5] That said, the broad consensus emerging from extant studies is that the average CTA does not create value for its investors (e.g. Elton et al. 1987, 1989, 1990; Bhardwaj et al. 2014). Yet, as indicated by their rapidly growing assets under management (AUM) from USD 24.9 billion to USD 339.7 billion between 1994 and 2016,[6] CTAs have become a popular investment vehicle for practitioners and a fundamental component of today's financial markets.[7] We offer a new perspective on this puzzle. More specifically, we employ one of the largest and cleanest CTA datasets explored so far to analyze the performance of CTAs, discuss the cross-sectional variations within the category, assess CTA manager skill and performance persistence, and examine whether managerial compensation is justified by managerial performance.

Apart from their ever-growing presence, CTAs are also unique in that even while they are one of the more populous categories of alternative investments, their investment strategies are relatively undiversified and identifiable, making it is easier to benchmark and evaluate their performance (Fung and Hsieh 2001). Such a unique advantage in modelling returns not only results in an accurate estimation of CTA performance but also enables us to circumvent the opaqueness of hedge fund investments and gain valuable insights into the operational efficiency of the alternative investments universe.

We find that CTA managers generate economic and statistically significant positive net excess returns. Further, we find that pre-fees alphas are positive and significant, indicating that CTA managers beat passive benchmark strategies. Following the rationale of Berk and

[5] They are often excluded from hedge fund studies, such as Bollen (2013), Agarwal et al. (2009) or Titman and Tiu (2011).
[6] Information on the industry's AUM refers to Barclay's yearly estimates of the industry's overall assets under management. Accessed via https://www.barclayhedge.com/research/indices/cta/mum/CTA_Fund_Industry. html and https://www.barclayhedge.com/research/indices/ghs/mum/HF_Money_Under_Management.html. In terms of AUM, CTAs became the third-largest hedge fund category in 2016, after Fixed Income (USD 556.2 billion) and Multi-Strategy (USD 360 billion) hedge funds.
[7] The growing popularity in the CTA industry, its increasing AUM, and associated risk factors are also evident in the recently increasing number of financial newspaper articles, for example, "Trend is your friend, say investors flocking to futures," "Computer-driven trend hedge funds thrive despite falling markets," or "Risk in new form of "portfolio insurance" sparks fear."

van Binsbergen (2015), we also find evidence that CTA managers add significant value to their customers and that CTA performances are persistent for a horizon of up to three years. Finally, we show that CTAs' compensation scheme predicts future performance, providing managers with an avenue to signal their skill to investors. While previous papers have invoked investor irrationality or severe information asymmetry to reconcile their findings with the continued growth of CTAs, our results are indicative of a well-functioning, competitive marketplace with rational investors and fund managers. In fact, our results are perfectly in accordance with the main predictions of the Berk and Green (2004) model. One, there is significant and persistent cross-sectional variation in manager skill. Two, investors compete to invest with successful managers. Finally, managerial compensation, functioning as a balancing mechanism, is set so that the ex-ante net alpha is zero.

Our analysis is based on data derived from Barclay's Hedge Fund Database (BarclayHedge). The database covers on average 70% of the industry, in terms of AUM. Risk and Portfolio Management AB (RPM), a managed account industry specialist based in Stockholm, Sweden, provide us with the data. Since RPM has been downloading the entire BarclayHedge database daily since 2002, data entries are not rewritten and no return histories are deleted (Patton et al. 2015). The dataset is therefore largely free of graveyard-bias and captures the wide cross-sectional dynamics of alive as well as defunct funds that stopped reporting during our sample period. First, equipped with this rich dataset, we construct equally and value-weighted portfolios of CTAs and show that funds generate on average 4.1% and 4.5% annualized net excess returns. These returns are net of all fees and are delivered to investors. Furthermore, we make use of an additional, small but representative proprietary dataset, provided by RPM, which contains solely realized returns and validates our findings. We show that portfolios constructed from BarclayHedge and from the proprietary dataset have the same distributional characteristics, highlighting the accuracy of our findings and verifying the economic and statistically significant performance of CTAs.

Second, to identify cross-sectional variations among CTAs, we use a novel trading strategy classification obtained from RPM. The classification is based on RPM's private information about a fund and on the fund's own trading strategy description, which it reports to BarclayHedge. All funds that start to report to BarclayHedge are categorized according to one of the four strategy groups: systematic and discretionary trend followers and their non-trend following counterpoints. In contrast to classifications that are available from commercial hedge fund databases, our fund categorization allows us to distinguish between funds that use trend-following trading strategies (trend follower) and those that use a different trading approach (non-trend follower), for example, short-term or fundamental traders. Our analysis shows that the differentiation between these groups is crucial and that return dynamics across these trading strategies are fundamentally different from each other. For example, systematic and discretionary trend followers generate 6.0% and 7.4% average annualized returns, compared to only 3.5% and 1.8% by non-trend following CTAS.

Third, we discuss additional attractive characteristics of CTA returns, such as their positive skewness and correlation with other assets classes. Approximately 64% of our funds have positively skewed returns, indicating that CTAs might be attractive to investors with preferences for skewed returns (Polkovnichenko 2005; Brunnermeier et al. 2007; Mitton and Vorkink 2008). Furthermore, we show that CTA returns move strongly counter cyclically to equity markets. In times of equity market turmoil (S&P500 average: −10.1%), CTAs' average monthly excess return is at least 1.7%; and when equity markets flourish (S&P500 average: 8.4%), CTAs average excess return is −0.8%. Further, in extreme events, CTAs' return generating process is almost entirely uncorrelated with those of hedge funds—during months with the highest and lowest returns of the hedge fund research index, trend-following CTAs constantly produce returns between 2.4% and 3.5%. Even though CTAs are often classified as a subcategory of hedge funds, similar to Liang (2004), our analysis emphasizes substantial differences between these two asset classes and the possible diversification benefits from including CTAs in an investor's portfolio that cannot be obtained by investing in other active investment vehicles, such as hedge funds.

Fourth, we find that CTAs generate abnormal gross returns over and above benchmark trading strategies such as time series momentum (Moskowitz et al. 2012) and option straddle factors (Fung and Hsieh 2001). For the equally weighted and value-weighted CTA portfolios, the gross alpha is 8.4% and 6.4% on an annual basis, respectively. Furthermore, we show that CTAs, especially systematic trend followers, exploit price movements during periods of market turmoil. During these times, they produce an annual gross alpha of 27.36%, indicating that they successfully exploit price trends during crisis periods.

Next, we use a recent approach by Berk and van Binsbergen (2015) to analyze the value added by CTA managers. In line with Berk and Green (2004) and Berk (2005), the authors argue that the amount of capital funds attract from investors is a better measure of managerial skill than the pre-fees regression alpha. Since the profitability of a fund depends on the return as well as the amount of capital managed by a CTA, the authors construct a proxy for a fund's added value that takes both dimensions into account. We find large cross-sectional variation in managerial skill. Specifically, we find that 41% of CTAs in our sample generate negative value, compared to standard time series momentum strategies. Moreover, we find that the average added value of a CTA is USD 0.49 million per month.

Finally, using the valued added measure we show that CTA performance is persistent for up to three years. Sorting funds into quintile portfolios, the top 20% of CTAs significantly outperforms the bottom 20% over various forecasting horizons. In line with the argument that funds with greater investment skills demand higher compensations, we also find that the costliest investments in CTAs outperform funds that demand less compensation. This analysis shows that funds with higher accruing fees are more successful and that managers can use their compensation as credible signal of their skill. These findings are indicative of an efficient CTA market.

Our paper is most closely related to the existing literature examining the return dynamics of CTAs, most notably to Bhardwaj et al. (2014). In contrast to their results, our findings suggest that CTAs generate significant excess net returns to investors, that these net returns are positively skewed, and that CTAs generate significant pre-fees alpha, especially during periods of equity market stress. A likely explanation for the difference in results is that our analysis is based on a substantially larger set of CTAs, allowing for a wider representation of market dynamics. It covers on average 70% of the industry in terms of AUM, which is more than three times larger than the 21% industry coverage in Bhardwaj et al. (2014).

In addition, we are the first to provide insight into the heterogeneity of CTA trading strategies, show that there is significant and persistent cross-sectional variation in the skills of CTA managers, and that CTA manager pay is commensurate with manager performance. In this respect, our paper is also closely related to Berk and van Binsbergen (2015), who similarly examine managerial skill in the mutual fund universe.

While we focus solely on CTAs, our results also contribute to the larger debate on the rationality of investors who place money with fund managers. For example, Griffin and Xu (2009), find no evidence for constant significant positive hedge fund alphas. In contrast, Agarwal and Naik (2000), Agarwal et al. (2009), and Ibbotson et al. (2009) argue in favor of the hypothesis that hedge fund managers are skilled and generate abnormal returns beyond standard beta-risk factors. Our findings are consistent with this view that fund managers exhibit significant and persistent skill, and that "being able to pick good hedge funds can therefore be highly rewarding" (Stulz 2007).

Finally, while Brown and Goetzmann (2015), Kazemi and Li (2009) and Gregoriou et al. (2010) use fund classifications available in commercial databases to identify performance differences among CTAs and hedge funds, we use a novel classification system to explicitly distinguish between trend- and non-trend-following CTAs. As we highlight in various exercises, their trading strategies and performances are substantially different from each other. In contrast to Arnold (2013), who also distinguishes trend-followers and other CTA trading strategies, we do not analyze factors that determine the survival of funds but rather examine performance differences between these trading strategies. Earlier papers that have used the same fund classification (Elaut and Erdös 2016) focus on only one trading strategy, but do not compare performance differences among CTAs.

The rest of this paper proceeds as follows. In the next section we introduce the datasets we use for our analysis and describe in detail the steps of data cleaning taken to alleviate the impact of possible biases. In section 3, we discuss CTA performance as well as dynamics of net-of-fee returns. Section 4 assesses the managerial skill of CTA managers and the persistence of CTA returns. Section 5 concludes.

2 Data

The main underlying database for our analysis is Barclay's Hedge Fund Database (BarclayHedge). Risk and Portfolio Management AB (RPM), a managed account industry specialist based in Stockholm, Sweden, provide us with the data. BarclayHedge is the single most comprehensive database for CTAs. Compared to other commercially available hedge fund databases, it has a low proportion of missing information and large coverage of defunct funds, which have stopped reporting to the data provider (Joenväärä et al. 2016). For our analysis, we focus on funds' flagship programs, which refer to a fund's longest track record and highest assets under management. This leaves us with 3,017 individual CTAs and 208,959 fund-time observations for the period 1985 to December 2015. In order to allow for comparison between our results and the previous literature, we follow the same cleaning procedure outlined in Bhardwaj et al. (2014). Table 1 summarizes each step and its impact on the dataset.

[Insert Table (1)]

Since most commercial hedge fund databases begin to keep a track record of defunct funds in 1994, we restrict our analysis to the post-January 1994 period and drop returns associated with earlier reporting dates. This should reduce the impact of a potential survivorship bias in our database (Elaut et al. 2016). Further, we only consider funds that report information denominated in US dollars and exclude the records of 174 CTAs that use a different base currency. We also delete nine funds, for which we cannot identify an exact reporting start date, 36 entries that do not report returns "net all fees" and one entire fund history that reports unrealistic returns, such as −99.99%. Also, to allow for more than two months' reporting delay, we do not include funds added to BarclayHedge after December 2015.[8] Lastly, to be able to construct a value-weighted index, we delete CTAs that do not report assets under management (AUM) for the first or last observation. For missing AUM observations within a fund's record, we estimate the AUM by linear interpolation between the first and last available non-zero entry.[9]

After applying these filters, we are left with a sample of 2,620 funds and 195,682 cross-sectional observations to construct an equally weighted (EW) portfolio CTA index. The value-weighted (VW) index is based on a cross-section of 1924 CTAs and 131,485. In terms of size, the underlying data for our analysis consist of approximately three times as many CTA flagship programs as previous studies on CTA performance. In terms of AUM we cover on average 70% of the CTA industry over the entire sample period, which is significantly larger than the industry coverage of 21% in Bhardwaj et al. (2014).[10]

2.1 Biases in commercial hedge fund databases

It is well documented in the academic literature (for a recent survey see e.g. Agarwal et al. 2015) that commercial hedge fund databases are subject to various biases. Concerning CTAs in particular, Fung and Hsieh (1997) find that the average annual return of surviving funds is 3.4% higher than the average annual return of their total sample of 901 CTAs in the period 1986–1996. Bhardwaj et al. (2014) show that EW and VW indices that include solely

[8] We obtained the database in March 2016.

[9] This approach closely follows Bhardwaj et al. (2014) even though the authors only delete funds with missing information about AUM for the first reported observation.

[10] We use BarclayHedge's estimate of the CTA industry size as benchmark. The annual data of the estimated industry size are accessible via: https://www.barclayhedge.com/research/indices/cta/mum/CTA_Fund_Industry.html.

surviving funds generate 4.15% and 2.21% higher average annualized returns than portfolios of both alive and defunct funds. Including defunct funds in the analysis, therefore, takes into account the fact that worse performing funds may stop reporting and drop out of the database. In our sample, the performance of EW and VW indices would be artificially inflated by 2.5% and 1.2%, respectively, if we considered only the 507 funds still alive at the end of our sample period and omit those that dropped out over time.

In addition to survivorship bias, we account for funds' tendency to report returns retrospectively after they have entered the database, termed "backfill bias" (Gregoriou et al. 2010). Since CTAs use commercial databases to market their performance to investors, backfilled returns can lead to an artificial upward bias of the return structure. A common approach in the literature has been to exclude the first 12–24 months of the analysis to account for possibly retrospective reported return structures. However, as Bhardwaj et al. (2014) pointed out, a generic screen of the first "x-month" of reported returns does not clean the data sufficiently. They find that funds backfill on average 31 months in their sample. Instead of discarding a fixed number of first few months of each fund, the authors recommend using the fund's reporting start date as indicator and to exclude all reported returns prior to this date from the analysis.

In our version of BarclayHedge, we can follow the authors' suggested practice for most of our sample period and delete a fund's entire history prior to its entry in the database. We can infer the start of a fund's report history in BarclayHedge since RPM has downloaded the entire databases daily since February 2002 and flags the first entry of a fund to the database. We use this flag to minimize a potential upward bias in our analysis, caused by backfilled returns. For the first eight years, January 1994–January 2002, for which the reporting start date cannot be pinned down, we take a conservative approach and delete the first 36 reported months of a fund's track record.

Further, funds may revise their reports ex-post or even ask database vendors to delete the entire performance records after a fund stops reporting to the database (Patton et al. 2015). If a fund has performed poorly in the past, it might have a greater incentive to delete its history, leading to an upward bias among defunct CTAs. Since our data have been downloaded and stored daily by RPM, our BarclayHedge version is largely free of this "graveyard" bias.

2.2 CTA trading strategies

To understand and assess performance differences among CTAs, we supplement information on return dynamics from BarclayHedge with a trading strategy classification, which is obtained from RPM and allows us to distinguish between trend- and non-trend-following CTAs. Funds that enter BarclayHedge are categorized weekly based on their return dynamics and their own trading description. An overview of the trading classifications is given in Table 2.

Insert Table (2)

Table 2 shows three different levels of classification. As shown in column (1) funds can be identified as discretionary or systematic trading CTAs. Systematic traders are characterized by their use of algorithmic trading models and an extensive quantitative analysis of financial data that forms the basis for funds' investment decisions. In contrast, for discretionary strategies managers' ability to exploit chart patterns or divine global supply/demand imbalances from fundamental data plays a much more fundamental role. Column (2) distinguishes between trend-following funds and non-trend followers. Trend-following funds take directional long and short positions in various asset classes and generate returns by exploiting persistent price trends (Kaminsky 2011). In contrast, we consider non-trend followers as fundamental, short-term, commodity and FX traders. This classification is a novel feature of our analysis, since we can distinguish between the following strategy classifications, which are not available in any commercially available hedge fund database: systematic trend follower, systematic non-trend follower, discretionary trend follower, and discretionary non-trend follower.[11] However, as our analysis shows, it is crucial to account for the heterogeneity among systematic and discretionary funds, since their return dynamics are fundamentally different from each other. Using RPM's strategy classification, we aim to reduce any "strategic self-misclassification" (Brown and Goetzmann 2015, p. 103) that may result from purely self-reported strategies.

[11] While Elaut and Erdös (2016) use the same classification to analyze systematic trend followers, our aim is to provide an understanding of the overall industry dynamics and to show differences across all trading strategies. Similarly, Baltas and Kosowski (2013) rely on the trading style classification available in BarclayHedge and only distinguish between systematic and discretionary traders.

2.3 Summary statistics

For our analysis, we focus on CTAs with 24 months' reported information, which is a sufficiently long return history that is indicative of real return dynamics (Bhardwaj et al. 2014). Table 3 summarizes the characteristics of our dataset.

[Insert Table (3)]

As shown in Table 3, the EW and VW indices consist of 1,274 and 936 CTAs that report at least 24 months of returns. Two-thirds of these funds are systematic traders, while only 317 funds are categorized as discretionary. Less than 10% belong to the category "Others." The average size of a CTA accounts for USD 234 million, measured by AUM of the last reported observation. However, there is a large variation in fund size across trading strategies. Systematic funds with an average size of USD 280 or USD 380 million assets under management for trend and non-trend followers are substantially larger than discretionary funds. Further, the long-lived CTAs with an average reporting time of 81.2 months tend to be systematic trend followers. The remaining sample average is approximately 64 months. Lastly, as indicated by the final row, most funds at the end of our sample are systematic funds.

3 CTA Performance

To evaluate the performance of CTAs, we start by examining the characteristics of funds' net excess returns—net returns in excess of the 3-Month Treasury Bill. To begin with, panel A of Table 4 shows the annualized average net excess return and volatility for the EW and VW indices for the period January 1994—December 2015. Over the entire sample period, the average annualized return accounts for 4.1% and 4.5% for the EW and VW index, respectively. Strikingly, both portfolios generate returns that are significantly different from zero at the 1% level, as indicated by the high t-statistic. The results are fundamentally different from earlier studies arguing that CTAs do not produce positive returns to investors. For example, Bhardwaj et al. (2014) find net excess returns are used up entirely by funds' high fee structure. Using a substantially larger cross-section of funds, representing on average 70% of the total CTA industry in terms of AUM, we show that CTAs' net-of-fee returns are economic and statistically significant. CTAs' profitability might be one simple explanation for the growing assets under management in the industry.

We also find CTAs' positive performance is largely driven by systematic traders, who generate significant positive returns of 5.1% and 3.1% for trend and non-trend followers, respectively. In contrast, the performance of discretionary funds is not necessarily significantly different from zero. Also, even though trend-following funds appear to generate higher returns, these benefits are associated with higher levels of risk. While the annualized average volatility of VW systematic and discretionary non-trend-following portfolios is 5.8% and 6.5%, respectively, it increases to 11.7% and 15.7% for trend-following counterparts.

Even though various existing biases in all commercial databases have been identified by academic research, an issue for all studies so far has been that no source of validation is available to verify the process of data cleaning and analysis results. In our study, we alleviate this major shortcoming by using a proprietary dataset of realized CTA returns as a validation mechanism. The data are provided by RPM and are based on realized returns from a set of 51 representative managers that report directly to RPM. While the cross-section of this dataset is smaller than the BarclayHedge coverage, it is worth highlighting that the returns from this database are realized rather than reported returns. Importantly, this implies that these data do not suffer from backfill or graveyard bias, or any form of retrospective window-dressing. Furthermore, since the set of CTAs has been actively managed by RPM, funds have been added to and dropped from the database. Therefore, the set of funds also consists of alive and defunct funds, circumventing concerns about survivorship bias. Even though the number of funds is small, the return dynamics are a representative sample of the overall CTA industry. For example, the correlation between a value-weighted index of the benchmark returns and BarclayHedge's CTA index is 0.83.

To alleviate concerns about remaining or undetected biases in our dataset, we compare the return dynamics of our EW and VW CTA portfolios from BarclayHedge with EW and VW indices based on realized returns from RPM's proprietary dataset. We conduct a t-test to assess if the indices based on reported return and realized return data are on average significantly different from each other. We postulate that if our results were driven by data biases or inadequate data cleaning, we would reject the null hypothesis that the reported return and realized return data have the same return dynamics. Also, we conduct the Kolmogorov-Smirnov (KS) test to check if the distribution of returns between the indices is significantly different. Failing to reject the null hypothesis, however, implies that the dataset of realized returns is representative of the overall industry, strengthening our line of argument. The results of these assessments are shown in Table 5.

[Insert Table (5)]

To start with, Table 5 shows the average annual return of BarclayHedge and the set of funds that we use for validating our results. While the difference between indices is slightly larger for the EW portfolios, it only accounts for 0.7% on an annual basis. Despite the performance differences, both indices largely follow the same dynamics. The correlation coefficient between EW and VW indices is 0.80 and 0.82, respectively. We interpret these values as a first indication that indices constructed from the proprietary data can be considered as a representation of the overall industry dynamics. Further, in column (5) we test the null hypothesis that both indices generate the same average return and in column (6) we test the null hypothesis that both return series are drawn from the same distribution.

As shown in Table 5, columns (5) and (6), we are not able to reject the null hypothesis for either of the two tests. The t-statistics for the differences in mean returns are only 0.5 and 0.3 for the EW and VW index, respectively. Similarly, we are not able to reject the null hypothesis that returns are drawn for the same distribution, as seen from the small KS-statistics of 0.11 and 0.09 for the EW and VW index, respectively.

These results are crucial for our study as well as for papers examining the performance of hedge funds in general. First, they validate the steps of data cleaning, described in the previous section. They show that survivorship and backfill bias are the main forms of biases and that their impact can be significantly alleviated by including all defunct funds from the analysis and by deleting the entire return history prior to the first reporting date. Moreover, not being able to reject the null hypotheses suggests that our findings are not driven by artificially inflated return dynamics, but that they reflect accurately the level of profits generated by CTAs. This validation exercise provides further evidence that CTAs generate significantly positive net excess returns. Furthermore, the low values of the KS-test confirm the representative status of indices based on realized return data.

3.1 Attractive return dynamics

In this section, we analyze additional return characteristics that may further explain the growing popularity of CTAs among investors. We begin by assessing the skewness of returns at the individual fund level. Figure 1 shows the distribution of skewness for each fund's returns, where the red bar denotes funds whose returns have a skewness of zero.

[Insert Figure (1)]

As indicated by Figure 1, approximately 64% of funds have returns with positive skewness. In fact, for most funds the return skewness is 0.5. The maximum fund-level skewness is 6.18, resulting in a stretched right tail of the distribution. The mean and median are 0.27 and 0.25, respectively, highlighting the positively skewed distribution of returns at the fund level. The descriptive analysis suggests that investors, who prefer a larger upside risk and or have preferences for skewed returns, may allocate some of their capital to CTAs.

We confirm that CTAs serve as an alternative investment opportunity because they generate positive returns during times when equity markets perform particularly poorly. While this has been generally shown by previous studies (Kazemi and Li 2009; Bhardwaj et al. 2014), in our analysis we contribute to the literature by assessing how CTAs perform in comparison to hedge funds and by pointing out performance differences across trading strategies.[12] Table 6 shows the monthly average excess return for the two CTA indices, the S&P 500 as proxy for equity markets and the Hedge Funds Research Index (HFRI).

[Insert Table (6)]

As shown in panel A, CTAs generate average monthly net excess returns of 1.7% and 1.8% in bear markets when returns from equities are performing particularly poorly. In the worst 5% months of the S&P 500, its average monthly return accounts for −10.1% and hedge funds generate negative returns of −3.5%. The latter can be explained by the investment focus of most hedge funds on long-equity driven strategies. Conversely, during equity bull markets when the S&P 500 shows positive returns of 8.4%, CTA returns are negative. The same countercyclical dynamics appear when we assess the 5% best or worse months of the EW and VW indices in panels B and C, respectively.

In panel D, we depart from the existing literature and examine the tail correlation of CTA and hedge fund returns. Since CTAs are often considered a sub-category of hedge funds, we analyze the extent to which these two active investment classes show similar return dynamics. Interestingly, panel D clearly highlights how the timing of the return generating process of CTAs is fundamentally different during extreme events. The countercyclical correlation that we observed with equity markets does not exist. During the best and worst 5% months of the HFRI, returns of CTAs are essentially identical. While the HFRI index swings between −4.1% and 4.2%, the VW–CTA index generates 1.8% in both periods. This analysis

[12] We use Hedge Fund Research's value-weighted hedge fund index (HFRI) as a proxy for hedge fund returns. The data are obtained via Datastream.

shows that in extreme events, the two asset classes are largely uncorrelated with each other and indicates that the return generating process of CTAs cannot be replicated by either equity markets or hedge funds.

Overall, Table 6 suggests that CTAs' countercyclical return movements are an additional benefit to investors while allocating capital to CTAs. Clearly, these benefits are not only reflected by smoothed returns across bear and bull markets, but also by lower return volatility achieved through risk diversification. As shown in panel B, these benefits cannot be obtained by investing in hedge funds, since their returns differ from CTAs' return structure.

[Insert Table (7)]

In Table 7 we repeat the assessment of assets' co-movements but we distinguish between the performances of individual trading strategies. From panel A, we note that trend-following CTAs are more sensitive to equity market swings than non-trend-following funds. For example, systematic trend followers fluctuate between 3.1% and −2.1% in the worst and best 5% months of the S&P 500 returns, while non-trend followers generate 0.5% and 0.2%, respectively. Similar dynamics can be observed for discretionary funds, for which returns fluctuate between 2.7% and −0.7% for trend followers and only between 0.3% and 0.2% for non-trend-following funds. Further, panel B reflects the disconnect between hedge fund and CTA returns. The thoroughly positive returns of all four trading strategies in HFRI's good and bad times point toward the fundamentally different investment approach between the two active investment classes. In line with our earlier findings, this analysis suggests that not only average returns but also higher moments and the timing of return generation are crucial determinants for investors' decisions to allocate capital to CTAs.

4 Managerial Skill in the CTA Industry

Our analysis of CTA performance has so far focused on the return generating process of net of fee excess returns. However, to make further statements about the skills of managers, we follow the literature and assess the gross returns of CTAs. Since most funds report net of fee returns to BarclayHedge, we follow the approach of French (2008) to obtain gross returns for each CTA in our database.

For most funds, the reported fees consist of an annual management fee and a performance fee, which is charged only when the fund generates returns over a certain threshold. The management fee ranges from 0% to 20% with a mean of 1.8% and a standard deviation of 1%. The performance fee ranges from 0% to 50% and has an average of 20% and a standard deviation of 5%. Unfortunately, BarclayHedge does not provide information about a fund's high-water mark or hurdle rate. Therefore, we take the most conservative approach and assume all funds have a high-water mark and for all CTAs we choose the 3-Month Treasury Bill as a hurdle rate. Allowing for both features ensures that we do not overestimate gross returns artificially.[13]

As shown in Table 8, gross excess returns, defined as returns before fees but more than the risk-free rate, are approximately three times larger than net excess returns for the EW index, and roughly twice as large for the VW index. The impact of fees on the difference between net and gross excess returns is comparable to Bhardwaj et al. (2014) who construct gross returns using the same approach. In contrast to their paper, however, we find that gross and net excess returns are significantly different greater than zero, as indicated by the high t-statistics.

[Insert Table (8)]

Next, equipped with EW and VW gross return indices, we assess whether funds can produce abnormal returns in excess of different alternative trading strategies. We use Fung and Hsieh's (2001) portfolio straddle factors as a first benchmark strategy. The authors argue that trend-following strategies can be replicated by using option portfolio straddles and, therefore, are expected to explain a large proportion of the variation in gross CTA returns.[14] Second, we use time series momentum factors (TSMOM) by Moskowitz et al. (2012) as simple normative benchmarks.[15] Since CTAs generate returns by exploiting large price trends, momentum trading is an alternative benchmark that replicates comparable return structure.[16] Like the CTA gross indices, benchmark strategies do not include transaction costs, which makes using gross returns more accurate than using net returns. As shown in

[13] We use different specifications and find that the impact of high water mark on CTA gross returns is small.
[14] The authors construct portfolio straddle factors for five different asset classes: bonds (PTFSBD), foreign exchange (PTFSFX), commodities (PTFSCOM), interest rates (PTFSIR) and stock markets (PTFSSTK).
[15] Time series momentum strategies are constructed for commodities (TSMOMCOM), equities (TSMOMEQ), bonds (TSMOMBD) and foreign exchange (TSMOMFX).
[16] Bhardwaj et al. (2014) employ momentum, basis, and value based benchmark portfolios, but they find that CTA gross returns are significantly related only to momentum based long-short portfolio returns.

panel B of Table 8, CTA gross returns outperform all the nine individual strategies, the S&P 500 and Barclay's Aggregate Bond Index (AGG) in terms of Sharpe Ratio.

While CTA returns appear to have better Sharpe Ratio we also test if managers can generate abnormal returns over and above these simple trading strategies. We postulate that a significant gross alpha would indicate that CTAs generate returns that beat passive trading strategies through their security selection skills and/or marketing timing ability. The results for the EW and VW indices are shown for both models in Table 9. In addition to the portfolio-straddle (PTFS) and time series momentum factors (TSMOM), we include returns from the S&P 500 and the AGG index as passive benchmarks (Bhardwaj et al. 2014).

Table 9 shows regression outcomes for different model specifications. As displayed, independent of the right-hand side variables, the intercept term is statistically significant at the 1% level. Furthermore, the intercept is also economically significant, highlighting the existence of managerial skills among CTAs. For example, as shown in column (4), when the VW index is the dependent variable and time series momentum factors are used as benchmark strategies, CTAs can generate 0.44% abnormal returns per month (5.3% annualized). Also, as shown in column (6), even adding PTFS and TSMOM factors in the same model (column (5)), leaves a significant abnormal gross excess return of 0.53% per month (6.4% annualized). Similar findings are seen in Table 11 with abnormal returns ranging from 0.37% (4.4% annualized) for systematic trend followers to 1.26% (15.12% annualized) for discretionary trend followers.

Furthermore, our regression analysis shows that the PTFS and TSMOM factors explain a large proportion of the variance in CTAs' returns. For example, if solely PTFS factors are used as regressors, the adjusted $\bar{\bar{R}}^2$ accounts for at least 0.21 and for the TSMOM factors, adjusted $\bar{\bar{R}}^2$ increases to even 0.30 and 0.34 for EW and VW, respectively. Moreover, the combination of the two sets of factors results in an adjusted $\bar{\bar{R}}^2$ of up to 0.48, explaining nearly half of the variance of CTA returns. This significant increase, when combining the two sets of factors, highlights that PTFS and TSMOM factors capture different dynamics of CTAs' return generating process. Table 11 shows how the explanatory power of these factors varies between CTA trading strategies. Generally, TSMOM factors explain a larger degree of return variance than PTFS factors, pointing toward the similarities between time series momentum and CTAs' trend-following strategies. For systematic and discretionary trend followers the

$\bar{\bar{R}}^2$ is 0.38 and 0.24 when solely the TSMOM factors are employed as regressors, while the $\bar{\bar{R}}^2$ remains comparably low for non-trend followers (0.14 and 0.06). Combining both sets of factors in one regression again leads to high explanatory power of up to 0.47, confirming our use of these factors as appropriate benchmark strategies.

4.1 Crisis alpha

The diversity in trading strategies and managerial skill becomes even more apparent when looking at CTA returns in times of equity market turmoil. While the positive gross excess intercept term can be interpreted as an indicator of a manager's skill in general, we want to investigate further whether CTAs can make use of their skill during downturns in equity markets. CTAs generate positive excess returns of up to 3% during the worst 5% months of the S&P 500 (Table 7). Here we analyze whether these returns are subject to a trading strategy that cannot be replicated by the PTFS or TSMOM factors. We test for the existence of crisis alpha, by extending the previous regression by an additional intercept term and by estimating the following model:

$$R_t^G = \alpha_1 + \alpha_2 \mathbb{1} + \pi_t^{j,B} + \epsilon_t \tag{1}$$

where

$$\pi_t^{1,B} = \beta_1 + \beta_2 T\,SMOMCOM_t + \beta_3 TSMOMEQ_t + \beta_4 TSMOMBD_t + \beta_5 TSMOMFX_t$$

$$\pi_t^{2,B} = \beta_1 + \beta_2\, PTFSBD_t + \beta_3 PTFSFX_t + \beta_4 PTFSCOM_t + \beta_5 PTFSIR_t + \beta_5 PTFSSTK_t$$

where R_t^G refers to the gross excess return of an EW or VW index, α_1 is an intercept term and $\pi_t^{j,B}$ is the risk premium of a benchmark return strategy. Again, we use Fung and Hsieh's (2001) (FH) portfolio straddle factors (j = 1) or Moskowitz et al.'s (2012) time series momentum factors as a benchmark (j = 2). To measure the skill of CTAs during crisis periods, we allow for α_2, where $\mathbb{1}$ refers to a dummy variable term, set equal to 1 during the 5% worse performing months of the S&P 500. Accordingly, the skill of a CTA manager during market downswings is captured by the joint impact of the two intercept terms (α_{Crisis}= α_1+α_2). The intercept α_1 captures the average skill of managers during the remaining periods. The results are shown in Table 11. For brevity, we focus on the two intercept terms and their joint impact.

[Insert Table (11)

As seen in panel A, independent of the explanatory variables, the intercept term α_1 is positive and statistically significant. For the dummy variable intercept term (α_2) only EW indices and the VW index with FH factors as regressors show significant coefficients at the 10% level or higher. Concerning the joint impact (α_{Crisis}), we find that both intercept terms are significant at least at the 10% level for all six specifications. For the time series momentum strategies, we find that the average monthly return in non-crisis times accounts for 0.49% and 0.37% for the EW and VW index, respectively. In crisis times this value triples to 1.70% abnormal monthly gross excess returns for the EW index and even 1.42 % for the VW index. Both values are not only economically but also statistically significant at the 5% and 10% level. Overall, CTAs appear to be particularly profitable investment opportunities during equity market downturns.

Panel B provides insights about what kind of trading strategy can generate abnormal gross excess returns during crisis periods. All but systematic trend funds generate significant and positive monthly alphas during non-crisis periods (α_1). However, during times of market turmoil, only systematic trend followers can generate statistically significant alphas that account for more than 2% in each month. The crisis alpha (α_{crisis}) is statistically significant at the 5% level. These findings are in line with Kazemi and Li (2009) who argue that systematic funds have a better market timing ability than discretionary traders, implying that systematic traders successfully adjust their portfolios just before equity turmoil and subsequently generate higher returns from directional investments with or against long-lasting price trends. Furthermore, the result can be linked to earlier studies (Kaminsky 2011; Kaminsky and Mende 2011) that refer to crisis alpha as profits that are generated during crisis periods by exploiting large price trends. Our analysis indicates that systematic trend followers are most adept at benefiting from distressed markets.

4.2 Managerial skill and performance persistence

Having established CTA managers' skill through our analysis of gross returns, in this section we assess their performance using an alternate measure: the amount of capital that funds are able to extract from financial markets. To this end, we use an empirical procedure developed by Berk and van Binsbergen (2015) to estimate the value added by a fund as the gross excess return over a specific benchmark strategy, multiplied by its assets under management. Berk and van Binsbergen (2015) argue that this measure is more precise than net or gross abnormal returns obtained from standard regression models, as it takes into account the number of assets managed by a fund. For example, since the size of CTAs ranges between USD

10,000 and USD 5.3 billion,[17] the added value of two funds with the same abnormal return might vary greatly from each other because of the differences in the size of the funds' AUM. This dimension is not captured by the gross alpha. Therefore, calculating the added value of a CTA allows us to assess managerial skill from a new perspective that takes return dynamics and fund size into account.

According to Berk and van Binsbergen (2015), the value added by a fund between period $t-1$ and t is defined as:

$$V_{it} = q_{i,t-1} \left(R_{i,t}^{G} - R_{i,t}^{B}\right) \tag{2}$$

where $q_{i,t-1}$ are fund i's assets under management in period $t-1$ measured in 2005 dollar terms,[18] $R_{i,t}^{G}$ is its gross return and $R_{i,t}^{B}$ is a return from an alternative benchmark investment that we calculate below. Once we construct the valued added for each individual CTA, we calculate the average value $\hat{S}_i$ a fund generates over its entire lifetime as

$$\hat{S}_i = \sum_{t=1}^{T} \frac{V_{it}}{T_i} \tag{3}$$

Similarly, the average value added across all funds is given by

$$\bar{S} = \frac{1}{N} \sum_{i=1}^{N} \hat{S}_i \tag{4}$$

where N refers to the total number of funds, represented in BarclayHedge. Lastly, we follow Berk and van Binsbergen (2015) and calculate a weighted measure of the average value added by taking into account the number of years a fund is actually reporting to BarclayHedge, that is

$$\bar{S}_W = \frac{\sum_{i=1}^{N} T_i \hat{S}_i}{\sum_{i=1}^{N} T_i} \tag{5}$$

[17] Values refer to real AUM of the first reported entry to BarclayHedge.

[18] We transform nominal AUM to real AUM dividing it P_t/P_0, where P_t is the US-CPI index in period t and P_0 US CPI index in year 2005.

Since more skilled managers stay alive for a longer period of time and, therefore, add more value, we would expect the weighted measure $\bar{S}_W$ to be larger than the simple cross-sectional average $\bar{S}$.

To construct the value added (V_{it}) for each fund, we use Moskowitz et al.'s (2012) time series momentum factors as a benchmark trading strategy. More precisely, we estimate

$$R_t^G = \beta_1 + \beta_2 T\,SMOMCOM_t + \beta_3 TSMOMEQ_t + \beta_4 TSMOMBD_t + \beta_5 TSMOMFX_t \quad (6)$$

where β_i is the regression coefficient associated with one of the four time series momentum factors. Then, we reconstruct R_t^B from the regression's fitted values, so that the time series of benchmark returns obtained has the same level of risk implied by the four-TSMOM factor model. We choose these factors as a benchmark strategy for several reasons. First, benchmark factors should be tradeable portfolios that serve as simple passive benchmark strategies. This condition is clearly fulfilled by our benchmark since investors could simply reconstruct the TSMOM factors by investing into short and long portfolios, depending on an asset's prior returns. Second, previous research has emphasized CTAs' extensive use of time series momentum strategies (Baltas and Kosowski 2013; Elaut and Erdös 2016). The high $\bar{R}^2$ in our regression analysis of up 0.48 stresses the high explanatory powers of this trading style. Third, Moskowitz et al. (2012) argue that their time-series momentum factors are implementable strategies that generate the same payoff structure as Fung and Hsieh's (2001) options straddle factors. Since time series momentum factors are easier to implement, we choose a passive strategy over the dynamic option straddle factors.

To alleviate concerns that results are driven by the growing size of the industry, we follow Berk and van Binsbergen (2015) and plot the log number of funds reporting to BarclayHedge as well as the log fund size of different percentiles over the entire sample period. Figure 2 illustrates that the median fund size (base year 2005) remains comparably stable over the entire period, while the number of reporting CTAs is growing, particularly since 2001. The growth of the industry's total AUM can therefore be attributed to an increasing number of CTAs, rather than an increase in the size of CTAs. These industry dynamics are comparable to those reported by Berk and van Binsbergen (2015).

[Insert Figure (2)]

As shown in Table 12, the average added value by a CTA is USD 0.49 million (base year 2005) and the reporting life time-weighted average is USD 1.27 million. Both numbers are significantly greater than zero at the 5% level using a one-sided t-test. Moreover, these values are substantially higher than the USD 0.27 and USD 0.14 million added value of mutual funds in the study by Berk and van Binsbergen (2015). In line with the authors, we argue that the differences in the cross-sectional means highlight that more talented managers have a longer lifespan. However, it is worth noting that, as demonstrated in the lower half of Table 12, there is a substantial cross-sectional variation in managerial skill. Value added by CTAs ranges from a loss of nearly USD 4 million in the bottom 1% to profits of USD 6.82 million in the very top. Furthermore, roughly two-fifths of the 926 funds do not add significant value. It is worth noting that Berk and van Binsbergen (2015) find that up to 59% of mutual funds are not able to outperform passive benchmark strategies. Our results indicate that CTA managers are more skilled than mutual fund managers—a reassuring figure given that CTA managers' compensation is orders of magnitude greater than mutual fund managers'.[19]

[Insert Table (12)]

Next, we test for persistence in managerial skill. To this end, we employ a skills ratio as defined by Berk and van Binsbergen (2015):

$$SKR_i^\tau = \frac{\hat{S}_i}{\sigma_i^\tau} \tag{7}$$

Where $\hat{S}_i = \frac{\sum_{t=1}^{\tau} V_{it}}{\tau}$ and $\sigma_i^\tau = \sqrt{\left(\sum_{t=1}^{\tau}\left(V_{it} - \hat{S}_i^\tau\right)^2\right)/\tau}$. In line with the authors, we take the following approach. First, we split the sample into sorting and forecasting periods. In the sorting sample, funds are sorted in quintiles according to their level of skill. The minimum number of reported months for each fund i is 24 and we re-estimate the skills ratio for each point in time τ based on an extending window approach, including all the fund information from period 1 until τ. Second, for each τ we then estimate the value added for each fund in the periods $[V_{i,\tau+m} \dots V_{i,\tau+m+h}]$, where h refers to the forecasting horizon and m to the minimum number of reported months after period τ. For each point in time we estimate the added value with information from the forecasting period only, not the sorting period. Since we estimate the benchmark return for each point in time with four time series momentum

[19] As highlighted by Stulz (2007), the compensation schemes of mutual funds and hedge funds differ fundamentally from each other. Mutual fund managers' compensation is more strictly regulated, usually depends solely on the fund's assets under management and investors pay no additional performance fee. In contrast, the performance fee is a substantial component of a CTA manager's compensation and our results suggest that more skilful managers use a higher fee structure to signal their skill.

factors, we chose m = 40.[20] Concerning the forecasting horizon, we use different lengths for h, ranging between h = 3 and h = 36 months. The upper bound is chosen to account for the fact that the average lifetime of funds is approximately 70 months so that funds in the sorting period may not report any longer in the forecasting period. At the end, we obtain a time series of monthly average value added for each of the five portfolios. To evaluate persistence, we examine how often the valued added by the bottom 20% (Portfolio 1) is outperformed by the top 20% (Portfolio 5) and in how many months the latter outperforms the former. Results are shown in Table 13 and Figure 3.

[Insert Table (13) and Figure (3)]

Table 13 shows the value added by the funds in the top 20% and in the bottom 20% of our sample. As displayed, the values added by the two groups of CTAs differ significantly from each other. For example, the predicted added value of the bottom 20% is only USD 0.1 million, while the top 20% of CTAs' added value accounts for USD 3 million. As indicated by the large t-statistics, the added value between the two groups differs significantly across all forecasting horizons. This indicates that managers with more managerial skill persistently perform better than their less skilled peers. In addition, we find that in almost every month the top 20% outperforms the bottom 20%. The most skilled CTAs outperform the least skilled managers 96% of the time for the shortest forecasting horizon (h = 3). Furthermore, in Figure 3 the solid line shows the average added value (y-axis) for each portfolio (x-axis) for all six forecasting horizons. Independent of the forecasting horizon, h, we find that more skilled funds (Portfolio 5) extract more value from capital markets than less skilled managers (Portfolio 1). We interpret this finding as evidence that better performance is not due to managers' luck but rather to their managerial skills.

Finally, we assess if investors can infer *a priori* whether some managers are more skilled than others. Since managerial skill is a scarce good and the cross-sectional variation is large, rational investors would prefer to allocate their capital to CTAs that provide the best performance. In line with Berk and van Binsbergen (2015), we assess whether investors can learn about managers' future performance based on their current compensation. If compensation predicts future performance, managers could use it as a credible and

[20] The minimum number of reporting months is chosen to be m=40 to allow for a sufficient number of degrees of freedom in each of our rolling regressions. Results are qualitatively similar to other specifications, such as e.g. m=30 or m=50.

observable signal of their skill and attract more capital from investors. The existence of such a signalling mechanism would indicate an efficient and competitive CTA market (Akerlof 1970). To control for the *ex-ante* predictability of future performance, we sort funds into quintile portfolios based on their compensation, which is defined as accrued fees multiplied by AUM. Using only the overall fee is problematic because the CTA fee structure is not very diverse. In our sample, 53% of funds report the typical 2/20 fee structure of management and performance fees. On the other hand, the amount of capital managed by a CTA varies greatly in the cross-section and is crucial for managerial compensation.

[Insert Table (14) and Figure (4)]

Table 14 provides support for our hypothesis that investors compete to allocate money to successful CTA managers. As indicated by the high t-statistics, funds that demand the highest compensation from investors outperform funds with the lowest compensation scheme. The value added by the costliest top 20% exceeds the performance of the bottom 20% in at least 72% of all months. Figure 4supports our claim. In all cases, CTAs in Portfolio 5 add more value than funds in the lower ranked portfolios for up to nine months. For h = 12 and h = 24, Portfolio 4 slightly outperforms the most expensive funds leading to a slight kink in the solid line. In addition, 95% confidence bands increase with a larger forecasting horizon (indicated by the scale of the y-axis), adding greater uncertainty about a fund's future performance. However, in the short run, high compensation *ex ante* predicts future performance. Therefore, our results indicate that managers use their compensation to signal their skills to investors, who use this information while determining their fund allocations. Overall, we conclude that the value added provides additional evidence of managerial skill in the CTA industry and that CTA managerial pay increases commensurably with performance.

5 Conclusion

The CTA industry has grown rapidly over the past 20 years. However, extant empirical evidence indicates that CTA managers have generated statistically insignificant net excess returns and have passive benchmarks. If such is the case, why do professional, sophisticated investors continue to invest in these underperforming funds? Is this a consequence of investor irrationality? Or does the market thrive because it is too opaque to be aware of its own failing? Clearly, the puzzling growth of CTAs raises fundamental questions about our understanding of the operational efficiency of the CTA industry and the alternative investments market at large. We employ a large and representative dataset of CTAs to provide a new perspective on the performance of CTAs, the skill of their managers, and the relation between CTA managers' pay and performance.

Our dataset is derived from the Barclay's Hedge Fund Database and data provided by Risk and Portfolio Management AB (RPM). The dataset has several advantages over those used in extant studies. First, it provides the most compressive of coverage of the CTA industry—70% of the total assets under CTA management, on average, between 1985 and 2015. Second, it is largely free of any graveyard bias as it has been downloaded by RPM on a daily basis for a large proportion of our sample period. Third, it enables us to classify CTAs into to four strategy groups: systematic and discretionary trend followers and their non-trend-following counterpoints. Additionally, we use a smaller proprietary dataset of realized CTA returns to validate our results obtained from the larger sample.

In contrast to earlier studies, we find that equally (EW) and value-weighted (VW) portfolios of CTAs generate on average 4.1% and 4.5% excess returns for investors on an annual basis. Notably, these returns are net of all fees. Despite high management and performance fees, CTAs are a profitable investment opportunity for investors. Our results also show that CTA returns are positively skewed, countercyclical to equity markets and largely uncorrelated with hedge fund returns. We also find that CTA managers outperform normative benchmarks, such as time series momentum strategies, and produce up to 8.4% abnormal gross excess return on an annual basis. Testing formally in a regression framework for the existence of "crisis alpha," we find that systematic trend-following funds produce on average more than 27% annualized abnormal returns by exploiting large price trends during crisis times. Next, measuring managerial skill by the amount of capital that CTAs extract from financial markets, we show that CTAs, on average, add value of USD 1.27 million per month, with roughly 60% of the CTAs in our sample generating more value than passive benchmark trading strategies. Finally, we find that the cross-sectional differences in managers' skills are persistent up to three years, ruling out the possibility that our evidence relating to managerial skill is driven by luck. Moreover, we show that managerial fees predict future performance, indicating that investors are able to identify and reward skilled managers.

Our results show the CTA market to be well-functioning, one in which rational investors compete to invest with skilled managers, whose compensation is set in equilibrium so that the expected net alpha is zero (Berk and Green 2004).

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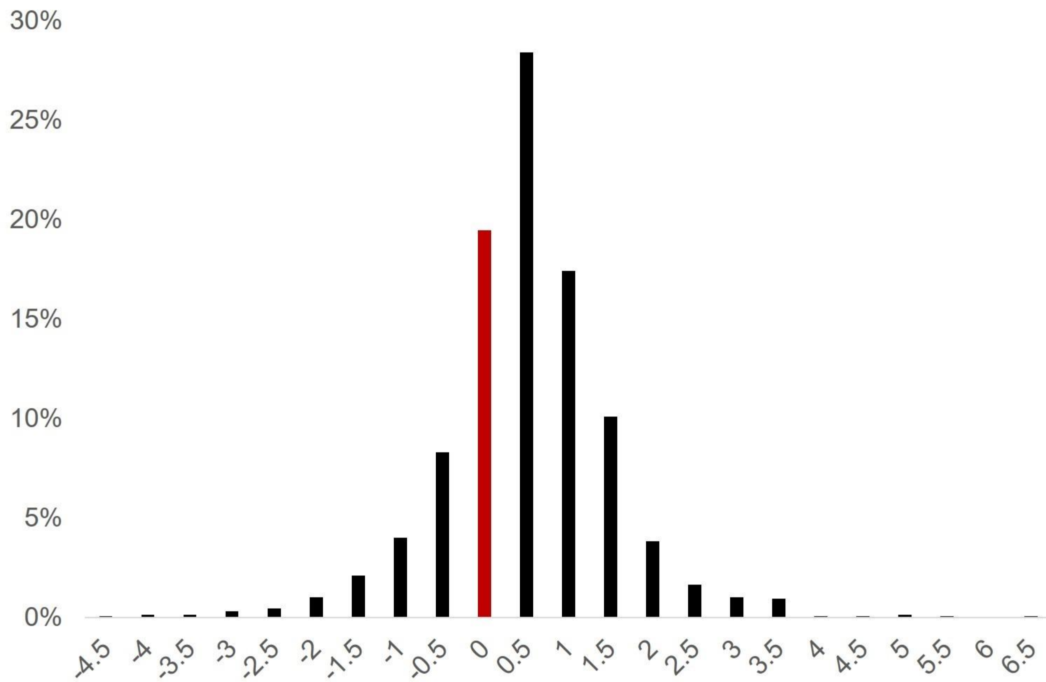
Figure 1: Fund-level Skewness



Skewness of returns at the fund-return level. X-axis denotes the level of skewness and y-axis refers to the proportional number of funds. Red bar marks funds with return skewness of zero.

Figure 2: Development: Real Assets Under Management

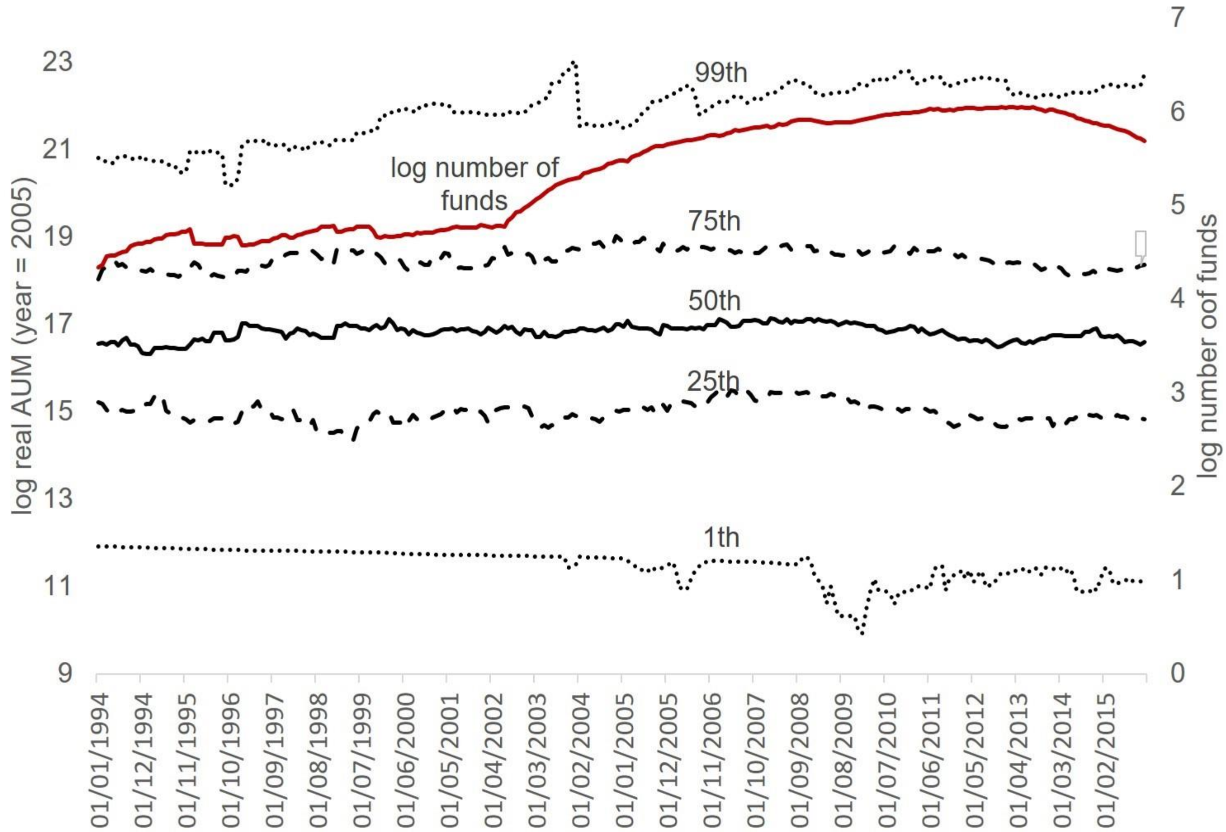


Figure 2 shows the development of the CTA industry. Log real AUM are displayed on the left axis (base year = 2005) and log number of funds on the right axis.

Figure 3: Predictability of Skills Ratio

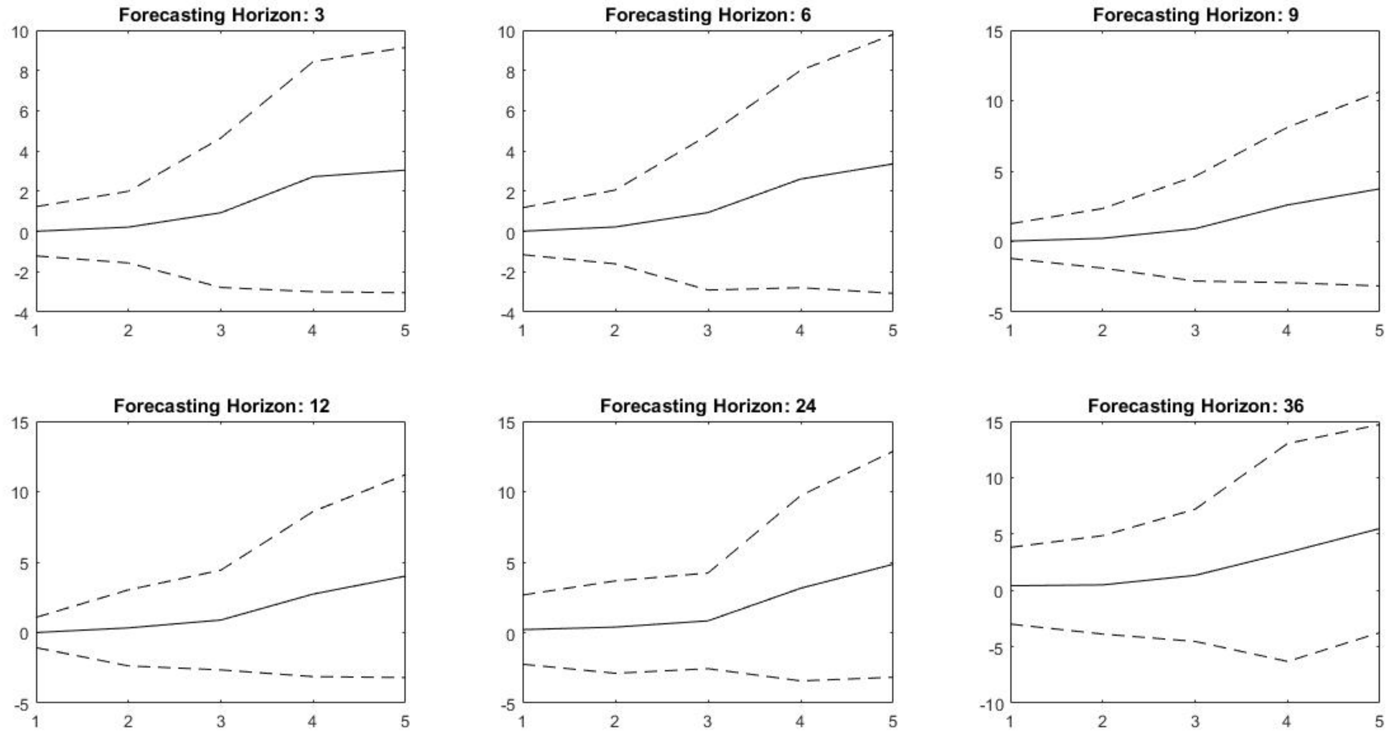


Figure 3 shows the value added of a CTA over different horizons. The y-axis measures added value in USD million (base year = 2005) and the x-axis refers to the five portfolios. Portfolio 1 refers to the CTA with the lowest skill ratio and Portfolio 5 to the CTA with the highest skill ratio. The solid line refers to the average added value, while the dashed lines refers to the 95% confidence intervals.

Figure 4: Predictability of Compensation Scheme

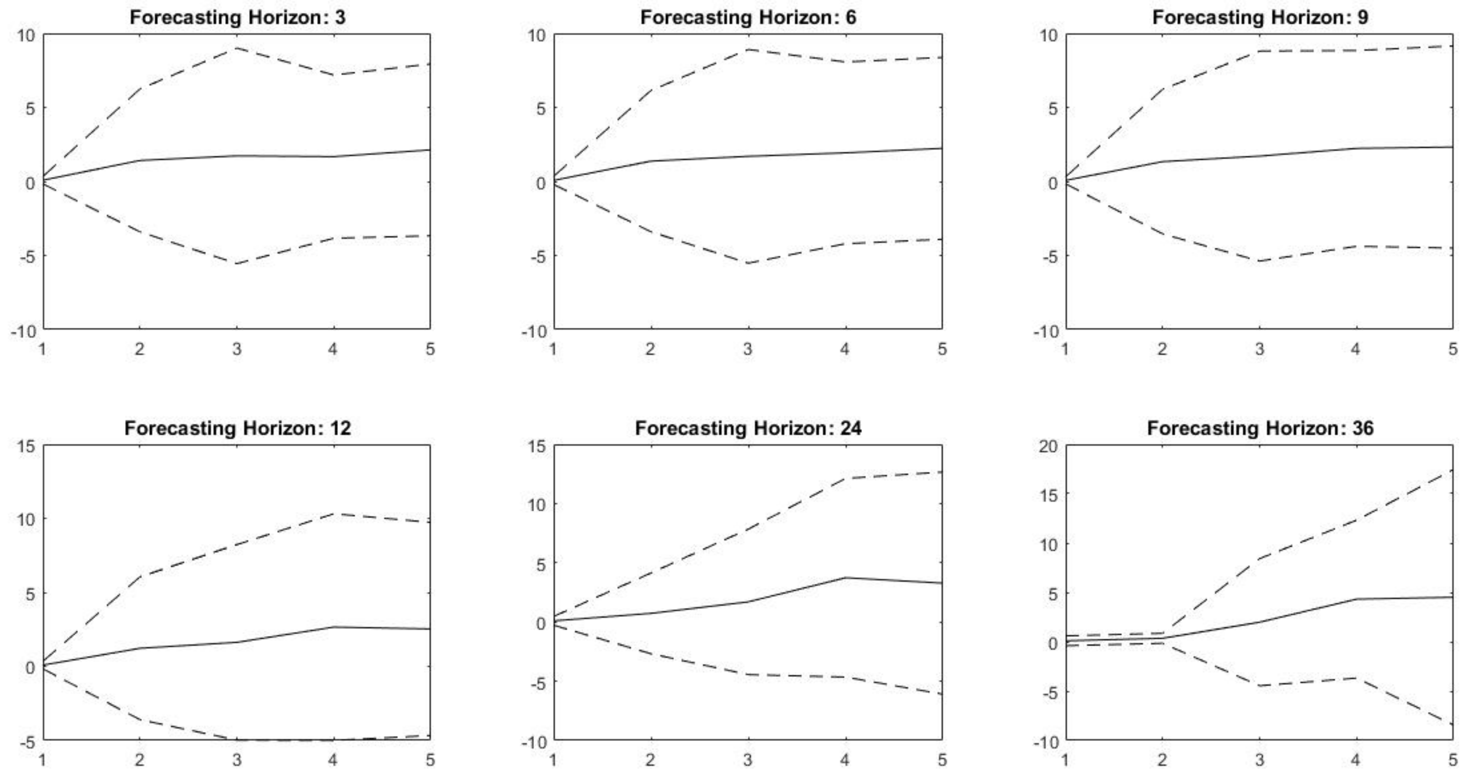


Figure 4 shows the value added of a CTA over different horizons. The y-axis measures added value in USD million (base year = 2005) and the x-axis refers to the five portfolios. Portfolio 1 refers to the CTA with the lowest compensation and Portfolio 5 to the CTA with the highest compensation. The solid line refers to the average added value, while the dashed lines refer to the 95% confidence intervals.

Table 1: Data Cleaning Steps

Table 1 summarizes data cleaning steps of Barclay's Hedge Fund Database as of 15/03/2016. The number of funds for an equally weighted (EW) portfolio (no minimum reporting time) is 2,620. The value-weighted (VW) portfolio consists of 1,924 individual CTA flagship programs. AUM refers to assets under management

Data screen	Number of funds removed	Funds remaining in the database
Starting Sample		3017
Stopped reporting before 1994	164	2853
Not reporting in USD	174	2679
Missing date of entry to database	9	2670
Not reporting "net all fees"	36	2634
Unrealistic return	1	2633
Funds created in 2016	13	2620
Funds with missing AUM	696	1924

Table 2: Trading Classification

Table 2 shows the different levels of strategy classifications provided by RPM. The different levels are indicated by columns (1) and (2). For example, funds can be classified as either systematic or discretionary. Further, these classes can be differentiated between trend and non-trend follower. Funds that cannot be classified are grouped into "Others."

Strategy Classification	
(1)	(2)
Systematic	Trend Follower
	Non-trend Follower
Discretionary	Trend Follower
	Non-trend Follower
Others	

Table 3: Summary Statistics

Table 3 provides summary statistics of funds with 24 or more reported returns. Information about individual trading strategies refers to the respective EW index. Numbers in brackets refer to the proportion of funds in the overall sample. Average size is denoted in millions of USD. Average age is measured in months. Funds are considered as "Alive" if they still report to BarclayHedge at the end of the sample period (December 2015).

			Systematic		Discretionary		
	EW Index	VW Index	Trend	Non-Trend	Trend	Non-Trend	Others
Number of Funds	1274	926	487 (38%)	355 (28%)	29 (2%)	288 (23%)	115 (9%)
Average Size	USD 234	USD 259	USD 280	USD 380	USD 45	USD 68	USD 55
Average Age	70.8	69.2	81.2	64.0	62.7	65.4	63.6
Alive Funds Dec 2015	323	296	136	96	4	59	28

Table 4: Performance of CTAs

Panel A shows the performance analysis for EW and VW portfolios of funds with at least 24 reported return observations. Panels B and C display the results for the individual trading strategy, when funds are either weighted on an equal or value basis. T-Test refers to the t-statistics of the null hypothesis that the average return equals zero. ***, **, * denote level of significance at the 1%, 5% ,and 10% level, respectively.

	Jan 1994–Dec 2015 Ann. Avg. Return	Ann. Volatility	T-Test
Panel A: All CTAs			
EW index	4.1%	7.2%	2.65***
VW index	4.5%	7.6%	2.81***
Panel B: By Trading Strategy (EW)			
Systematic Trend	5.1%	11.7%	2.03**
Systematic Non-trend	3.1%	4.3%	3.37***
Discretionary Trend	4.7%	15.0%	1.46
Discretionary Non-trend	2.8%	4.3%	3.1***
Panel C: By Trading Strategy (VW)			
Systematic Trend	6.0%	11.7%	2.41**
Systematic Non-trend	3.5%	5.8%	2.84***
Discretionary Trend	7.4%	15.7%	2.21***
Discretionary Non-trend	1.8%	6.5%	1.28

Table 5: Benchmark Comparison

Table 5 compares equally (EW) and value (VW) weighted portfolios of CTA returns reported to BarclayHedge with EW and VW portfolios based on realized return data, provided by RPM. The t-statistic refers to the test if the difference between the indices is, on average, different from zero. The column "KS-Test" refers to the Kolmogorov-Smirnov statistic, testing if both samples of funds are drawn from the same distribution. Note: EW index only covers the period April 2002–December 2015.

	Avg. Ann. Return				
	BarclayHedge	Realized Returns	Correlation	T-Test	KS-Test
EW Index	4.1%	2.7%	0.80	0.50	0.11
VW Index	4.5%	3.8%	0.82	0.30	0.09

Table 6: Bull and Bear Market

Table 6 shows average monthly excess returns for the best and worst 5% months (13 months each) of the equally weighted (EW) and value-weighted (VW) CTA portfolio, S&P 500 and HFRI.

Panel A: Best and worst 5% months of S&P 500				
	Worst 5% S&P 500 months			
	CTA EW	CTA VW	S&P 500	HFRI
Monthly Average ER	1.7%	1.8%	−10.1%	−3.5%
	Best 5% S&P 500 months			
	CTA EW	CTA VW	S&P500	HFRI
Monthly Average ER	-0.8%	−0.7%	8.4%	2.1%
Panel B: Best and worst 5% months of EW CTA Index				
	Worst 5% EW CTA months			
	CTA EW	CTA VW	S&P 500	HFRI
Monthly Average ER	−3.6%	−3.5%	2.1%	0.4%
	Best 5% EW CTA months			
	CTA EW	CTA VW	S&P 500	HFRI
Monthly Average ER	5.4%	5.0%	−2.1%	0.0%
Panel C: Best and worst 5% months of VW CTA Index				
	Worst 5% VW CTA months			
	CTA EW	CTA VW	S&P 500	HFRI
Monthly Average ER	−2.9%	−3.7%	1.2%	0.2%
	Best 5% VW CTA months			
	CTA EW	CTA VW	S&P 500	HFRI
Monthly Average ER	5.2%	5.2%	−2.4%	−0.1%
Panel D: Best and worst 5% months of HFRI				
	Worst 5% HFRI months			
	CTA EW	CTA VW	S&P 500	HFRI
Monthly Average ER	1.8%	1.8%	−8.5%	−4.1%
	Best 5% HFRI months			
	CTA EW	CTA VW	S&P 500	HFRI
Monthly Average ER	1.9%	1.8%	4.7%	4.2%

Table 7: Bull and Bear Markets: By Trading Strategy

Table 7 shows average monthly excess returns for each trading strategy in the best and worst 5% months (13 months each) of the S&P 500 and HFRI.

Panel A: Best and worst 5% of S&P 500 months

	Worst 5% S&P 500 months					
	Systematic Trend	Systematic Non-trend	Discretionary Trend	Discretionary Non-trend	S&P500	HFRI
Monthly Average ER	3.1%	0.5%	2.7%	0.3%	−10.1%	−3.5%

	Best 5% of S&P 500 months					
	Systematic Trend	Systematic Non-trend	Discretionary Trend	Discretionary Non-trend	S&P500	HFRI
Monthly Average ER	−2.0%	0.2%	−0.7%	0.2%	8.4%	2.1%

Panel B: Best and worst 5% of HFRI

	Worst 5% S&P 500 months					
	Systematic Trend	Systematic Non-trend	Discretionary Trend	Discretionary Non-trend	S&P500	HFRI
Monthly Average ER	3.3%	0.7%	3.5%	0.2%	−8.5%	−4.1%

	Best 5% of HFRI months					
	Systematic Trend	Systematic Non-trend	Discretionary Trend	Discretionary Non-trend	S&P 500	HFRI
Monthly Average ER	2.4%	1.1%	3.4%	0.9%	4.7%	4.2%

Table 8: Comparison of CTA and Benchmark Returns

Panel A provides summary statistics for EW and VW CTA portfolios before and after fees. The t-statistic refers to the null hypothesis that funds generate on zero average returns ($H_0 : \mu_{CTA} = 0$). Panel B shows summary statistics for Moskowitz et al.'s (2012) time series momentum factors, available at https://www.aqr.com/ library/data-sets/time series-momentum-factors-monthly and Fung and Hsieh's (2001) portfolio straddle factors (PTFS), available at https://faculty.fuqua.duke. edu/~dah7/HFRFData.htm. The abbreviations BD, FX, COM, IR, STK, EQ refer to bonds, foreign exchange, commodities, interest rates, stocks, and equities, respectively. SP500 refers to the VW index including dividends and AGG denotes Barclay's Aggregate Bond Index.

Panel A: Before and After Fee CTA Returns

	Avg. Ann. Return	Ann. Volatility	Ann. Sharpe Ratio	T-Statistic
		EW Index		
Before fees	11.5%	8.2%	1.4	6.54
After fees	4.1%	7.2%	0.56	2.65
		VW Index		
Before fees	10.6%	8.5%	1.24	5.83
After fees	4.5%	7.6%	0.6	2.81

Panel B: Summary Statistics of Benchmark Strategies

	Avg. Ann. Average	Ann. Volatility	Ann. Sharpe Ratio
TSMOMCOM	12.1%	15.3%	0.79
TSMOMEQ	20.1%	26.9%	0.75
TSMOMBD	16.6%	27.5%	0.60
TSMOMFX	12.3%	18.0%	0.68
PTFSBD	−19.2%	53.0%	−0.36
PTFSFX	−8.9%	67.4%	−0.13
PTFSCOM	−4.5%	49.5%	−0.09
PTFSIR	−11.9%	89.1%	−0.13
PTFSSTK	−58.4%	48.8%	−1.20
SP500	9.97%	14.8%	0.67
AGG	−0.11%	3.7%	−0.03

Table 9: Manager Skill and Gross Alpha

Table 9 shows the regression results for two models, with Fung and Hsieh's (2001) portfolio straddle factors (PTFS) and/or Moskowitz et al.'s (2012) time series momentum (TSMOM) factors used as explanatory variables. The abbreviations BD, FX, COM, IR, STK, EQ refer to bonds, foreign exchange, commodities, interest rates, stocks, and equities, respectively. Both models include the SP500 and Barclay's Aggregate Bond Index (AGG) as passive investment benchmark. The dependent variable is the VW CTA portfolio. The sample period is January 1994–December 2015. Coefficients are displayed in percentage terms. Numbers in parentheses refer to OLS t-statistics, based on Newey-West standard errors. ***, **, * indicate 1%, 5% and 10% level of significance, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	EW	VW	EW	VW	EW	VW
alpha	1.08***	1.00***	0.57***	0.44***	0.70***	0.53***
	(8.32)	(6.89)	(4.31)	(3.31)	(5.82)	(4.08)
TSMOMCOM			0.13***	0.12***	0.14***	0.12***
			(4.44)	(3.96)	(5.45)	(4.49)
TSMOMEQ			0.04**	0.06***	0.03**	0.05***
			(2.40)	(3.47)	(2.08)	(3.39)
TSMOMBD			0.09***	0.11***	0.07***	0.09***
			(5.38)	(6.23)	(4.54)	(5.28)
TSMOMFX			0.08***	0.09***	0.04	0.06**
			(3.04)	(3.36)	(1.58)	(2.33)
PTFSBD	0.02***	0.03***			0.02***	0.02***
	(2.82)	(2.65)			(2.62)	(2.61)
PTFSFX	0.04***	0.03***			0.04***	0.02***
	(6.02)	(4.19)			5.75	(3.43)
PTFSCOM	0.04***	0.03***			0.03***	0.02**
	(4.29)	(3.27)			(3.65)	(2.45)
PTFSIR	0.00	0.00			0.00	0.00
	(−0.89)	(−0.52)			(0.01)	(0.47)
PTFSSTK	0.01	0.01			0.01	0.00
	(1.45)	(1.13)			(1.04)	(0.47)
SP500	0.03	0.03	-0.02	-0.01	0.05*	0.05
	(0.90)	(0.87)	(-0.83)	(-0.33)	(1.68)	(1.54)
AGG	0.19	0.28**	0.15	0.18	0.08	0.13
	(1.62)	(2.23)	(1.25)	(1.42)	(0.73)	(1.12)
$\bar{R}^2$	0.31	0.21	0.30	0.34	0.48	0.43
N	264	264	264	264	264	264

Table 10: Manager Skill and Gross Alpha: By Trading Strategy

Table 10 shows the regression results for two models, with either Fung and Hsieh's (2001) portfolio straddle factors (PTFS) or Moskowitz et al.'s (2012) time series momentum (TSMOM) factors used as explanatory variables. The abbreviations BD, FX, COM, IR, STK, EQ refer to bonds, foreign exchange, commodities, interest rates, stocks, and equities, respectively. Both models include the SP500 and Barclay's Aggregate Bond Index (AGG) as passive investment benchmark. The dependent variable is the VW CTA portfolio. The sample period is January 1994–December 2015. Coefficients are displayed in percentage terms. Numbers in parentheses refer to OLS t-statistics, based on Newey-West standard errors. ***, **, * indicate 1%, 5% and 10% level of significance, respectively.

		Systematic Trend			Systematic Non-Trend			Discretionary Trend			Discretionary Non-Trend	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
alpha	1.31***	0.37*	0.56***	0.69***	0.48***	0.46***	1.57***	0.94***	1.16***	0.61***	0.50***	0.53***
	(5.91)	(1.88)	(2.87)	(5.86)	(4.11)	(3.85)	(5.21)	(2.92)	(3.72)	(4.76)	(3.71)	(3.91)
TSMOMCOM		0.20***	0.21***		0.05**	0.06**		0.25***	0.27***		0.03	0.04
		(4.47)	(4.99)		(2.06)	(2.34)		(3.49)	(4.05)		(1.15)	(1.34)
TSMOMEQ		0.10***	0.09***		0.02	0.01		0.01	-0.00		0.03*	0.01
		(3.83)	(3.83)		(1.06)	(0.93)		(−0.34)	(−0.10)		(1.64)	(0.68)
TSMOMBD		0.17***	0.14***		0.07***	0.06***		0.11**	0.06		0.01	0.01
		(6.49)	(5.45)		(4.55)	(4.07)		(2.51)	(1.57)		(0.43)	(0.49)
TSMOMFX		0.13***	0.09**		0.04*	0,02		0.10	0.02		0.02	−0.00
		(3.44)	(2.54)		(1.78)	(0.97)		(1.58)	(0.30)		(0.78)	(−0.09)
PTFSBD	0.04***		0.04***	0.01*		0.01	0.04**		0.04**	−0.01*		−0.01
	(2.79)		(2.90)	(1.75)		(1.10)	(2.37)		(2.04)	(−1.76)		(−1.60)
PTFSFX	0.04***		0.03**	0.03***		0.02***	0.07***		0.07***	0.03***		0.03***
	(3.35)		(2.44)	(4.21)		(3.74)	(4.36)		(4.21)	(3.89)		(3.64)
PTFSCOM	0.06***		0.04***	0.01		0.00	0.08***		0.07***	0.02*		0.02*
	(3.71)		(2.94)	(0.65)		(0.01)	(3.78)		(3.31)	(1.91)		(1.64)
PTFSIR	0.00		0.00	0.00		0.00	0.00		0.01	0.00		0.00
	(−0.54)		(0.51)	(−0.22)		(0.43)	(0.03)		(0.53)	(0.30)		(0.44)
PTFSSTK	0.03*		0.02	−0.01		−0.01	0.01		0.01	0.00		0.00
	(1.81)		(1.26)	(−0.96)		(−1.45)	(0.38)		(0.29)	(0.50)		(0.40)
S&P500	0.02	−0.04	0.05	0.07**	0.06**	0.08***	−0.06	−0.17**	-0.03	0.03	-0.00	0.03
	(0.44)	(−0.90)	(1.06)	(2.45)	(2.36)	(3.09)	(−0.89)	(−2.41)	(-0.44)	(0.95)	(-0.01)	(0.99)
AGG	0.49**	0.32*	0.26	0.11	0.02	−0.01	0.48*	0.57*	0.44	-0.42***	-0.37***	-0.43***
	(2.50)	(1.72)	(1.47)	(1.08)	(0.17)	(−0.10)	(1.80)	(1.90)	(1.59)	(−3.73)	(−2.95)	(−3.51)
$\bar{R}^2$	0.22	0.38	0.47	0.10	0.14	0.19	0.24	0.14	0.29	0.11	0.04	0.10
N	264	264	264	264	264	264	264	264	264	264	264	264

Table 11: Crisis Alpha

Table 11 shows coefficient estimates of equation (1), focusing on the two intercept terms. In panel A, as indicated, either the equally (EW) or value- (VW) weighted index is used as dependent variable and either Fung and Hsieh's (2001) portfolio straddle factors (FH), Moskowitz et al.'s (2012) time series momentum (TSMOM) factors, or both combined are used as explanatory factors. In panel B, VW indices are used as dependent variable. Numbers in parentheses refer to OLS t-statistics, based on Newey-West standard errors. ***, **, * indicate 1%, 5% and 10% level of significance, respectively.

Panel A: Crisis Alpha—All CTAs

	FH-Factors EW Index	FH-Factors VW Index	TSMOM-Factors EW Index	TSMOM-Factors VW Index	All Factors EW Index	All Factors VW Index
α_1	0.90***	0.78***	0.49***	0.37***	0.61***	0.46***
	(6.30)	(4.98)	(3.52)	(2.65)	(4.73)	(3.28)
α_2	2.08***	2.34***	1.21*	1.06	1.24*	0.98
	(3.07)	(3.10)	(1.71)	(1.49)	(1.94)	(1.40)
α_{Crisis}	2.98***	3.12***	1.70**	1.43*	1.85***	1.44*
	(3.96)	(3.74)	(2.23)	(1.86)	(2.65)	(1.89)
$\bar{R}^2$	0.33	0.24	0.30	0.35	0.48	0.43

Panel B: Crisis Alpha—By Trading Strategy

	TSMOM-Factors Systematic Trend	TSMOM-Factors Systematic Non-trend	TSMOM-Factors Discretionary Trend	TSMOM-Factors Discretionary Non-trend
α_1	0.24	0.47***	0.86**	0.45***
	(1.15)	(3.81)	(2.53)	(3.20)
α_2	2.04*	0.13	1.21	0.67
	(1.93)	(0.20)	(0.70)	(0.93)
α_{Crisis}	2.28**	0.59	2.07	1.12
	(1.99)	(0.88)	(1.11)	(1.44)
$\bar{R}^2$	0.39	0.20	0.14	0.04

Table 12: Manager Skill and Added Value

Table 12 shows the value added by CTA managers over Moskowitz et al.'s (2012) time series momentum factors. Values are given in million USD (base year = 2005). The null hypothesis tested is whether the cross-sectional weighted average or the cross-sectional mean is larger than zero (formally: $H_0 > 0$) ***, **, * indicate 1%, 5% and 10% level of significance, respectively.

Cross-sectional weighted average	1.27
Standard error of the weighted mean	0.02
p-value	0.04**
Cross-sectional mean	0.49
Standard error of the mean	6.81
p-value	0.01**
1st percentile	−3.94
5th percentile	−0.31
10th percentile	−0.21
50th percentile	0.006
90th percentile	0.57
95th percentile	1.47
99th percentile	6.82
Percent with less than zero	41%
Number of funds	926

Table 13: Skill Ratio and Performance Persistence

Table 14 shows the average value added by CTAs (in USD million; base year = 2005) sorted in the bottom and top portfolios for different forecasting horizons. The t-statistic refers to the test whether the average value added test in the bottom and top portfolios are the same. The table also shows the number of times the top quintile outperforms the bottom quintile. Returns from Moskowitz et al.'s (2012) time series momentum factors are used as benchmark trading strategy. Portfolios are sorted based on a manager's skill ratio.

Forecasting horizon	Bottom 20% Value Added	Top 20 % Value Added	T-statistic	Top 20% outperforms bottom 20%
3	0.01	3.0	13.2	96%
6	0.02	3.4	13.6	96%
9	0.04	3.7	14.0	97%
12	0.01	4.0	14.3	99%
24	0.21	4.9	14.9	94%
36	0.41	5.5	14.1	84%

Table 14: Compensation Scheme Ratio and Performance Persistence

Table 14 shows the average value added by CTAs (in USD million; base year = 2005) sorted in the bottom and top portfolios for different forecasting horizons. The T-statistic refers to the test whether the average value added test in the bottom and top portfolios are the same. The table also shows the number of times the top quintile outperforms the bottom quintile. Returns from Moskowitz et al.'s (2012) time series momentum factors are used as benchmark trading strategy. Portfolios are sorted based on a manager's compensation scheme.

Forecasting horizon	Bottom 20% Value Added	Top 20 % Value Added	T-statistic	Top 20% outperforms bottom 20%
3	0.08	2.1	9.7	79%
6	0.07	2.2	9.5	83%
9	0.07	2.3	8.8	80%
12	0.09	2.5	9.0	82%
24	0.10	3.3	8.6	81%
36	0.10	4.5	8.2	72%