Risk-taking behavior of Commodity Trading Advisors

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Abstract

The asymmetric nature of performance-based compensation in hedge funds introduces a moral hazard problem in which investors bear the negative consequences of fund managers' risk choices. We analyze whether risk shifting by a hedge fund manager is related to the manager's investment strategy and her survivorship concerns. Using gross fund return from 1994 to 2014, we find that the tendency to increase risk following poor performance is weak (strong) when there are strong (weak) managerial survivorship concerns. At the same time, risk shifting is significantly less prevalent when a manager utilizes algorithms, instead of discretion, in an investment strategy. We introduce a new model for estimating the economic impact of risk-shifting on hedge fund managers and investors. We estimate that fund managers generate an additional 0.25% per annum in fees that negatively impact investors′ risk-adjusted returns.

Keywords: systematic manager, discretionary manager, survivorship concern, risk-shifting, hedge funds, moral hazard

1 Introduction

A typical hedge fund fee structure includes a management fee, calculated as a fixed percentage of the Net Asset Value of a fund, and an incentive fee calculated as a percentage of trading

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profits. Hedge funds often utilize both hurdle rates and a high water mark (HWM) provision in the calculation of incentive fees; hedge funds in managed futures called Commodity Trading Advisors typically do not employ hurdle rates[1] but still comply with the high water mark provision that requires the fund manager to make up past deficits prior to earning incentive fees. The HWM provision is intended to protect investors by requiring payment of incentive fees only on the amount attributable to new trading gains, or the gains in excess of the previous HWM.

The performance-based portion of the compensation is highly asymmetric and can be expressed as a long call option position with a strike at the HWM. Therefore, fund managers face a moral hazard issue because they have an incentive to increase risk when their previous performance has been disappointing. This has been modeled analytically by Carpenter (2000) who suggests that the incentive to increase risk is particularly high when the fund NAV is substantially below the HWM and, thus, the incentive contract is deep out of the money. Fung and Hsieh (1997) find that multi-fund CTAs have less incentive to increase risk after poor performance, an outcome that can be attributed to attempts by fund managers to protect their reputations among the investors in the other funds.

There has been some important empirical work done illustrating that hedge funds with poor performance tend to increase volatility, i.e., engage in risk-shifting behavior. Brown, Goetzmann, and Park (2001) (henceforth BGP) perform volatility ratio tests within a contingency table approach and report that risk-shifting is driven by relative rather than absolute fund performance.[2] BGP argue that the moral hazard issue is eliminated by the career concerns of fund managers.[3] Aragon and Nanda (2011) use a regression framework to demonstrate that there are factors, such as the HWM provision, managerial stake and low risk of fund closure, that reduce the amount of risk-shifting behavior that takes place among hedge fund managers.

[1]The fact that Commodity Trading Advisors do not employ hurdle rates is likely driven by the low interest rate environment since the CTA's unencumbered cash, which represent a large fraction of NAV, is delivering insignificant returns. As short-term rates start rising, investors will tend to negotiate hurdle rates.

[2]Schwarz (2012) introduce the concept of the sorting bias that can potentially drive results of the standard volatility ratio tests, present empirical evidence of the sorting bias in the studies of mutual fund risk-shifting behavior and suggest an alternative approach that is robust to the sorting bias. We test explicitly and confirm that our volatility ratio test is free of the sorting bias.

[3]BGP′s conclusions include risk-shifting behavior of both hedge funds and Commodity Trading Advisors.

Our study complements BGP and shows that managerial survivorship concerns curb moral hazard problem only conditionally. We find that when the hedge fund mortality rate is high (low), the evidence for risk-shifting is insignificant (significant).[4] Our study also provides new evidence of how fund managers' risk choices and investment strategies are related. By focusing on CTAs, hedge funds in the managed futures industry, we are able to classify funds as discretionary or systematic. We hypothesize that a manager that systematically follows a trading methodology is more immune to the moral hazard problem than is a discretionary manager that lacks the formulaic discipline of systematic trading.[5] Moreover, we develop a model that evaluates the economic impact of risk-shifting on fund managers and investors.[6]

We find that discretionary fund managers exhibit a significantly higher degree of risk-shifting than do systematic fund managers between January 1994 and December 2014. A sub-period analysis reveals that the difference in behavior is particularly strong during favorable market environments. By contrast, during unfavorable market environments, the difference in behavior is not significant as both types of fund managers avoid risk-shifting. This finding is consistent with previously documented arguments that survivorship concerns mitigate moral hazard. By quantitatively modeling the outcome of hedge fund risk-shifting, we estimate the average benefit to a manager to be 0.25% per annum and the average cost to the investor to be 4.5% per annum.

Our findings have important implications for policymakers and institutional investors. The moral hazard issue is particularly strong for fund managers who utilize discretionary investment strategies and when managers are competing in a favorable market environment. In their fund selection and risk management decisions, prudent investors should account for both time-series and cross-sectional variation in managers' risk shifting behavior.

[4]When mortality is high, survivorship is difficult and thus managerial career concern dominates. In contrast, when mortality is low and survivorship is easy, career concern is minimal.

[5]Note that a systematic manager is still able to implement 'systematic' changes in response to changes in incentives. As the industry evolve, a greater understanding of investor utility and appropriate money management (for example, Sanford and Zhongquan (2006)) has had a significant impact on the typical systematic manager. It is possible that systematic managers systematically scale down exposures in periods of increased market (and P&L) volatility.

[6]The amount of risk-shifting may be underestimated due to the missing data points for managers that failed to report their final losing months as they go out of business. Defunct managers are likely to have their most volatile moments immediately prior to liquidation, but such data are not included in the sample, because defunct managers tend to refrain from sending in the last couple of months of their performance and the databases rely heavily on manager self-reporting.

The remainder of the paper is structured as follows: Section 2 discusses the data, accounts for biases in the data, introduces the algorithm used for calculating the gross returns and presents key variables used in the paper; Section 3 explains our empirical methodologies; Section 4 summarizes and discusses the empirical results; Section 5 presents a model to estimate the economic outcome of the observed risk-shifting; and Section 6 presents concluding remarks.

2 Data and Variables

2.1 Data

We base our analysis on the BarclayHedge database, the largest publicly available database of Commodity Trading Advisors.[7] The original data set covers 4,909 active and defunct funds over the period between January 1992 and December 2014. We eliminate multi-advisors and all funds with peak value of assets under management (AUM) of less than US $ 10 million. The $10 million cutoff reflects the fact that institutional investors often have provisions that prevent them from representing more than 50% of the AUM of any single fund. Furthermore, small funds tend to exhibit the most bias and noise in their returns. We also eliminate all funds with abnormal monthly returns in excess of 100% and remove null returns after the point at which a fund becomes defunct. Finally, we limit the study to the funds that report returns net of all fees to ensure comparability. Figure 1 shows the total number of CTA funds in operation during each year of our sample period along with a breakdown of the number of funds that trade discretionary versus systematically. Systematic managers are defined as those that trade on technical models and make investment decisions algorithmically. Discretionary managers are defined as those that trade based on manager judgment. Since some funds do not report their style, the number of funds classified across the two groups is less than the total number of funds.

We account for survivorship bias and backfill/incubation biases, both of which are com-

[7]As we restrict the study to CTAs exclusively, the results may not be applicable for all hedge fund categories, especially those funds with high degrees of performance smoothing (high degrees of autocorrelation of returns).

mon in the hedge fund databases. We include the graveyard database of defunct funds to account for survivorship bias and start the evaluation period in January 1994, the point at which the dataset begins to include defunct funds.[8] The backfill and incubation biases arise from the voluntary nature of self-reporting. Typically funds go through an incubation period during which they build a track record using proprietary capital. Fund managers choose to start reporting to a database to raise capital from outside investors only if the track record is attractive and they are allowed to backfill the returns generated prior to their inclusion in the database. Since funds with poor performance are unlikely to report returns to the database, incubation/backfill bias arises. We use a combination of two approaches to mitigate backfill and incubation biases. The first methodology, suggested by Fama and French (2010), limits the tests to funds that reach AUM of $ 10 million in 2014 dollars. Since the AUM minimum is expressed in terms of 2014 dollars, we include a fund in 1994, for example, if it has more than about $ 6 million in AUM in 1994. Once a fund passes the minimum AUM threshold, it is included in all subsequent tests to avoid creating selection bias. Unfortunately, many funds, including very successful and established CTAs, originally reported only net returns for an extended period of time prior to including AUM data several years later. Using Fama′s methodology exclusively would completely eliminate large portions of valuable data for such funds. For this reason, we apply the technique suggested by Kosowski, Naik, and Teo (2007) that eliminates the first 24 months of data for such funds. After accounting for the above biases, we end up with a sample of 1,994 funds for the period between January 1994 and December 2014. The summary statistics for our sample are provided in Table 1.

We use the Barclay CTA index as the benchmark. For the risk-free rate, we use the one-month Treasury bill (secondary market rate) series with ID TB1MS issued by the Board of Governors of the Federal Reserve System.

In contrast with the existing studies, we investigate hedge fund risk-shifting using the gross-of-fee return. The measurement of risk shifting of fund managers is quite imprecise in the literature due to the fact that net-of-fee returns are often used due to the complexity of calculations and limited availability of gross return data. With a comprehensive algorithm,

[8] It is worth mentioning that including the graveyard file does not fully eliminate the bias since the databases rely heavily on manager self-reporting (Bollen and Pool (2009)). Managers that liquidate tend to refrain from sending in the last couple of months of their performance to the database.

we are able to empirically estimate the monthly gross returns of individual funds and the moneyness of each manager′s option. To the best of our knowledge, this is the first study of hedge fund risk-taking based on gross returns.

2.2 Variable Definition

The variables used in our analysis and in the algorithm of gross returns and fees are defined as follows:

1 AUM_t, Assets Under Management, is the total value of investments managed by the fund, calculated as NAV multiplied by the total number of shares at time t.

2 NAV_t, Net Asset Value, is the end-of-month asset value per share after the deduction of all fees and expenses.

3 GAV_t, Gross Asset Value, is the end-of-month asset value per share at time t before the deduction of all fees and expenses.

4 HWM_t is the high water mark at time t.

5 r_t is the monthly growth rate of the NAV at time t.

6 R_t is the monthly rate of return on GAV at time t.

7 MgmtFee% is the annual management fee due to the CTA.

8 IncentFee% is the incentive fee due to the CTA for returns above the HWM.

9 $AccInctFee_t$ is the accrued incentive fee that is due to the CTA but not yet paid.

The fund returns in period t are calculated as follows:

$$r_t = \frac{NAV_t - NAV_{t-1}}{NAV_{t-1}} \tag{1}$$

$$R_t = \frac{GAV_t - GAV_{t-1}}{GAV_{t-1}} \tag{2}$$

We follow Brooks, Clare, and Motson (2007), and calculate the gross return as follows:

$$R_t = \frac{NAV_t - NAV_{t-1} + MgmtFee_t + (AccInctFee_t - AccInctFee_{t-1})}{NAV_{t-1} + AccInctFee_{t-1}} \tag{3}$$

and

$$MgmtFee_t = NAV_{t-1} \times (\frac{1}{1 - \frac{MgmtFee\%}{12}} - 1)$$

$$AccInctFee_t = max(0, NAV_t - HWM_t) \times (\frac{1}{1 - \frac{IncentFee\%}{12}} - 1)$$

At the end of each year, the accrued incentive fee is paid to the manager and reset to zero and, if necessary, the high water mark moves upward to reflect this payout. The statistical characteristics of gross returns and net returns are quantitatively different. Table 2 gives the detailed comparisons. As observed in Table 2, the standard deviation of the gross returns is consistently higher than that of the net returns. Thus, using net returns is expected to underestimate risk and create bias in the evaluation of risk shifting.

To measure the distance to the high water mark, we define Moneyness as follows:

$$Moneyness_{y,6} = \frac{NAV_{y,6}}{HWM_{y,6}} \tag{4}$$

In this equation, $Moneyness_{y,6}$ represents a fund′s value at the end of June in year y compared to its previous maximum net asset value.

Following the literature, we construct a measure of risk shifting, Risk Adjustment Ratio (RAR), as follows:

$$RAR = \frac{July\ to\ December\ Volatility}{January\ to\ June\ Volatility} = \frac{\sqrt{\sum_{i=7}^{12}(R_i - \overline{R}_{7-12})^2}}{\sqrt{\sum_{i=1}^{6}(R_i - \overline{R}_{1-6})^2}} \tag{5}$$

RAR is a fund-year variable; it is the ratio of the volatility of returns over the second six months of a year to the volatility of returns over the first six months of the same year.

The normalized RAR is benchmarked by the median RAR of all funds,

$$Normalized\, RAR = RAR - Median\, RAR\, among\, all\, funds$$

In the above equations, Normalized RAR is a measure of how funds shift risk relative to other funds for a particular period. A value greater (less) than zero indicates that the fund in question increases its risk by more (less) than its peer group for the particular period in question. The normalized term provides a clearer picture of how a fund's RAR compares to the median.

3 Methodology

We apply two methodologies: 1) a volatility ratio test robust to the sorting bias (see Schwarz (2012)); and 2) a regression framework that is most similar to that used in Aragon and Nanda (2011).

3.1 Volatility Ratio Test

Our volatility ratio test follows the standard method of Brown, Harlow, and Starks (1996) in which a fund is assigned to one of two groups based on the fund′s moneyness at the end of the first 6 months of the year and its RAR calculated. The first group of high absolute performance funds consists of funds with positive moneyness, whereas the second group of low absolute performance funds includes funds with negative moneyness. For each group, positive RAR and negative RAR outcomes are recorded in separate cells of a 2 x 2 contingency table. If the negative-moneyness funds tend to have a higher percentage of funds with positive RAR when compared to that of the positive-moneyness funds, this is viewed as evidence of risk-shifting behavior driven by the moral hazard problem.

The standard volatility ratio test is potentially subject to sorting bias (Schwarz (2012)) since the performance sorting also sorts by risk. As a robustness check, we perform a correlation analysis of (Schwarz (2012)) and confirm that our inference from the volatility ratio test is not polluted by the sorting bias.

3.2 Regression Framework

The regression framework follows Aragon and Nanda (2011). In particular, we regress a fund's risk shifting on mid-year fund performance and a list of control variables, including lagged volatility, fund age, fund flow, management fee, and incentive fee. We estimate the panel regression as below,

$$\Delta risk = \alpha + \beta_1 Mo + \beta_2 Mo * I_{GoodMkt} + \beta_3 Mo * Size + \beta_4 Mo * I_{Dis} + \beta_5 Mo * I_{GoodMkt} * I_{Dis} + \Gamma * Z + \epsilon \tag{6}$$

where $\Delta risk$ is the volatility in the second half of the year minus volatility in the first half of the year; Mo (Moneyness) measures the distance to the HWM and is defined in section 2; GoodMkt is dummy variable for a good market environment that is set to 1 for 1994 to 2008 and zero for 2009 to 2014[9]; Size is the fund size measured by the log of AUM; Dis is a discretionary manager dummy that equals 1 for discretionary managers and 0 for systematic managers. We also add a list of control variables, Z, including fund age, capital inflow, management fee and incentive fee. As in Aragon and Nanda (2011), we include fund volatility over the first 6 months of the year in the regression model to control for mean reversion in the measurement error.

4 Empirical Results

A simple decile analysis provides an easy way to visualize the presence of risk-shifting behavior as it relates to the performance of fund managers. We sort funds into deciles based on their performance (moneyness or normalized return) at the end of the first 6 months of the year and report the median normalized RAR for each decile in Figure 2. As defined previously, RAR is the ratio of the volatility of returns in the second half of the year to the volatility of

[9] In robustness tests, we have applied two alternative definitions of good market dummy. One is defined by the mortality rate (below median), and the other is defined by the Barclay CTA index return (above zero). The results are available in the Appendix and they are all qualitatively similar.

returns in the first half of the year. Figure 2 uses normalized RAR, defined in section 2, as a fund′s RAR minus the median RAR of all funds. Thus, a decile with a value of 0.1 indicates that the median RAR of this decile is 10% higher than the median RAR calculated across all funds. The procedure is repeated for each year between 1994 and 2014, and the results are averaged by taking a mean of the median normalized RAR over the 21 years.

With the exception of the lowest decile, four out of the bottom five deciles of moneyness (the top panel) are found to have positive normalized RAR. Figure 2 is consistent with risk-shifting due to the moral hazard problem, indicating that underwater funds tend to increase risk by more than above water funds. In the bottom panel of Figure 2, relative return is used to sort funds into performance deciles. Here it appears that tournament behavior is at work as evidenced by the relatively large increase in risk taking among the poorer performing funds.

In this paper, we evaluate the variation in risk-shifting behavior among funds across two dimensions. The first dimension is within the time series where we investigate whether risk-shifting is conditional on market environment. BGP present empirical evidence that survival concerns mitigate the moral hazard problem in all types of hedge funds, including CTAs. We propose that the BGP observation is conditional; and only applies when managers are more concerned with survival than with fee income. The second dimension is cross sectional. We hypothesize that the risk-shifting behavior of discretionary managers is different from that of systematic managers. A systematic manager that formulaically follows a trading methodology is not necessarily immune to the moral hazard problem because the manager might implement systematic changes in response to changes in incentives. A discretionary manager does not use formulaic discipline in trading. Whether systematic managers make different risk choices than discretionary manager is a purely empirical question. Finding answers to these questions have important implications for institutional investors because they provide insight into the factors that have significant impact on risk-taking behavior.

4.1 Survival Concern versus Fee Income

BGP argue that the moral hazard problem can be mitigated by the survivorship concerns of fund managers which are particularly strong in the hedge fund space because of a high mortality rate. We posit that the BGP assertion is conditional rather than unconditional. Our hypothesis is that risk-shifting will disappear during periods of bad market environment when mortality is high and survivorship concerns dominate. However, other factors (e.g., better fee income) might take on greater weight during good market environments. In this section, we separate the entire sample period into two sub periods, 1994 to 2008 and 2009 to 2014. The choice of sub periods is based on the time series variation in mortality rate and CTA performance. As shown in Figure 3, the mortality rate is relatively low in the first sub period 1994 to 2008 (generally below 10%) and generally much higher in the second sub period 2009 to 2014, reaching 20% in 2014.The sample is also separated into sub periods based on the performance of the Barclay CTA index. Performance clearly trends up through the beginning of 2009 before struggling through July 2014. It is generally acknowledged that 1994-2008 was a good period for CTA funds, while 2009-2014 posed challenges for the CTA industry. While dividing the analysis into two lengthy historical periods is economically desirable, it is also problematic because it tends to cloud the interpretation.[10] For robustness, we employ two different definitions of good periods versus bad periods and rerun the tests. Specially, good (bad) periods include the years that have a below (above) median mortality rate by one definition, and good (bad) periods include the years in which the Barclay CTA index returns are positive (negative) by the other definition.

4.1.1 Volatility Ratio Test

Following prior studies, volatility ratio tests are performed yearly using a 2 x 2 contingency table of whether a funds̀ performance over January to June is above or below the high water mark and whether its RAR of the year is above or below the median. The percentages of funds in each of the four cells are calculated.

The statistical significance of our volatility ratio tests is gauged by the log odds ratio (OR) test. In the OR, a combination of the four cells is used to infer the strength of association between performance and RAR. To match the procedure of BGP, we calculate the t-stat of OR as well as the chi-square value for the contingency table.[11] These test statistics are valid

[10]The change in risk shifting may be the result of an average increase in trading sophistication or a significant change in the demands of investors for increased transparency and enhanced risk reporting.

[11]Same as in BGP, the t-stat and the Chi-Square number infer the same significance level.

under the assumption that CTA fund returns are serially and cross-sectionally independent.

In Table 3, the log odds ratio is 23% from 1994 to 2008, 6% from 2009 to 2014, and 15% over the entire period. So there is evidence that underwater funds increase risk in the second half of the year over the entire 21 years. But we argue that the overall evidence of risk shifting is driven by the first sub period (1994-2008) when the CTA industry performed well. During the second sub period of 2009 to 2014, the mortality rate of CTA funds is relatively high and fund managers are most concerned with survival. This fear constrains them from taking excessive risk. Therefore, we conclude that fund managers care more about incentive fee income in good market environments but care more about survival in bad market environments. Thus, fund investors should be most worried about the moral hazard problem when the market environment is positive for fund managers. In Table 3, we define market environment (good versus bad) in three different ways with qualitatively similar results. In one, the good market environment comprises a lengthy sub-period from 1994 to 2008; in a second, we define good market environment to be one in which the CTA mortality rate is below the median (see Figure 3); in the third, the good market environment includes the years in which the Barclay CTA index return is positive (see Figure 3).

Schwarz (2012) points out that the volatility ratio test suffers from the sorting bias, meaning risk levels are segmented during the return sorting process and resultant risk shifting findings may be due to simple mean reversion in the second half of the year. To examine the risk sorting bias in our results, we calculate the correlations between the amounts of risk sorting and the amounts of risk shifting evidence. More specifically, we follow Schwarz (2012) and use the Before Ratio and the Frequency Difference to measure the two, respectively. Frequency Difference is the difference between the High RAR and Low RAR percentages of the low-performance funds. Before Ratio is the ratio of the volatility of high performance funds to that of low performance funds over the first 6 months. Our calculation returns a moderate correlation of 0.23. More detail regarding the calculation is provided in the Appendix.[12] Therefore, we do not believe the results of our volatility ratio tests are affected by the sorting bias. Moreover, in the section that follows, we test the same hypothesis using

[12]Schwarz (2012) obtains a correlation of 0.79 in his unadjusted method, but the correlation decreases to a range of -0.19 to -0.08 after adjusting for the sorting bias.

a completely different approach.

4.1.2 Regression framework

Table 4 reports the results from estimating a regression-based model with and without variables of market environment for CTA funds. All models suggest that the coefficient on performance is negative, and that the results are more significant when market environment is excluded from the model. The interaction term of performance and market environment is negative, implying that the risk shifting is more pronounced when the fund managers are in a more favorable environment. Therefore, the regression results agree with the volatility ratio test in that changes to fund risk are negatively related to mid-year performance; an association that is mainly concentrated in the good years for the CTA industry. We also test for a fund size effect. Given that larger managers rely less heavily on incentive fees than do smaller funds, we expect larger funds to be more risk averse during periods of poor performance. To evaluate the role of fund size in this dynamic, we include an interaction term between fund moneyness and fund size in all our regression models. As hypothesized, the coefficient is significantly positive, indicating that smaller funds are more concerned with incentive fees than are larger funds which are more concerned with maintaining management fees and therefore engage more in risk-shifting. Table 4 applies the baseline definition of good market environment that identifies a lengthy period between 1994 and 2008. For robustness, we redo Table 4 using the two alternative definitions, of mortality rate and CTA index return, and confirm that our inference is robust. Details of these robustness checks are included in the Appendix.

4.2 Fund Strategy, Systematic Manager versus Discretionary Manager

Does fund strategy choice matter in manager's risk decisions? We answer this question by comparing the risk-shifting behavior of discretionary managers against systematic managers. While a systematic manager that formulaically follows a trading methodology is likely to be immune to the moral hazard problem, the manager may implement systematic changes in response to a change in incentives. A discretionary manager, on the other hand, seems to be more susceptible to the moral hazard issue due to a lack of the formulaic discipline that is inherent within systematic trading. We empirically compare the behaviors of systematic and discretionary managers within the regression framework.

In Table 5, we add a discretionary manager dummy to the regression equation. The coefficient of the mid-year fund performance quantifies the extent to which systematic managers shift risk. For discretionary managers, the coefficient of the interaction term is an additional factor in quantifying risk-shifting behavior. As expected, the coefficient of the interaction term is significantly negative, indicating that the propensity to shift risk among discretionary managers is significantly stronger than among systematic managers. Moreover, a three-variable interaction term (performance*good market*discretionary manager) is estimated to have a negative loading, leading us to infer that when the market environment is good, discretionary managers that are underwater at mid-year tend to increase their risk taking in the second half of the year. Similar to Table 4, Table 5 applies the baseline definition of a good market environment to be the lengthy period between 1994 and 2008. For robustness, we recalculate Table 5 using the two alternative definitions of mortality rate and CTA index return and find that our results are consistent. Details of these results are available in the Appendix.

5 Economic Impact of Risk-shifting on Fund Managers and Investors

In previous sections, we find statistically significant evidence of risk-shifting behavior induced by the moral hazard problem. In this section, we make an effort to estimate the impact of that behavior on fund managers and investors. It is possible that the economic impact is negligible for both parties or that investors tend to benefit from the risk-shifting of fund managers. However, if there is a significant cost to investors, the magnitude of that cost can be used in internal cost-benefit analyses to evaluate options for mitigating risk-shifting such as using managed accounts or performing frequent risk analyses of the underlying fund managers. In this section, we introduce a model that estimates the economic impact of risk-shifting behavior on fund managers and investors. We estimate the model for the period from 1994 to 2008, a period of strong risk-shifting behavior. We accomplish this by analyzing the returns of LH (low performance, high RAR), the group of funds that have increased risk-taking in response to negative absolute performance. More specifically, we compare the actual net returns of the funds with the hypothetical net returns of the funds calculated under the assumption of no risk-shifting during the second half of the year. The hypothetical returns are estimated using the factor model below.

$$R_m = \alpha + \beta_1 CTA_m + \beta_2 1_{July} CTA_m + \epsilon_m \qquad m = 1, ..., 12 \tag{7}$$

Specifically, we estimate the above factor model of gross return for each LH fund each year, where the dummy variable, 1_{July}, is 0 for January to June and 1 for July to December. We use the Barclay CTA index for the market factor. The coefficient, β_2, represents the shift in the systematic risk exposure from the first half of the year to the second half of the year with a positive value indicating an increase in exposure and a negative value indicating a decrease in exposure. The coefficient, β_2 is positive for every single year from 1994 to 2008 with an average value of 0.76 over the 15 years. Moreover, in most of the years, the average β_2 is positive at the 1% level of significance. Thus, LH funds increase risk taking in the second half of the year, consistent with our results in the previous sections.

Then we calculate the hypothetical gross returns of a fund from July to December using the parameters estimated in the previous regression and assuming no change in risk taking in the middle of the year ($\beta_2 = 0$):

$$R'_m = \hat{\alpha} + \hat{\beta}_1 CTA_m + \hat{\epsilon_m} \qquad m = 7, ..., 12 \tag{8}$$

Next, we apply the funds actual fee structure to the hypothetical gross returns to calculate its hypothetical net returns. We measure the income of a manager as the difference between gross and net returns. However, raw net returns are not appropriate for measuring the performance of investors. On average, higher risk should result in higher returns, but the marginal improvement in returns might not be justified on a risk-adjusted basis. Therefore, we use a Sharpe ratio to compare the risk-adjusted performance of investors with and without risk-shifting. Thus, the impacts on the manager and the investor are estimated by the following formulae:

$$\begin{aligned} d_{manager} &= (R - r) - (R' - r') \\ d_{investor} &= \frac{r - r_f}{\sigma_{r-r_f}} - \frac{r' - r_f}{\sigma_{r'-r_f}} \end{aligned} \tag{9}$$

The results are included in Figure 4, which shows the median impact of risk shifting on fund manager and investor returns each year from 1994 to 2008. As in Figure 4, the outcome for fund managers is almost always positive (1994 being the exception), indicating that CTA fund managers as a group have generated additional income from risk-shifting in every year except one during the sample period. The outcome for investors is much more volatile. When return is improved and the improvement is sufficient to justify the increase in risk, investors achieve a better Sharpe ratio. In this case, fund managers have been fortunate to increase exposure during a favorable market environment. However, in most years, the impact on investors risk-adjusted performance has been negative with investors getting exposed to greater risk without a corresponding increase in returns. The average annual benefit to a manager's return income is 0.25%, while the average cost to an investor's Sharpe ratio is 0.014, which represents a decline of 4.5% per annum.

6 Conclusion

In this paper, we have conducted a comprehensive analysis with the goal of gaining insight into the risk-taking behavior of hedge fund managers. For the period January 1994-December 2014, we find that fund managers who use more discretion in making investment decisions have a significantly higher degree of risk-shifting than fund managers who utilize automated trading algorithms. This result suggests that the moral hazard problem is of less concern to an investor when a manager follows a trading algorithm, something that has not been documented in the literature up to this point. The sub-period analysis reveals that the difference in behavior is particularly strong during periods of favorable market environment. In contrast, during unfavorable market environments, the difference in behavior is not significant as both types of fund managers avoid risk-shifting, consistent with previously documented arguments that survivorship concerns mitigate moral hazard. We introduce a simple model that evaluates the economic impact of risk-shifting on fund managers and investors. We estimate the average benefit to managers to be 0.25% per annum and the average cost to investor to be a 4.5% decrease in the Sharpe ratio per annum. Our findings have important implications for policymakers and institutional investors. The moral hazard problem is particularly strong for fund managers who rely on discretion, and prudent investors should account for that behavior in their fund selection and risk management decisions. Investors can explore creative ways of structuring performance-based compensation that rewards managers for taking a longer view rather than seeking to maximize short-term performance. For example, clawback provisions, used in other segments of the financial industry, might potentially serve that purpose, particularly for discretionary managers who are more likely to be engaged in risk-shifting behavior. Requiring fund managers to have a sizable personal stake in the fund could be another way to mitigate the issue.

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Figure 1: The Number of CTA Funds. This figure shows the total number of CTA funds in the sample by year. It also breaks out the number of funds by either discretionary and systematic trading. Systematic CTAs base their trading on technical models and investment decisions are made algorithmically. Discretionary traders instead base their trading decisions on manager judgment. Since there are funds that do not report their style, the sum of the number of funds of the two groups is less than the total number of funds.

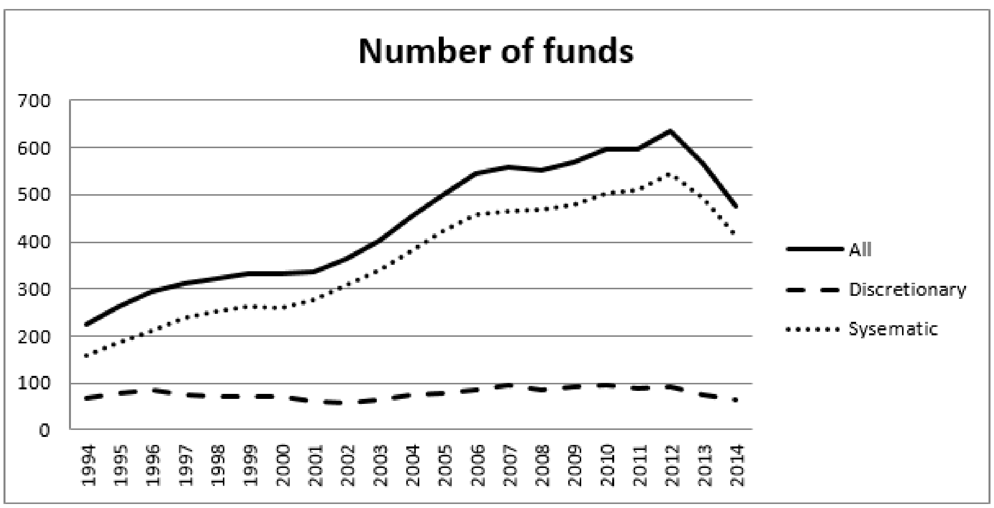

Figure 2: The Normalized RAR of Performance Deciles. The figure below illustrates the normalized RAR as a function of moneyness (top panel) and normalized return (bottom panel). Each year, all CTAs are sorted into deciles according to their performance over the first 6 months. Then the average median normalized RAR are calculated for each decile. The RAR is defined as the ratio of fund return volatility during the second half of the year to the volatility during the first half of the year. The figure uses normalized RAR, which is equal to RAR minus the median RAR of all CTAs.

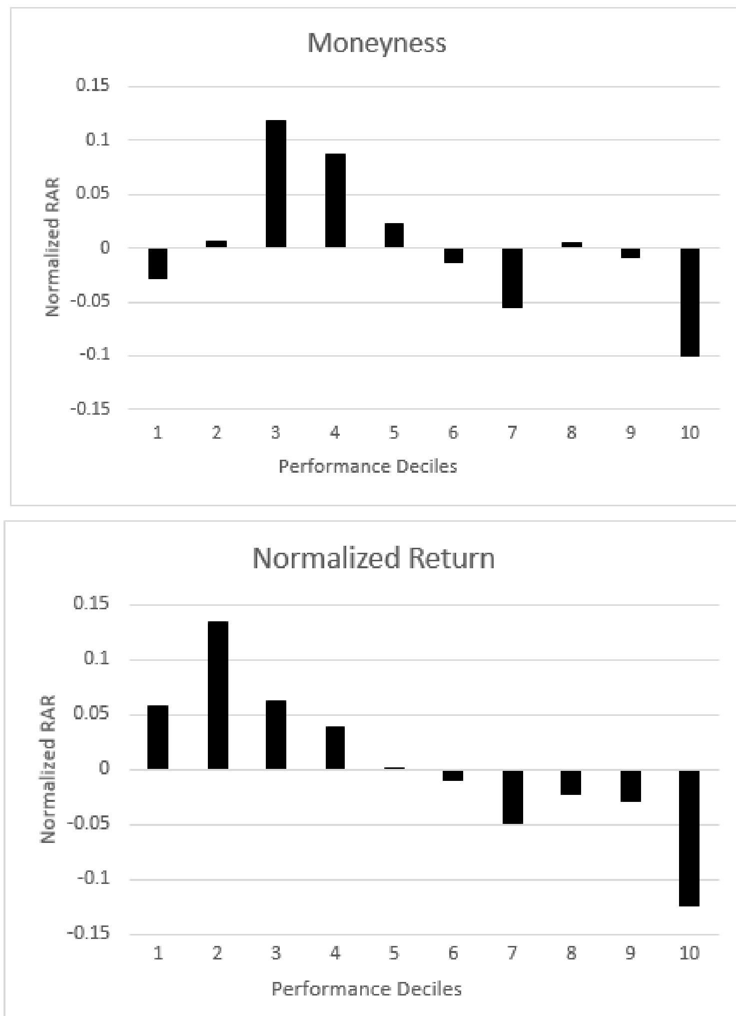

Figure 3: Mortatlity Rate and Performance of CTA funds. The top figure gives the ratio of the number of defunct funds to the total number of funds from 1994 to 2014. The bottom figure gives the annual return of the Barclay CTA index.

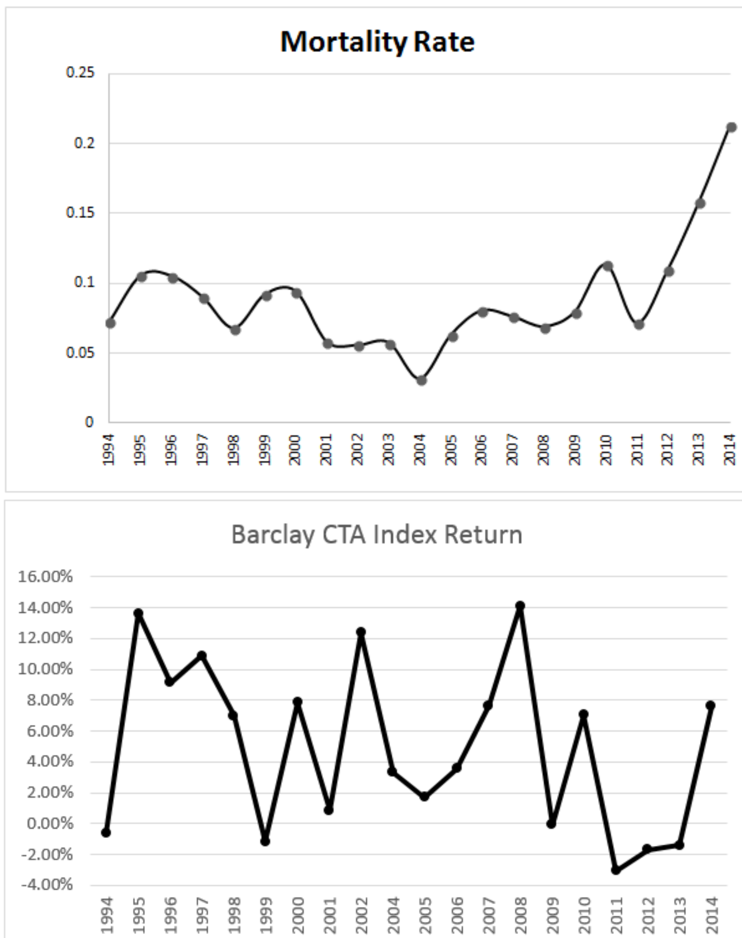

Figure 4: The Outcome of Risk Shifting. We estimate the benefit that managers gain from risk-shifting and the impact on investors over the sample period 1994-2008. A manager's income is the difference between gross return R and net return r; an investor's income is the Sharpe ratio of the net returns. By calculating the hypothetical fund return assuming no shift in risk, R'(gross) and r'(net), we estimate the impact of shift in risk by comparing the real income and hypothetical income of both manager and investor. The left scale represents the median impact on an investor's Sharpe ratio, while the right scale represents the median impact on manager's income.

$$d_{manager} = (R - r) - (R' - r')$$
$$d_{investor} = \frac{r - r_f}{\sigma_{r-r_f}} - \frac{r' - r_f}{\sigma_{r'-r_f}}$$

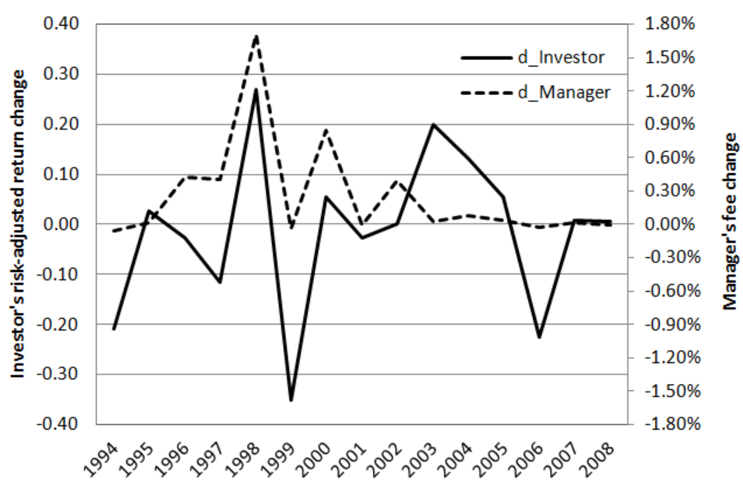

Table 1: Summary Statistics of CTA Fund Sample. This table below reports the summary statistics of key variables for the sample of 1,994 CTA funds over the 1994-2014 period. We limit our analysis by excluding funds with less than 24 of months performance. CTAs are separated into two distinct styles: systematic and discretionary. Systematic CTAs base their trading on technical models and investment decisions are made algorithmically. As the name implies, discretionary managers instead base their trading decisions on their own discretion. Fund Age is the number of years since a funds inception date; Fund Size is the average total assets under management (AUM); Gross Return is the back-solved return based on net returns and the fee structure of each fund; Net Return is the average net-of-fee monthly returns in a funds sample period; Management Fee and Incentive Fee are presented as percentage numbers. Inflow is the average capital inflow, winsorized at a 1 % level. The statistics reported include mean, standard deviation, minimum, median and maximum.

	Mean	**Std**	**Min**	**Median**	**Max**
			Discretionary		
Mgmt	1.99%	0.84%	0.00%	2.00%	6.00%
Inc	20.25%	3.77%	0.00%	20.00%	40.00%
Gross Return	1.05%	6.14%	-55.40%	0.49%	113.84%
Net Return	0.70%	5.62%	-55.73%	0.29%	98.72%
Age(year)	6.89	4.65	2.08	5.71	21.00
Size(Million $)	63.56	99.07	0.37	31.04	800.28
Inflow(%)	2.01%	4.32%	-47.49%	0.00%	86.14%
			Systematic		
Mgmt	1.77%	0.87%	0.00%	2.00%	6.00%
Inc	19.81%	5.20%	0.00%	20.00%	50.00%
Gross Return	0.99%	6.28%	-64.72%	0.51%	109.93%
Net Return	0.64%	5.60%	-64.80%	0.33%	99.87%
Age(year)	7.43	4.65	2.08	6.17	21.00
Size(Million $)	359.17	1990.63	0.36	35.74	22412.50
Inflow(%)	1.38%	3.03%	-47.49%	0.00%	86.14%
			ALL		
Mgmt	1.77%	0.88%	0.00%	2.00%	6.00%
Inc	18.85%	6.49%	0.00%	20.00%	50.00%
Gross Return	0.97%	5.91%	-99.74%	0.54%	117.25%
Net Return	0.64%	5.31%	-99.99%	0.36%	99.87%
Age(year)	7.07	4.54	2.08	5.75	21.00
Size(Million $)	190.47	1117.47	0.36	29.25	24750.00
Inflow(%)	1.54%	3.40%	-47.49%	0%	86.14%

Table 2: Summary Statistics: Net Return vs Gross Return. In this table we report the descriptive statistics of net returns (Net), and gross returns (Gross) for systematic, discretionary, and all CTA funds from January 1994 to December 2014. We limited our analysis by excluding funds with less than 24 months of performance. The mean, standard deviation and Sharpe ratio are based on the monthly returns of each fund. We also report skewness, kurtosis, and the first order autocorrelation coefficient. The Jarque-Bera (JB) statistic has an asymptotic chi-squared distribution with two degrees of freedom and is used to test the null hypothesis that the data come from a normal distribution. We report the average p-value of JB.

Style	N	type	Mean	Std	Skewness	Kurtosis	Sharpe	Auto1	JB test
Discretionary	264	Gross	0.89%	4.21%	0.55	5.91	0.27	0.04	0.64%
		Net	0.55%	3.76%	0.42	5.79	0.19	0.04	0.96%
Systematic	1027	Gross	0.88%	5.14%	0.43	4.58	0.19	-0.03	4.48%
		Net	0.56%	4.59%	0.31	4.37	0.13	0.00	8.06%
All	1994	Gross	0.84%	4.73%	0.32	5.29	0.22	-0.01	2.52%
		Net	0.53%	4.25%	0.21	5.17	0.16	0.02	3.82%

Table 3: Volatility Ratio Tests by Market Environment. Cell proportions are calculated for 2x2 classifications according to a funds absolute performance for the first six months of each year, and risk adjustment ratio (RAR). To be included in the analysis, each fund is required to have a complete return history for the year. Funds are assigned annually into four groups based on whether the return is above (H) or below (L) the HWM, and the RAR is above (H) or below (L) the median. The log-odds ratio is reported in this table. The t-value of the log-odds ratio and the Chi-square numbers are calculated in the same way as in Brown, Goetzman, and Park (2001). Significance levels of 10%, 5%, and 1% are represented by one, tow or three asterisks, respectively. Results are reported for good and bad market environment, defined in three different ways and over the whole period.

	N	**Log Odds**	**Std Error**	**t-value**	**Chi-Square**	**P-value**	
			Two Lengthy Sub-periods				
1994-2008	4251	0.23	0.06	3.60	12.99	0.03%	***
2009-2014	2794	0.06	0.08	0.70	0.48	48.65%	
			By Mortality				
Below Median	3420	0.22	0.07	3.15	9.91	0.17%	***
Above Median	3628	0.10	0.07	1.43	2.05	15.21%	
			By Barclay CTA Index Return				
Positive	4656	0.24	0.06	4.07	16.63	0.00%	***
Negative	2392	-0.02	0.08	-0.24	0.06	80.82%	
All	7045	0.15	0.05	3.13	9.81	0.17%	***

Table 4: Regression Framework for Risk-shifting Comparison between Good and Bad Market Environments. This table gives the results of CTA managers' risk-shifting behavior based on market conditions. We divide the sample into two lengthy periods where 1994-2008 represents a good environment and 2009-2014 represents a bad environment. Mo represents the moneyness during the first half of the year. We use "GoodMkt" to represent the positive market dummy. Several control variables are added, such as volatility over the first 6-month of the year (LagRisk), age, inflow, management fee, incentive fee and year effect. The first row of each variable reports the parameter estimates while the second row reports the Newey-West t-statistics associated with that parameter. The significance levels of 10%, 5%, and 1% are indicated by one, two or three asterisks, respectively. In the following equation, $\Delta risk$ is the volatility over the second half of the year minus the volatility over the first half of the year; Mo (Moneyness) measures the distance to the high water mark and is defined in section 2; GoodMkt is a good market environment dummy and is set to 1(0) for 1994 to 2008 (2009 to 2014). Fund size is measured by the log of assets under management (AUM). We also add a list of control variables Z, including fund age, capital inflow, management fee and incentive fee. We also include volatility over the first 6 months of the year in the regression model to control for mean reversion in the measurement error.

$$\Delta risk = \alpha + \beta_1 Mo + \beta_2 Mo * I_{GoodMkt} + \beta_3 Mo * Size + \beta_4 Mo * I_{Dis} \\ + \beta_5 Mo * I_{GoodMkt} * I_{Dis} + \Gamma * Z + \epsilon$$

	1		2		3		4		5		6	
Mo	-0.012		-0.004		-0.036		-0.006		-0.005		-0.007	
	-1.720	*	-0.453		-4.392	***	-0.620		-0.483		-0.778	
Mo*Size	0.000		0.000		0.001		0.001		0.001		0.000	
	-0.458		-0.500		3.244	***	2.884	***	2.874	***	-0.502	
Mo*GoodMkt			-0.096				-0.044		-0.045		-0.011	
			-1.683	*			-4.094	***	-3.999	***	-1.651	*
GoodMkt			0.015						0.047			
			1.670	*					4.195	***		
LagRisk	-0.337		-0.354								-0.334	
	-14.909	***	-15.099	***							-14.409	***
Age	0.000		0.000		0.000		0.000		0.000		0.000	
	1.635		1.682	*	-2.349	**	-1.736	*	-1.345		1.712	*
Inflow	0.000		0.000		0.001		0.001		0.000		0.000	
	0.369		-0.675		1.372		1.454		0.268		0.393	
Mgmt Fee	0.011		0.032		0.031		0.029		0.030		0.011	
	0.186		0.507		0.491		0.459		0.445		0.183	
Incentive Fee	0.038		0.041		0.014		0.014		0.016		0.037	
	3.945	***	4.102	***	1.239		1.267		1.322		3.930	***
Intercept	0.020		0.009		0.023		-0.003		-0.013		0.016	
	3.901	***	1.176		3.921	***	-0.409		-1.517		2.135	**
R2	0.255		0.163		0.123		0.130		0.016		0.255	

Table 5: Regression Framework for Risk-shifting Comparison between Discretionary and Systematic Managers. This table gives the results of CTA managers' risk-shifting behavior based on the classification of managers. We define CTA market environment by two lengthy sub-periods: 1994-2008 is good environment while 2009-2014 is bad environment. Mo represents the moneyness during the first half of the year. We use "GoodMkt" to represent good market dummy and "Dis"' to represent discretionary manager dummy. Several control variables are added, such as first 6-month volatility (LagRisk), age, inflow, management fee, incentive fee and year effect. The first row of each variable is the parameter estimates while the second row is the Newey-West t-statistics associated with that parameter. *, **, and *** indicate 10%, 5%, and 1% significance levels. In the following equation, $\Delta risk$ is the second half year volatility minus the first half year volatility; Mo (Moneyness) measures the distance to high water mark and is defined in section 2; GoodMkt is good market dummy and equals to 1(0) for 1994 to 2008 (2009 to 2014); Dis is the discretionary manager dummy and equals to 1 (0) for discretionary (systematic) manager; we also add a list of control variables Z, including fund age, capital inflow, management fee, incentive fee. We also include first-6-month volatility in the regression model to control for mean reversion in the measurement error.

$$\Delta risk = \alpha + \beta_1 Mo + \beta_2 Mo * I_{GoodMkt} + \beta_3 Mo * I_{Dis} + \Gamma * Z + \epsilon$$

	1		2		3		4		5	
Mo	-0.009		-0.004		-0.018		-0.013		-0.006	
	-1.617		-0.557		-3.110	***	-2.525	**	-0.898	
Mo*Dis	-0.031		-0.021		-0.002		-0.006		-0.006	
	-2.335	**	-1.658	*	-1.576		-5.994	***	-6.063	***
Mo*GoodMkt			-0.004						-0.010	
			-0.401						-1.030	
Mo*Dis*GoodMkt			-0.008							
			-3.926	***						
GoodMkt			0.014							
			1.338							
LagRisk	-0.347		-0.366				-0.347		-0.344	
	-15.129	***	-15.486	***			-15.072	***	-14.581	***
Dis	0.025		0.020							
	1.846	*	1.493							
Age	0.000		0.000		0.000		0.000		0.000	
	1.651	*	1.597		-1.432		1.648	*	1.739	*
Inflow	0.000		0.000		0.001		0.000		0.000	
	0.509		-0.521		1.491		0.503		0.534	
Mgmt Fee	0.020		0.048		0.033		0.024		0.024	
	0.339		0.762		0.527		0.411		0.409	
Incentive Fee	0.039		0.042		0.013		0.039		0.039	
	4.149	***	4.188	***	1.175		4.134	***	4.119	***
Intercept	-0.016		-0.007		0.021		0.020		0.014	
	2.905	***	0.899		3.677	***	3.832	***	1.917	*
R2	0.260		0.175		0.121		0.261		0.261	

Appendices

A. Sorting Bias Tests

Schwarz (2012) points out that the volatility ratio test suffers from the sorting bias, meaning risk levels are segmented during the return sorting process and risk shifting findings may be the result of simple mean reversion in the second half of the year. To examine the risk sorting bias in our results, we calculate the correlations between the amounts of risk sorting and the amounts of risk shifting evidence. More specifically, we follow Schwarz (2012) and use Before Ratio (BR) and Frequency Difference (FD) to measure the two, respectively. Frequency Difference is the difference of the High RAR and Low RAR percentages of the low-performance funds. Before Ratio is the ratio of the volatility of high performance funds to that of low performance funds over the first 6 months of the year. It is a measure of risk sorting. Values of this ratio greater than 1 indicate that the risk levels of portfolios with good performance are significantly higher in the first half of the year and ratio values less than 1 indicate that portfolios with bad performance exhibit significantly greater risk in the first half of the year.

The correlation between these two ratios indicates the significance of the risk sorting bias noted by Schwarz (2012). A high correlcation means that we cannot differentiate whether the risk-shifting behavior results from changing risk within the fund strategy or simply mean reversion during the second half of the year. Therefore, the sorting bias test is important. However, our calculation yields a moderate correlation of 0.23 at a significance level of 31%. [13] Therefore, we believe the results of our volatility ratio tests are unaffected by the sorting bias.

Year	**1994**	**1995**	**1996**	**1997**	**1998**	**1999**	**2000**	**2001**	**2002**	**2003**	**2004**	**2005**	**2006**
FD	-0.06	0.19	0.00	0.13	0.15	0.07	0.30	0.11	0.16	0.03	0.07	0.03	0.13
BR	1.21	2.78	0.89	1.52	0.83	1.09	1.02	0.94	2.07	2.00	0.52	0.92	1.54

Year	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**Correlation**	**P Value**
FD	0.01	0.03	0.10	-0.04	-0.07	0.11	-0.11	0.18		
BR	1.46	2.45	0.80	0.87	0.68	0.96	0.91	1.13	0.23	31.37%

[13] Schwarz (2012) obtains a correlation of 0.79 in his unadjusted method, but the correlation decreases to a range of -0.19 to -0.08 after adjusting for the sorting bias.

B. Alternative Definitions of Good Market and Bad Market

In the baseline tests, we define a good market environment as a lengthy period between 1994 and 2008. Dividing the sample into two lengthy historical periods is economically desirable but also problematic because it clouds the interpretation. For example, the change in risk shifting may be the result of an average increase in trading sophistication or a significant change in the demands of investors for increased transparency and enhanced risk reporting. To alleviate the concern, we employ two alternative definitions of good periods versus bad periods. Specially, good (bad) periods include the years that have less than (greater than) median mortality by one definition, and good (bad) periods include the years in which the Barclay CTA index was positive (negative). The following tables replicate analyses of Tables 4 and 5 for market conditions, defined by mortality rate and CTA index return.

Table 4 with Market Environment Defined by Mortality Rate

	1		2		3		4		5		6	
Mo	-0.012		0.001		-0.036		-0.020		-0.018		-0.011	
	-1.720	*	0.147		-4.392	***	-2.144	**	-1.777	*	-1.335	
Mo*Size	0.000		0.000		0.001		0.001		0.001		0.000	
	-0.458		-0.527		3.244	***	3.092	***	3.073	***	-0.464	
Mo*GoodMkt			-0.096				-0.031		-0.028		-0.013	
			-1.679	*			-2.845	***	-2.463	**	-1.657	*
GoodMkt			0.008						0.027			
			0.751						2.362	**		
LagRisk	-0.337		-0.337								-0.336	
	-14.909	***	-14.437	***							-14.598	***
Age	0.000		0.000		0.000		0.000		0.000		0.000	
	1.635		-0.023		-2.349	**	-2.100	**	-2.246	**	1.640	
Inflow	0.000		0.000		0.001		0.001		0.000		0.000	
	0.369		-0.639		1.372		1.332		0.202		0.367	
Mgmt Fee	0.011		0.080		0.031		0.031		0.047		0.011	
	0.186		1.256		0.491		0.501		0.701		0.188	
Incentive Fee	0.038		0.044		0.014		0.014		0.018		0.038	
	3.945	***	4.314	***	1.239		1.295		1.483		3.946	***
Intercept	0.020		0.007		0.023		0.009		0.000		0.019	
	3.901	***	0.967		3.921	***	1.162		-0.036		2.961	***
R2	0.255		0.150		0.123		0.126		0.010		0.255	

Table 4 with Market Environment Defined by CTA Index Return

	1		2		3		4		5		6	
Mo	-0.012		0.005		-0.036		-0.010		-0.012		0.000	
	-1.720	*	0.533		-4.392	***	-0.876		-1.071		-0.040	
Mo*Size	0.000		0.000		0.001		0.001		0.001		0.000	
	-0.458		-0.586		3.244	***	3.238	***	3.182	***	-0.422	
Mo*GoodMkt			-0.016				-0.036		-0.035		-0.017	
			-1.912	*			-3.196	***	-3.098	***	-1.731	*
GoodMkt			0.024						0.042			
			2.541	**					3.766	***		
LagRisk	-0.337		-0.344								-0.334	
	-14.909	***	-15.213	***							-14.696	***
Age	0.000		0.000		0.000		0.000		0.000		0.000	
	1.635		0.385		-2.349	**	-2.211	**	-2.068	**	1.664	*
Inflow	0.000		0.000		0.001		0.001		0.000		0.000	
	0.369		-0.550		1.372		1.278		0.217		0.331	
Mgmt Fee	0.011		0.066		0.031		0.031		0.037		0.011	
	0.186		1.066		0.491		0.503		0.549		0.195	
Incentive Fee	0.038		0.041		0.014		0.012		0.013		0.037	
	3.945	***	4.115	***	1.239		1.123		1.146		3.862	***
Intercept	0.020		-0.001		0.023		0.032		-0.011		0.025	
	3.901	***	-0.140		3.921	***	4.811	***	-1.193		3.932	***
R2	0.255		0.173		0.123		0.127		0.026		0.256	

Table 5 with Market Environment Defined by Mortality Rate										
	1		2		3		4		5	
Mo	-0.0088		0.0098		-0.0177		-0.0129		-0.0034	
	-1.6167		0.5169		-3.1097	***	-2.5250	**	-1.8331	*
Mo*Dis	-0.0305		-0.0368		-0.0017		-0.0063		-0.0063	
	-2.3347	**	-2.2593	**	-1.5759		-5.9940	***	-5.9908	***
Mo*GoodMkt			-0.0186						-0.0168	
			-0.4745						-0.2552	
Mo*Dis*GoodMkt			0.0048							
			-2.6181	***						
GoodMkt			0.0121							
			0.7115							
LagRisk	-0.3473		-0.3580				-0.3471		-0.3501	
	-15.1295	***	-14.7793	***			-15.0721	***	-14.7680	***
Dis	0.0245		0.0281							
	1.8456	*	1.9832	**						
Age	0.0001		-0.0001		-0.0001		0.0001		0.0001	
	1.6509	*	-0.2645		-1.4317		1.6476	*	1.6526	*
Inflow	0.0003		-0.0005		0.0011		0.0003		0.0003	
	0.5088		-0.4699		1.4913		0.5033		0.5015	
Mgmt Fee	0.0196		0.0920		0.0328		0.0239		0.0241	
	0.3386		1.3789		0.5274		0.4111		0.4127	
Incentive Fee	0.0393		0.0467		0.0132		0.0393		0.0394	
	4.1488	***	4.4862	***	1.1749		4.1340	***	4.1345	***
Intercept	0.0160		0.0011		0.0213		0.0200		0.0269	
	2.9055	***	0.3766		3.6769	***	3.8321	***	2.9131	***
R2	0.2622		0.1595		0.1213		0.2608		0.2608	

Table 5 with Market Environment Defined by CTA Index Return										
	1		2		3		4		5	
Mo	-0.0088		0.0067		-0.0177		-0.0129		0.0005	
	-1.6167		0.9077		-3.1097	***	-2.5250	**	0.0724	
Mo*Dis	-0.0305		-0.0283		-0.0017		-0.0063		-0.0064	
	-2.3347	**	-2.1907	**	-1.5759		-5.9940	***	-6.0955	***
Mo*GoodMkt			-0.0138						-0.0185	
			-1.4883						-1.9340	*
Mo*Dis*GoodMkt			-0.0046							
			-2.1772	**						
GoodMkt			0.0240							
			2.6101	***						
LagRisk	-0.3473		-0.3547				-0.3471		-0.3446	
	-15.1295	***	-15.5315	***			-15.0721	***	-14.8741	***
Dis	0.0245		0.0252							
	1.8456	*	1.9633	**						
Age	0.0001		0.0000		-0.0001		0.0001		0.0001	
	1.6509	*	0.1333		-1.4317		1.6476	*	1.6992	*
Inflow	0.0003		-0.0003		0.0011		0.0003		0.0003	
	0.5088		-0.4385		1.4913		0.5033		0.4641	
Mgmt Fee	0.0196		0.0783		0.0328		0.0239		0.0247	
	0.3386		1.2709		0.5274		0.4111		0.4241	
Incentive Fee	0.0393		0.0427		0.0132		0.0393		0.0384	
	4.1488	***	4.2756	***	1.1749		4.1340	***	4.0469	***
Intercept	0.0160		-0.0051		0.0213		0.0200		0.0247	
	2.9055	***	-0.6924		3.6769	***	3.8321	***	3.9436	***
R2	0.2622		0.1817		0.1213		0.2608		0.2618	