Gamma Trading Skills in Hedge Funds

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Abstract

This paper explores the gamma trading, timing and managerial skills of individual hedge funds across categories. We replicate the non-linear payoffs of hedge funds with traded options, with the option features being endogenously defined in our replication model. On top of providing a flexible tool to create individual benchmarks for the payoff curvature of hedge fund, the model helps assigning hedge fund styles into three categories: directional with market timing skills, non-directional and market timers. Overall, our empirical results show that, on 30% of replicated funds in our sample (10,958 funds), there is no evidence of the presence of selection skills once a fund performance is adjusted with respect to the option-based benchmark and the traditional option-based factors of Agarwal and Naik (2004). This research has an incremental potential to stimulate additional research in the field of hedge funds performance replication through passive strategies.

Keywords: Derivatives, Hedge Funds, Portfolio Management.

JEL classifications: G10, G12, G13.

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Introduction

Because hedge funds display option-like payoffs (Fung and Hsieh 2001; Mitchell and Pulvino 2001; Titman and Tiu 2011; Hübner, Lambert, and Papageorgiou 2015), the literature has designed option-based factors to capture the convex or concave nature of hedge funds' trades (Agarwal and Naik 2004; Fung and Hsieh 2004; Jurek and Stafford 2015; Agarwal, Arisoy, and Naik 2017). Despite the explanatory power provided by these factors, the methodologies used to construct these factors may lack flexibility when choosing the right type of options to trade as a result of the highly opportunistic nature of hedge fund trading. For example, among the most common option-based factors used in the literature, Fung and Hsieh (2004) evaluate the performance of funds using look-back straddles on bond, currency and commodity indices; however options on these indices are (1) not directly traded, (2) only valid for European-style options and (3) mature in a fixed interval of 3 months. Agarwal and Naik (2004) introduce option-based strategies that systematically buy on the first day of the month a call or a put option with pre-defined moneyness (at-the-money (ATM) or out-of-the-money (OTM)) and maturity (one month) on the S&P 500 index. Although widely accepted as explanatory variables in the hedge fund industry, the technical features of these option-based risk factors might not reflect an accurate replication of the dynamics of hedge fund strategies.[1]

Moreover, if a manager has free access to a complete traded derivatives market on the fund's benchmark, there are many ways in which she can distort the payoff of her portfolio and it is important to provide an adjustment to it (see, Hübner 2016; Ingersoll et al. 2007). Because option-like strategies such as hedge funds' exhibit a non-linear payoff, an evaluation of skills, which is associated with the intercept of a regression model, may be artificial. Indeed, the alpha of exotic investments with option-like payoffs from a typical linear regression is different from the alpha of a traditional portfolio (e.g., equities, bonds). The role of skills in these exotic investments should thus be contingently adjusted for the non-linearities in their payoffs. For instance, a quadratic model, such as the Treynor and Mazuy (1966) model to assess market timing skills, shifts (by construction) upward the alpha of a strategy that has a negative OLS coefficient on the quadratic term because

[1] For instance, as Jurek and Stafford (2015, p. 2198) note, "*options selected by fixing moneyness have higher systematic risk, as measured by delta or market beta, when implied volatility is high, and lower risk when implied volatility is low*". DeRoon and Karehnke (2017, p. 7) add that because "*these models effectively restrict additional assets to be a fixed linear combination of non-linear returns, they are unable to account for general forms of non-linearities*".

the average squared market return is positive (DeRoon and Karehnke 2017). This is confirmed in our data: funds with a positive OLS coefficient on the quadratic term deliver, on average, a negative alpha (between -0.40% and -0.27% per month), while funds with a negative OLS coefficient on the quadratic term show, on average, a positive alpha of between 0.60% and 0.95% per month. However, these funds with a negative quadratic term have a payoff resembling that of a short put option and appear to perform well in mean-variance frameworks because such frameworks fail to capture the left-tail risks of portfolios with non-linear payoffs (Agarwal and Naik 2004). Additional empirical studies (Coggin, Fabozzi, and Rahman (1993) and Jiang (2003)) also report evidence of an artificial negative correlation between the intercept and the quadratic coefficients.

To address the first issue regarding the flexibility in option-like payoffs, this paper examines and models the gamma trading of hedge funds. We evaluate cross-sectional timing skills among a large sample of hedge funds (using the consolidated sample from the merger of Hedge Fund Research (HFR) and Morningstar).

To address the second issue regarding the alpha biases, we provide an option-based adjustment of the alpha for funds with an option-like payoff. We apply a flexible, passive, option-based model that uses tradable options and serves as a benchmark to adjust the performance of a fund. This approach provides better accuracy for inferences distinguishing between "skilled" and "dumb" alpha – positive market timing versus shorting naked put options (Jurek and Stafford 2015). We show that the convexity or concavity of hedge funds' trades influences the assessment of fund managers' skills, and after combining our replication with standard option-like factors used in the literature, we observe almost no managerial skills for hedge funds during the sample period.

To achieve these objectives, we build on an option-based replication framework. This framework defines the option features ("the Greeks") that would match the non-linear payoffs captured by the linear and quadratic coefficients of the Treynor and Mazuy (1966, TM) model. The model works well because the Greeks of the option – i.e., Delta and Gamma – can be used to match the linear and quadratic terms of the TM model – i.e. beta and lambda. The option-based replication strategy is intended to be passive, such that the alpha from the strategy (the remaining Greek, Theta) can be viewed as a benchmark for the replicated fund performance. The performance of the fund is redefined as the outperformance with respect to this alpha.

To the best of our knowledge, this paper is the first to identify, at the individual level, a fund's option profile and the impact of the option profile on the fund's alpha and to adjust this alpha through a flexible option-based replication strategy. Our findings are twofold. First, our methodology categorizes the payoffs of approximately 30% of our hedge fund samples into three main categories: directional with market timing skills (long-short hedge funds), non directional/convergence bets (relative value, market-neutral) and market timing (multi-strategy, CTAs). Second, we show the impact of these non-linear payoffs on managerial skills. We find positive adjusted alpha for market timing skills with directional bets ($\sim$ 0.40% per month) and non-directional bets ($\sim$ 1.25% per month) but negative adjusted alpha for negative timing (short put, approximately -1.50% per month) and convergence bets (top straddles, approximately -1.00% per month). The adjustments strongly depend on the curvature of the payoff.

Although researchers may detect alpha when estimating multi-factor models, such findings could be due to luck or model misspecification. The definition of luck is thus commonly assessed through bootstrap analysis. Such bootstrapping methods circumvent small sample size issues by randomly selecting historical funds returns to reconstruct an empirical distribution of alpha t-statistics. This method enables us to test whether the actual alpha (or skill) generated by a fund is greater than the artificial alphas that arise from random selections (or luck). While many studies have been dedicated to developed bootstrapping methods to evaluate the persistence of performance in the fund industry (Kosowski, Timmermann, and Wermers 2006; Chen and Liang 2007; Jiang, Yao, and Yu 2007; Kosowski, Naik, and Teo 2007; Fama and French 2010; Cao et al. 2013), no prior work focuses specifically on the nature of the gamma trading of hedge funds and the implications that it has for evaluating their performance. In this paper, we employ Fama and French (2010)'s bootstrap method to assess the performance in our hedge fund sample after adjusting the funds' returns for the embedded gamma trading of the funds' trades (option-like profile). Our research has applications in performance analysis, as we show that after adjusting funds' returns for the non-linear payoffs from options, the residual cross-sectional distribution of alphas does not show any significance in our sample (see Figure 7f).

The rest of the paper is organized as follows. Section 1 extends the TM model under the option-based replication framework. Section 2 describes the option and hedge fund data used to perform the option-based replication of individual hedge fund returns. Section 3 presents the results in terms of goodness-of-fit and alpha correction. Section 4 provides robustness tests of our framework (in progress). Section 5 concludes on the different ways of constructing the option-based replication strategy and their implications for performance measurement.

1 Model

1.1 The Treynor and Mazuy Model and its Extensions

The quadratic regression model of Treynor and Mazuy (1966) is one of the classical return-based models to detect fund convexity from market timing skills. In this model, the timing skill of a fund manager is captured by the loading on the squared market return (quadratic term), and it detects ex post whether the manager participates, on average (although not systematically) in upward market movement and mutes losses in downward market movement. If the model detects such participation, then the fund's payoff with respect to the benchmark is convex and the manager is accorded the label "market timer". The quadratic model takes the following form:

$$R_{i,t} = \alpha_{TM} + \beta Rm_t + \gamma Rm_t^2 + e_t \tag{1}$$

where γ represents the coefficient of timing ability. A positive slope coefficient means that an investor participates, perhaps not systematically but rather on average, in bullish market trends. While this model is a classical approach to estimate the market timing skill of a fund manager, empirical evidence shows that the TM model may deliver a poor picture of skills (Kryzanowski, Lalancette, and To 1997; Becker et al. 1999; Bollen and Busse 2004; Comer, Larrymore, and Rodriguez 2009).

To improve the specification of the model, Chen and Liang (2007) integrate five lagged instruments that are conditional on the benchmark used in the TM model and control for "public information". By public information, the authors mean macroeconomic variables that may provide future information about the current economic conditions of the market (e.g., Ferson and Schadt 1996; Becker et al. 1999; Graham and Harvey 1996; Ferson and Siegel 2001; Jiang 2003). Indeed, Avramov et al. (2011) highlight the need to use conditional information to evaluate managers' market timing skills. The variables to control for public information are the demeaned series (over the analyzed fund period) of the three-month T-bill yield, the term spread between 10-year and three-month Treasury bonds, the quality spread between Moody's BAA- and AAA-rated corporate bonds, and the dividend yield of the S&P 500 index and the VIX. All variables are lagged by one period. The first four instruments are obtained from the Federal Reserve Bank of St. Louis, the dividend yield is retrieved from OptionMetrics, and the VIX is from CBEO from WRDS. Using the same notation as in Chen and Liang (2007), the model becomes

$$R_{i,t} = \alpha_{TM} + \beta Rm_t + \gamma Rm_t^2 + \sum_{l=1}^{L} \delta_l z_{l,t-1} Rm_t + e_t \tag{2}$$

with z_l being the demeaned (over the fund period) series of the lagged instruments. It remains unclear whether the intercept and the quadratic term ($\alpha_{TM} + \gamma Rm_t^2$) should be regarded as different sources of skills. Fama (1972) describe the former as the stock selection ability and the latter as the market timing skills of a manager. However, if one believes that the quadratic term (γRm_t^2) can be passively replicated, then the only source of skill that can be counted as performance is the intercept of the TM model (α_{TM}). We follow the idea of Hübner (2016) and introduce an option-based replication strategy that is intended to replicate the linear and quadratic terms of the TM model, and we adjust the intercept using that of the passive option-based replication strategy. In the next section, we describe in greater detail the framework used to replicate the curvatures of a fund's payoff.

1.2 Option Replication Strategy

Building on the framework of Treynor and Mazuy (1966), a growing stream of literature has investigated the ability of hedge funds to anticipate the variations of market returns and other variables such as liquidity and volatility (Cao et al. 2013) or even market returns and volatility simultaneously (Chen and Liang 2007). These studies support that the ability to time these variables can be identified as a source of superior hedge fund performance. Evidence also indicates that a sub-sample of these funds exhibits such timing abilities even after accounting for option-based risk factors. In contrast to traditional option-based risk factors cited in the recent literature, such as Fung and Hsieh (2004), Agarwal and Naik (2004) and Jurek and Stafford (2015), the derivative-based replication strategy offers a flexible choice of the option's moneyness and maturity at each observed period. The aim of the strategy is to select, in each month, the option that best replicates the linear and quadratic terms of the TM model (or its extensions) at the individual fund level.

Because the option Greeks in the OptionMetrics database are not normalized according to the underlying stock price and the price of the option, we first need to normalize the option Greeks based on the Taylor expansion of the option value (V). The option can take the form of either a call or a put option, such that our final equation resembles the equation in the TM model. From the Taylor series expansion, the approximation of the option value (V) on a security with price S at time t is obtained by

$$dV \approx \frac{\partial V}{\partial S} dS + \frac{1}{2}\frac{\partial^2 V}{\partial S^2}(dS)^2 + \frac{\partial V}{\partial t} dt + o(t) \tag{3}$$

with $\frac{\partial V}{\partial S}$ being the Delta of the option (Δ_v), $\frac{\partial^2 V}{\partial S^2}$ being the Gamma of the option (Γ_v), and $\frac{\partial V}{\partial t}$ being the time decay of the option, named Theta (Θ_v). The remaining term $o(t)$ incorporates the Vega, Rho, and higher moment effects on the change in the option value. We consider this term to be close to zero for short periods of time, such that we make the assumptions that the volatility of the underlying (σ^2) and the interest rate (r) are constant. Moreover, controlling for the VIX and the three-month T-bill in the conditional TM model leaves us fairly confident that setting aside the Greeks vega and rho should not strongly impact the results of the replication model.

Substituting the Greek annotations into equation (3) we have,

$$dV \approx \Delta_v dS + \frac{1}{2}\Gamma_v (dS)^2 + \Theta_v dt + o(t) \tag{4}$$

Writing equation (4) in discrete time yields

$$V_t - V_{t-\Delta t} = \Delta_v (S_t - S_{t-\Delta t}) + \frac{1}{2}\Gamma_v (S_t - S_{t-\Delta t})^2 + \Theta_v \Delta t \tag{5}$$

where V_t is the price of the option for the underlying S_t, and Δt is the time interval and is equal to one month (1/12). Finally, the normalization of the option return and its Greeks takes the following form when the underlying stock S_t is substituted by the market M_t:

$$R_t^v = \underbrace{\frac{M_{t-\Delta t}}{V_{t-\Delta t}}\Delta_v}_{\text{(1) Normalized Delta}} Rm_t + \frac{1}{2}\underbrace{\frac{M_{t-\Delta t}^2}{V_{t-\Delta t}}\Gamma_v}_{\text{(2) Normalized Gamma}} Rm_t^2 + \underbrace{\frac{\Theta_v}{V_{t-\Delta t}}}_{\text{(3) Normalized Theta}} \Delta t \tag{6}$$

with $R_t^v = (V_t - V_{t-\Delta t})/V_{t-\Delta t}$ and $Rm_t = (M_t - M_{t-\Delta t})/M_{t-\Delta t}$. We have (1) the normalized Delta, (2) the normalized Gamma, and (3) the normalized Theta of the option.[2] For the sake of clarity, we refer, in the remainder of the paper, to the normalized Delta as Δ, the normalized Gamma as Γ, and the normalized Theta as Θ. The approximation of the option return using the Taylor expansion is written as follows:

[2]According to Ivy Option Metric's reference manual (version 3.1 1/11/2017, p. 22), "the theta of an option indicates the change in option premium as time passes, in terms of dollars per year". In our analysis, the annualized theta is thus multiplied by 1/12 (Δt) to scale the value to a monthly basis.

$$R_t^v = \Delta_v Rm_t + \frac{1}{2}\Gamma_v Rm_t^2 + \Theta_v \Delta t \tag{7}$$

with R_t^v being the return of the option over the interval Δt (1-month), Δ_v, Γ_v, Θ_v being the normalized Delta, Gamma and Theta of the option, respectively, and Rm_t being the return of the underlying stock index (S&P 500) at time t.

1.3 Replication with One Option

The process to achieve the option-based replication strategy can be described in two steps. The first step consists in finding, in each period, the option that best fits the linear and quadratic terms of the TM model by filtering the options list and finding the option with the closest match to the ratios $2\Delta_{\tau,\kappa}/\Gamma_{\tau,\kappa} = \beta/\gamma$.

The closest match attributes one option with maturity (τ) and moneyness (κ) to each monthly return observation of a fund. Compared to classic option-based factors, our model does not pre-define the choice of the maturity and moneyness of the option.

The second step is to solve for the weight (w) that satisfies the following conditions:

$$\begin{cases} \beta = w\Delta_{\tau,\kappa} \\ \gamma = w\frac{1}{2}\Gamma_{\tau,\kappa} \end{cases} \tag{8}$$

The replication strategy also has budget constraints that are satisfied by solving for the exposure w to the selected option and allocating a proportion $(1-w)$ to the risk-free rate. To replicate the payoff of a fund manager with a directional bet (β) and a non-directional bet (γ), the model takes the following form:

$$R_t^{\tau,\kappa} = w(\Delta_{\tau,\kappa} Rm_t + \frac{1}{2}\Gamma_{\tau,\kappa} Rm_t^2 + \Theta_{\tau,\kappa}) + (1-w)Rf_t + o(\Delta t) \tag{9}$$

where $\Delta_{\tau,\kappa}$, $\Gamma_{\tau,\kappa}$, and $\Theta_{\tau,\kappa}$ are the normalized Delta, Gamma and Theta of an option with maturity (τ) and moneyness (κ), Rm_t is the return of the underlying stock index (S&P 500) at time t, and w is the weight allocated to the selected option. The intercept (hereafter, alpha) of the passive strategies composed of a single option is given by

$$\alpha^{\tau,\kappa} = w\Theta_{\tau,\kappa} + (1-w)Rf_t \tag{10}$$

Because this alpha comes from a purely passive strategy, its value can be used to adjust fund performance by subtracting $\alpha^{\tau,\kappa}$ from the traditional alpha of the TM model:

$$\begin{aligned} \pi^{\tau,\kappa} &= \alpha^{'}_{TM} - \alpha^{\tau,\kappa} \\ &= \alpha^{'}_{TM} - w\Theta_{\tau,\kappa} + (1-w)Rf_t \end{aligned} \tag{11}$$

with $\alpha^{'}_{TM} = \alpha_{TM} + (1-\beta)Rf_t$.

Depending on the sign and significance level[3] of the parameters (β and γ), the replication strategy will either be long ($w > 0$) or short ($w < 0$) one type of option, i.e., a call or a put. For instance, a positive exposure to both the market, $\beta > 0$, and convexity, $\gamma > 0$, forces the strategy to be a long position ($w > 0$) in single call option on the benchmark index (here, the S&P 500) and the remainder of the portfolio ($1-w$) to be invested in the risk-free asset (Rf – the one-month T-Bill from Ibbotson). Conversely, a negative exposure to the market, $\beta < 0$, and a positive convexity, $\gamma > 0$, entails a long position ($w > 0$) in single put option. A short position in a call (put) is triggered when the exposure to the market is positive (negative) and the convexity is negative, $\gamma < 0$. To better visualize the payoffs of these strategies, we display in Figure 1 the quadratic fit function of the average fund performance with a payoff identified as a long or short call option (left plots). Plots on the right display the average curvature of the fund replicated by either a long or short put option with respect to the market return.

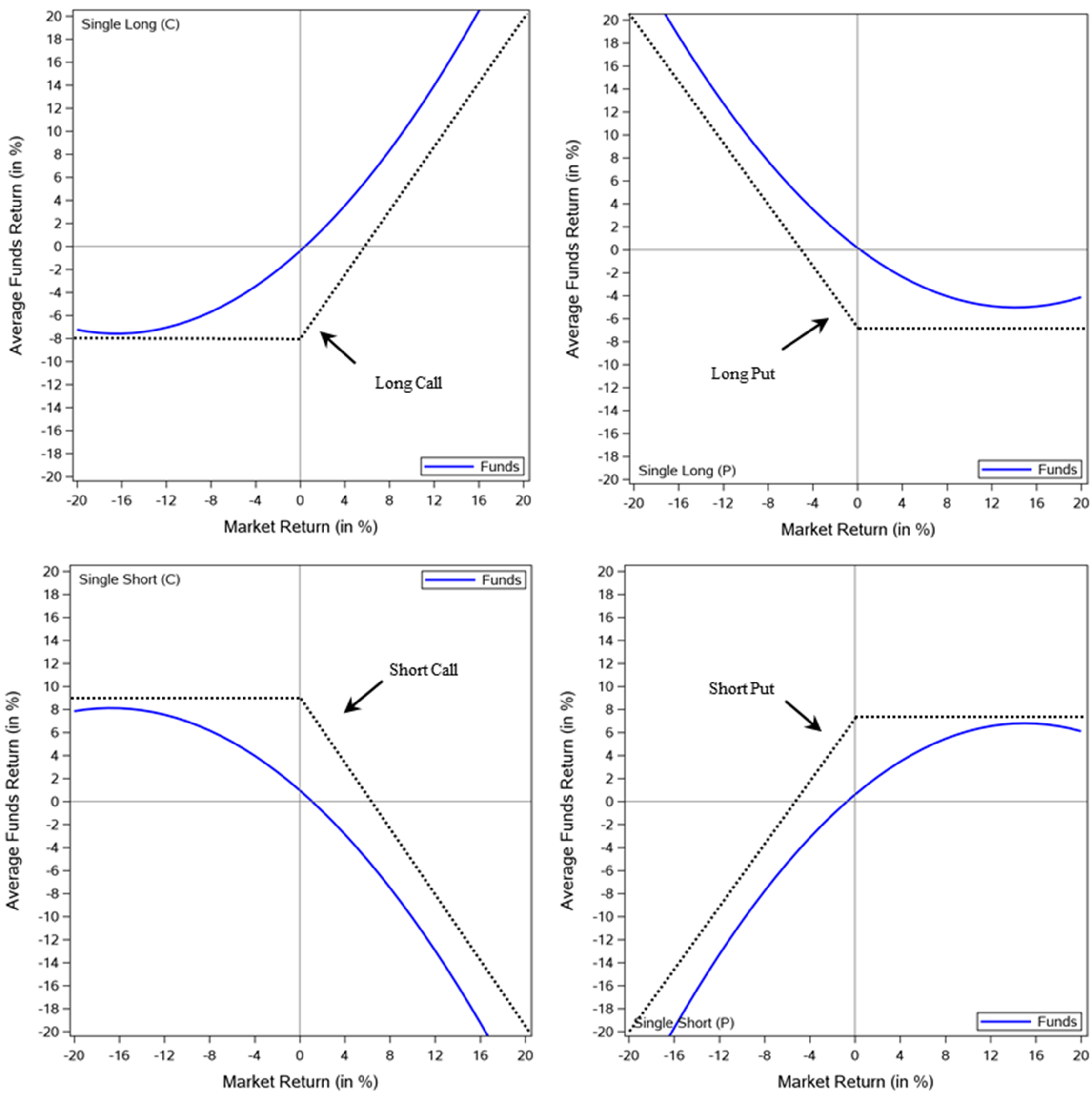
1.4 Replication with Two Options

Thus far, we have described the method to replicate the payoffs of funds with a significant directional bet ($\beta \neq 0$). However, some hedge fund strategies may seek to have no directional bet. The most well-known hedge fund strategy intended to achieve this objective is known as the market-neutral strategy. We identify the replication of strategies with a neutral directional bet and a positive and significant non-directional bet as a long (bottom) straddle and as a short (top) straddle when the non-directional bet is negative and significant. The situation of a market neutral fund cannot be replicated by a simple strategy involving just one call or one put. To create an option portfolio with a zero (or very low) Delta and positive or negative Gamma, the appropriate strategy is the bottom or the top straddle. The bottom (top) straddle consists of going simultaneously long

[3] Note that in our applications, we use the Newey-West adjustment for standard errors and apply a lag of t=3.

Figure 1: Call and Put Payoffs

The figure represents the average curvatures of hedge funds with a $\beta > 0$ or $\beta < 0$ and $\gamma > 0$ or $\gamma < 0$. For illustrative purposes, we report the payoff functions of a long call and put in the upper left and right plots, respectively. We report the payoff functions of a short call and put in the lower left and right plots, respectively. We estimate the quadratic fit function of an average fund's performance (blue line) by averaging the coefficients of the Treynor and Mazuy model over the funds with significant coefficients. The convexity is then reconstructed with respect to the market returns (from -20% to 20%). The figures are illustrated with respect to the market returns.



(short) on a call and a put with the same strike and maturity. To activate the straddle, the portfolio beta, which is close to zero, is separated into two parts: a long part $\beta^+ > 0$ and a short part $\beta^- < 0$. To ensure the identical convexity of each option, we set $\gamma = \gamma^+ + \gamma^-$, where $\beta^+/\gamma^+ = -\beta^-/\gamma^-$. Using the same subscripts as the original author for the Greeks of the call option (+) and the put option (-), the performance of this non-directional fund is given by

$$\begin{aligned} R_t^{\tau,\kappa} &= w_{\tau,\kappa}^+(\Delta_{\tau,\kappa}^+ Rm_t + \frac{1}{2}\Gamma_{\tau,\kappa}^+ Rm_t^2 + \Theta_{\tau,\kappa}^+) \\ &+ w_{\tau,\kappa}^-(\Delta_{\tau,\kappa}^- Rm_t + \frac{1}{2}\Gamma_{\tau,\kappa}^- Rm_t^2 + \Theta_{\tau,\kappa}^-) \\ &+ (1 - w_{\tau,\kappa}^+ - w_{\tau,\kappa}^-)Rf_t + o(\Delta t) \end{aligned} \tag{12}$$

The first step to filter the options list is modified from that in the last subsection, and we should now find the *call* and *put* options with the closest match to the following ratio: $\Delta_{\tau,\kappa}^+/\Gamma_{\tau,\kappa}^+ = -\Delta_{\tau,\kappa}^-/\Gamma_{\tau,\kappa}^-$.

The second step attributes one call and one put option with the same maturity (τ) and moneyness (κ) to each monthly return observation of a fund. The weights (w^+ and w^-) are then solved to find

$$\begin{cases} \beta = w_{\tau,\kappa}^+\Delta_{\tau,\kappa}^+ + w_{\tau,\kappa}^-\Delta_{\tau,\kappa}^- \\ \gamma = \frac{1}{2}(w_{\tau,\kappa}^+\Gamma_{\tau,\kappa}^+ + w_{\tau,\kappa}^-\Gamma_{\tau,\kappa}^-) \end{cases} \tag{13}$$

Alternatively,

$$\frac{\beta}{\gamma} = \frac{2(w_{\tau,\kappa}^+\Delta_{\tau,\kappa}^+ + w_{\tau,\kappa}^-\Delta_{\tau,\kappa}^-)}{w_{\tau,\kappa}^+\Gamma_{\tau,\kappa}^+ + w_{\tau,\kappa}^-\Gamma_{\tau,\kappa}^-} \tag{14}$$

The alpha of the passive strategies composed of a call and put option is given by

$$\alpha^{\tau,\kappa} = w_{\tau,\kappa}^+\Theta_{\tau,\kappa}^+ + w_{\tau,\kappa}^-\Theta_{\tau,\kappa}^- + (1 - w_{\tau,\kappa}^+ - w_{\tau,\kappa}^-)Rf_t \tag{15}$$

The adjustment from the passive strategy is done by adjusting the fund performance by subtracting $\alpha^{\tau,\kappa}$ from the original alpha of the TM model. In Figure 2, we illustrate the quadratic function of the average fund performance with a payoff identified as a short (long) position in both a call and a put option in the left (right) plot.

Another reason that the replication of a fund payoff with a single option may not be sufficient is that some funds are categorized as single call or put strategies only because the model or the

Figure 2: Straddle Payoffs

The figure represents the average curvature for hedge funds with an insignificant $\beta = 0$ and $\gamma > 0$ or $\gamma < 0$. For illustrative purposes, we report in the left plot the payoff of the bottom straddle strategy (long call and long put), while the right plot displays the payoff of the top straddle strategy (short call and short put). We estimate the quadratic fit function of an average fund's performance (blue line) by averaging the coefficients of the TM model over the funds with significant quadratic coefficients. The convexity is then reconstructed with respect to the market returns (from -20% to 20%).

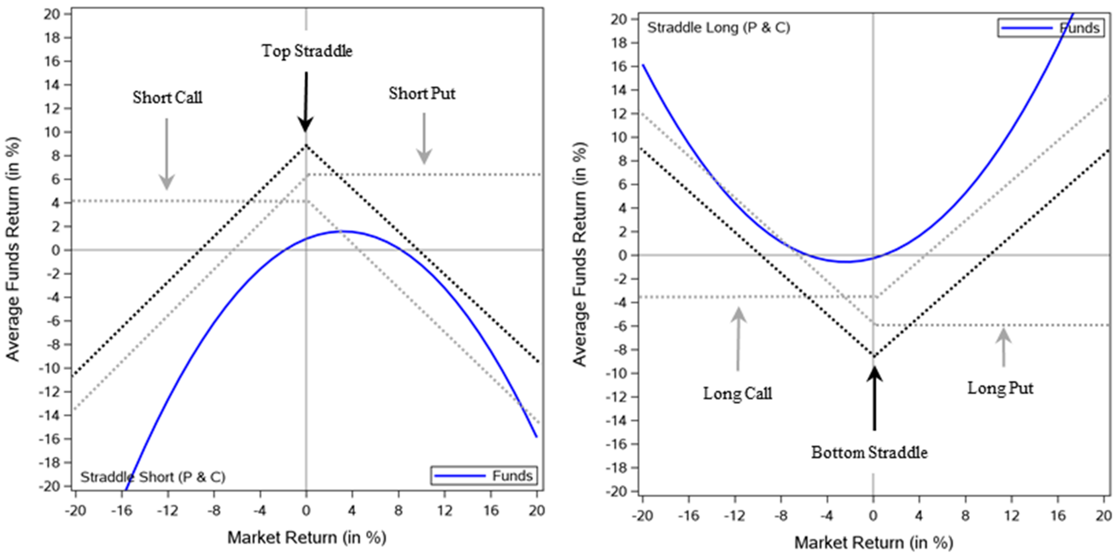
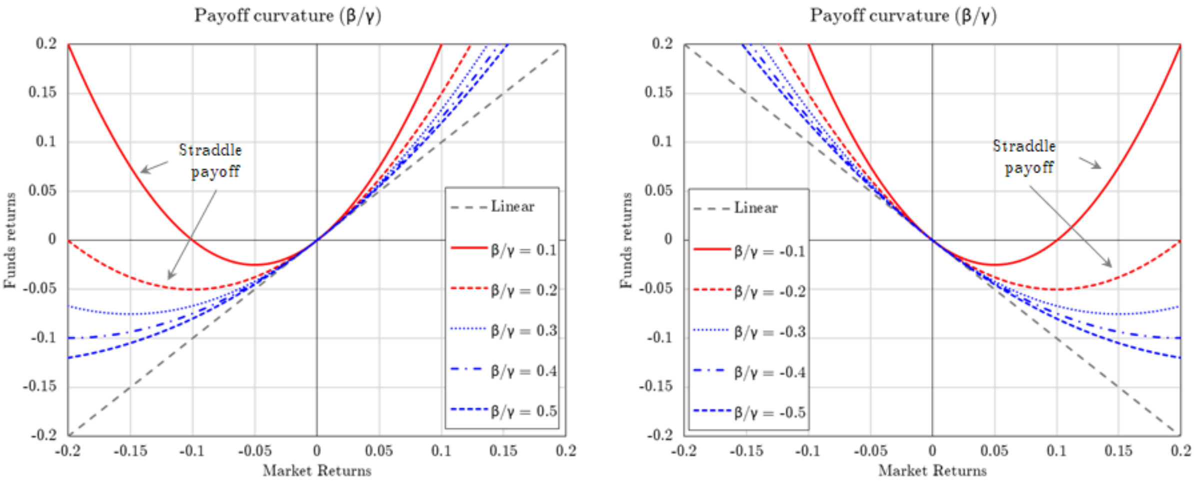


Figure 3: Payoff Curvatures

The figure represents the curvature of a hypothetical fund with a β of 1 and a ranges of different ratios β/γ. For illustrative purposes, we report in the left plot the payoff when the sign of the β is positive and in the right plot the payoff when the sign of the β is negative. In this case, both funds have positive market timing skills ($\gamma > 0$). The convexity is reconstructed with respect to the market returns (from -20% to 20%).



benchmark is misspecified. Thus, we end up with a very high γ and, hence, very low ratio ($|\beta/\gamma|$). However, the payoff estimated from a quadratic regression clearly resemble that of a straddle, as displayed in Figure 3. At least, this is what the regression estimates tell us – regardless of the R^2 of the model. In the first picture, we show that the payoff for a ratio lower than 0.2 tends to resemble that of a bottom straddle. Note that this 0.2 cutoff works for realistic values of market returns (from -20% to 20% on a monthly basis).

To identify a fund's payoff, we impose the condition that if a fund has a ratio $|\beta/\gamma|$ lower than 0.20, then its payoff should be replicated through a straddle strategy. Although this threshold seems arbitrary, it nevertheless visually appears to be a natural cutoff for identifying a fund's payoff as a straddle.

In Table 1, we report a summary of the model procedures to replicate a fund's payoff according to both the loading of the parameters and the significance threshold of the parameters' p-values.

In the next section, we describe the consolidated data obtained (1) from OptionMetrics (WRDS) for the options and their Greeks and (2) from the merger of HFR and Morningstar databases for our hedge funds sample.

Table 1: Option Replication Strategies

This table summarizes the types of strategies involving options that replicate all possible patterns of the TM regression. In our applications, we use a significance level of 10% for the p-values of the linear and quadratic parameters. This table presents the payoff identifications to apply the option-based replication strategies.

	Quadratic Exposure	
Directional exposure	$\gamma > 0$	$\gamma < 0$
$\beta > 0$ and $\lvert\beta/\gamma\rvert > 0.2$	Long call	Short put
$\beta \approx 0$ or $\lvert\beta/\gamma\rvert < 0.2$	Bottom straddle	Top straddle
$\beta < 0$ and $\lvert\beta/\gamma\rvert > 0.2$	Long put	Short call

2 Data

2.1 Options and Greeks

OptionMetrics provides data on the historical price, implied volatility and Greeks for the US equity and index options markets. We restrict our use of OptionMetrics data to the Standard and Poor's (S&P) 500 composite index (ID 108105) and retrieve options with a standard settlement date, that is, where the special settlement flag (ss_flag) is equal to 0, with positive bid and ask prices, and the options expire on the Saturday following the third Friday of the month (Agarwal and Naik 2004).[4] We only retain observations from the first day of each month for which the open interest (volume) is greater than zero and that have valid implied volatility and Delta. Our sample period ranges from January 1996 to December 2015.

2.2 Hedge Funds

2.2.1 Merger of the databases

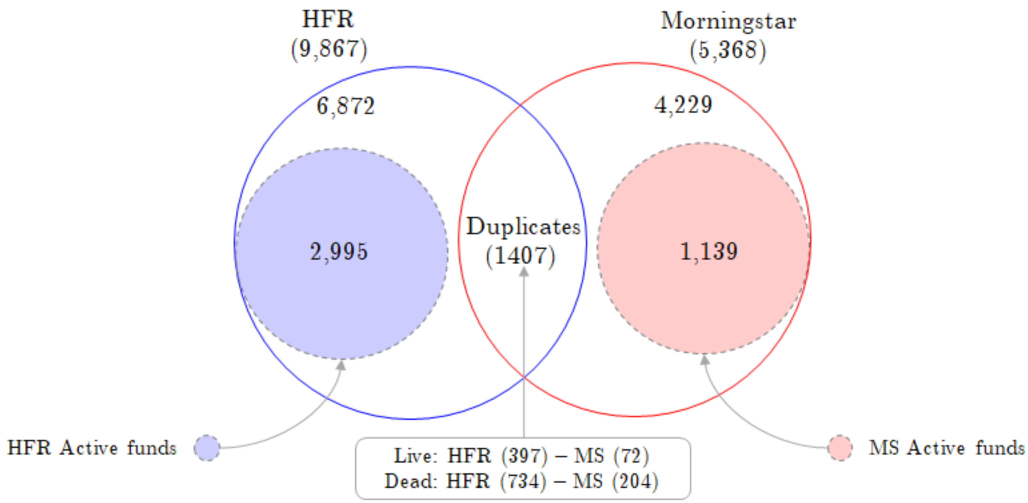
In this paper, we employ a sample of hedge funds from the merger of the HFR and Morningstar databases. To carry out the merger, we follow the procedures of Joenväärä, Kosowski, and Tolonen (2016). Because merging multiple databases is not an exact science, in addition to the phrase

[4]The restrictions are identical to those used in the replication of the option risk factors of Agarwal and Naik (2004) developed by WRDS.

matching[5] used by the authors, we extend the identification of duplicate funds with a similar level of the smoothing index following the procedure of Getmansky, Lo, and Makarov (2004). The combination of a close match from the smoothing index and the phrase matching procedure gives fairly good results to identify duplicates in our databases. Indeed, this combination allows us to work simultaneously on the name and the returns of a fund (see Section 2.2.2 for further details). In the appendix of this paper, we describe the treatments applied prior to constructing our consolidated sample of hedge funds.

Figure 4: Illustration of the Database Coverage

This figure illustrates the coverage of hedge funds in our consolidated database after treatments. The diagram displays the overlap -– by database — of the share classes as of December 2015.



We illustrate in Figure 4 that the number of active and dead funds that are specific to each database after treatments is equal to 6,872 and 2,995 for HFR and to 4,229 and 1,139 for Morningstar, respectively. Concerning the duplicates, the Venn diagram shows that there is a total of 1,407 duplicates between HFR and Morningstar, of which 397 active funds are attributed to HFR, 72 active funds are attributed to Morningstar, 734 dead funds are attributed to HFR, and 204 dead funds are attributed to Morningstar. To choose whether a fund should belong to one database or the other, we select the fund from the provider that reports the most observations – generally HFR in our sample.

[5]The Jarko-Wink procedure matches funds that achieve a high correlation percentage (99%) in the name of their funds.

Because each database reports different hedge funds classifications, Joenväärä, Kosowski, and Tolonen (2016) propose categorizing hedge funds into twelve primary strategies. We also follow their approach, such that our results can be easily replicated using other providers' data. Table 2 shows the categories documented in this paper and the table that Joenväärä, Kosowski, and Tolonen (2016) use to construct these primary strategies can be found in the appendix of this paper. Our final sample contains 10,958 of the 15,235 unique funds that we identified in our databases. The sample period ranges from January 1996 to December 2015. Of the full sample, 3,805 are funds of funds and 4,357 are equity-oriented funds. Finally, 4,282 remained alive as of December 31, 2015, and 11,227 became defunct during the sample period.

2.2.2 Unsmoothed return

Hedge funds are prone to performance manipulations (Ingersoll et al. 2007). Specifically, Getmansky, Lo, and Makarov (2004) focus on the issue of "performance smoothing," which is a common practice in the hedge fund industry to artificially reduce fund volatility by reporting only a fraction (X%) of the gains in a month and retaining the other fraction (1-X%) to compensate for potential future losses.[6] This practice tends to smooth the performance of a fund and makes mean-variance risk measures, such as the Sharpe ratio, appear more attractive. To address this misleading smoothing phenomenon, it is common practice to first "unsmooth" observed returns and then conduct performance evaluation on the resulting adjusted returns (Kosowski, Naik, and Teo 2007; Aragon 2007; Titman and Tiu 2011; DeRoon and Karehnke 2017). Getmansky, Lo, and Makarov (2004) proposed the following model of return smoothing:

$$R_t^0 = \theta_0 R_t + \theta_1 R_{t-1} + ... + \theta_k R_{t-k} \tag{16}$$

where R_t^0 is the observed return, R_t is the true return of a fund and θ_k is the loading on the k^{th} lag of the realized return. In the model, θ_k values are constrained to fall within an interval from zero

[6] For instance, Agarwal, Bakshi, and Huij (2009) reveal that hedge funds tend to manage returns and earn higher fees by retaining gains in early parts of the year and reporting them in December. Huang, Liechty, and Rossi (2012) demonstrate how retaining gains to offset future losses increases a fund's alpha by reducing its beta coefficients. In other words, reducing return volatility (smoothing returns) turns risk (β) into performance (α). Finally, Asness, Krail, and Liew (2001) show that lagged market returns are often significant explanatory variables for the returns of supposedly market-neutral hedge funds.

Table 2: Funds Coverage across Primary Strategies

This table reports the number of funds that fall into the primary strategies as defined by Joenväärä, Kosowski, and Tolonen (2016) after applying the treatments used in their paper. We report the number of funds conditional on the original database, that is, Hedge Fund Research (HFR) or Morningstar (MS). The last column indicates whether the category is included in our empirical analysis.

	HFR (Dead)	HFR (Live)	MS (Dead)	MS (Live)	Total	Included (Y/N)
CTA	537	197	310	122	1166	Yes
Emerging Markets			121	22	143	No
Event Driven	480	240	133	51	904	Yes
Fund of Funds	1631	574	1354	246	3805	No
Global Macro	37	27	206	54	324	Yes
Long Only			67	83	150	No
Long/Short	1867	872	1234	384	4357	Yes
Market-Neutral	348	88	133	19	588	Yes
Multi-Strategy	932	518	193	59	1702	Yes
Relative Value	697	373	206	59	1335	Yes
Sector	302	104			406	Yes
Short Bias	41	2	99	34	176	Yes
Undefined			173	6	179	No
Total	6872	2995	4229	1139	15235	
Total Selected	5241	2421	2514	782	10958	

to one and to sum to one. In common application, k is set to 2 such that smoothing takes place only over the current quarter (i.e., the current month and the previous two months), and the observed return is a weighted average of the fund's true returns over the most recent three months (k+1), including the current period. This averaging process captures the essence of smoothed returns in several respects. The true unsmoothed return is then obtained by inverting the previous equation as follows:

$$R_t = \frac{R_t^0 - \hat{\theta}_0 R_t - \hat{\theta}_1 R_{t-1} - ... - \hat{\theta}_k R_{t-k}}{\hat{\theta}_0} \tag{17}$$

The procedure is applied through a moving average (MA) process using maximum likelihood estimation for the parameters. The model also imposes two additional restrictions: (1) the process should be applied on demeaned returns and (2) be invertible. In the rest of our analysis, we use unsmoothed returns for the principal reason that return-smoothing behavior yields a more consistent set of returns over time with lower volatility and, therefore, a higher Sharpe ratio. Similar to DeRoon and Karehnke (2017), we note that the adjustment for smoothing does increase the average volatility from 3.58% to 4.49% in our sample, which leads to a decrease in the average fund's Sharpe ratio from 0.23 to 0.15 per month. However, it leaves the mean returns fairly unchanged, i.e., average raw returns (0.54%) and average unsmoothed returns (0.51%). Finally, we also use the measure of smoothing index to filter the duplicates in our database (as described in the previous section). The smoothing index is computed as follows:

$$\xi = \sum_{j=0}^{k} \theta_j^2 \in [0, 1] \tag{18}$$

where θ_j are the parameters from the MA process estimated in equation (16). The smoothing index is often compared to the Herfindhal index, as it gives an estimate from 0 to 100% of the smoothing behavior of a fund. An index value of zero implies substantial smoothing behavior in a fund's returns, while an index of one suggests no smoothing.

2.3 Instrumental variables

In Table 3, we report the descriptive statistics of the variables used in the empirical part of this paper. Panel A displays the average return, standard deviation, and the minimum and maximum of the S&P 500 index over the sample period ranging from January 1996 to December 2015. We also report the first-order auto-correlation estimate and its respective p-value as in Chen and Liang (2007). In Panel B, we report the option-based factors using the same notations as in the original work of Agarwal and Naik (2004) and Fung and Hsieh (2004).

For the option-based factors developed in Agarwal and Naik (2004), the ATM call option on the S&P 500 index is denoted SPCa, SPPa represents the ATM put option, SPCo represents the OTM call option, and SPPo denotes the OTM put option strategy. These option-based risk factors are based on a strategy that buys on the first day of the month an option (call or put) with a fixed moneyness of ATM or OTM on the S&P 500 and a maturity of one month. The option is then sold on the first day of the next month, and a new option with the same moneyness and maturity is bought back to continue the process of the strategy. The option-based factors from Fung and Hsieh (2004) are the return of a portfolio of lookback straddles on bond futures (PTFSBD), on currency (foreign exchange) futures (PTFSFX), on commodity futures (PTFSCOM), on short term interest rate (PTFSIR) and on the stock market (PTFSSTK).[7] Panel C reports the instrumental variables defined in Section 1.1, that is, the three-month T-bill yield (TB3MS), the term spread between 10-year and three-month Treasury bonds (T10Y3M), the quality spread between Moody's BAA- and AAA-rated corporate bonds (Quality spread), and the dividend yield (Rate) of the S&P 500 index and the end-of-the-month VIX divided by $\sqrt{12}$ to form the monthly estimate of market volatility as in Chen and Liang (2007).

Before determining whether the adjustment of the intercept is valid, it is important to assess the efficiency of the replication fit for the linear and quadratic terms of the TM model. Section 3.1 is devoted to this evaluation.

3 Hedge Funds' Gammas and Corrected Alphas

To determine whether the robustness of the identification of the funds' payoff provides a plausible alpha adjustment. We first analyze the fit of the parameters from the option-based replication strategy. We then review the characteristics of the selected options of the strategies, i.e., the average moneyness and maturity of the options. We finally test the degree of intercept correction delivered by the strategy on the funds' alpha through a bootstrap test similar to Fama and French (2010).

[7] All the information is available on David Hsieh's website.

Table 3: Variables: Descriptive Statistics

This table reports the descriptive statistics of the variables used to explain hedge funds' returns. We display, from Panels A to C, the average return, standard deviation, minimum and maximum of and the first order auto-correlation with its respective p-value for the following list of variables: the S&P 500 index, the ATM call option on the S&P 500 (SPCa), the ATM put option on the S&P 500 (SPPa), the OTM call option on the S&P 500 (SPCo), the OTM put option strategy on the S&P 500 (SPPo), the return of a portfolio of lookback straddles on bond futures (PTFSBD), on currency (foreign exchange) futures (PTFSFX), on commodity futures (PTFSCOM), on short term interest rate (PTFSIR) and on the stock market (PTFSSTK), the three-month T-bill yield (TB3MS), the term spread between 10-year and three-month Treasury bonds (T10Y3M), the quality spread between Moody's BAA- and AAA-rated corporate bonds (Quality spread), and the dividend yield (Rate) of the S&P 500 index and the end-of-the-month VIX divided by $\sqrt{12}$, which forms the monthly estimate of market volatility (VIX m). The sample period ranges from January 1996 to December 2015.

	Mean	STD	Min.	Max.	ρ_1	p-value
Panel A: Benchmark						
S&P 500	0.006	0.044	-0.169	0.108	0.069	0.980
Panel B: Option-based Factors						
SPCa	-0.025	0.821	-0.996	2.417	-0.034	1.000
SPCo	-0.036	0.874	-0.995	3.000	-0.041	0.999
SPPa	-0.218	0.858	-0.966	3.332	0.119	0.756
SPPo	-0.247	0.875	-0.971	3.459	0.129	0.677
PTFSBD	-0.018	0.149	-0.266	0.689	0.108	0.832
PTFSFX	-0.005	0.186	-0.300	0.692	0.042	0.999
PTFSCOM	0.001	0.145	-0.247	0.648	-0.033	1.000
PTFSIR	-0.013	0.264	-0.351	2.219	0.216	0.080
PTFSSTK	-0.049	0.145	-0.302	0.666	0.139	0.590
Panel C: Instruments						
TB3MS	0.024	0.022	0.000	0.062	0.991	0.000
T10Y3M	0.017	0.012	-0.008	0.038	0.963	0.000
Rate	0.018	0.005	0.000	0.028	0.872	0.000
Quality_spread	0.010	0.004	0.006	0.034	0.960	0.000
VIX_m	6.101	2.270	3.008	17.289	0.829	0.000

3.1 Fit of the Replication Strategies

There are many potential choices of measures to assess the quality of fit of a replication strategy. Amenc et al. (2010) argue that natural and straightforward measures are the correlation coefficient and the beta of the clone strategy with the fund's returns. However, the authors emphasize that despite being natural candidates to evaluate a clone strategy, these directional measures also present some shortcomings. For instance, they only concentrate on the volatility rather than the returns of the strategy. Thus, Amenc et al. (2010) suggest complementing the information from the correlation/beta with measures that better track the errors of fit of the clone strategy, namely the annualized root mean squared error (RMSE) and the annualized geometric average excess return (AER). According to all of these measures, the results suggest that the fit of our replications is statistically acceptable, for instance, if we assess the quality of fit through the beta of the replication strategy with respect to the initial fund's return. We can express the OLS regression as follows:

$$R_t^{TM} = \beta R_t^{OB} + e_t \tag{19}$$

where $R_t^{TM} = \beta Rm_t + \gamma Rm_t^2$ are the linear and quadratic parameters of the TM model, and $R_t^{OB} = w\Delta_v Rm_t + w\frac{1}{2}\Gamma_v Rm_t^2$ are the equivalent parameters estimated from the option-based strategy. The null hypothesis of the t-test is simply $H_0 : \beta - 1 = 0$.

This approach tests whether the replication strategies perform well at replicating the convexity/concavity of a fund that exhibits a significant quadratic coefficient in the TM model. If the beta is not statistically different from one, then we can conclude that the quality of the fit is good because the linear and quadratic terms of the replication strategy are statistically similar to the linear and quadratic terms of the fund.

If, however, we are interested in assessing the fit by tracking error measures, Amenc et al. (2010) propose using the annualized root mean squared error (RMSE) and the annualized geometric average excess return (AER). The authors explain that the first risk measure can be considered the tracking error of the clone strategy and defined formally as

$$RMSE = \sqrt{\frac{12}{T}\sum_{t=1}^{T}(R_t^{OB} - R_t^{TM})^2} \tag{20}$$

where R_t^{TM} and R_t^{OB} are the returns from the linear and quadratic terms of the TM model and the option-based replication strategy, respectively. T is the fund's total number of observations. Concerning the second measure (AER), Booth and Fama (1992) explain that the geometric average return is an useful performance measure because it represents the growth rate that an investor would have earned if she had held a portfolio since day one. Thus, in addition to yielding information on the portfolio's arithmetic average return (μ), it also captures the variation of the portfolio's returns (volatility, σ). Motivated by the characteristics of the traditional geometric average return, Amenc et al. (2010) extend the measure to a geometric AER to capture the both the first- and second-order moments in the measurement of the replication strategy. They annualize the metric to provide a more economically sensible interpretation of the results. The annualized geometric AER is thus defined as

$$AER = \left[\prod_{t=1}^{T} (1 + R_t^{OB} - R_t^{TM})^{\frac{12}{T}} \right] - 1 \tag{21}$$

where a low (high) RMSE tells us that the quality of fit of the replication is good (bad), and the AER is an indicator of under- or over-performance of the replication strategy compared to the actual hedge fund return.

We first report in Table 4 a similar test to that in Glosten and Jagannathan (1994) to analyze the cross-sectional distribution of the t-statistics. The table displays the distribution of the t-statistics using the Bonferroni correction for the p-values. The results suggest that there is no evidence that the model poorly replicates the funds' payoffs. Indeed, the Bonferroni p-values for the minimum and maximum t-statistics are always higher than 10%. This suggests that we cannot statically reject the hypothesis that the payoff replication strategy is different from the fund's payoff. Interpretations are similar if we replace the Bonferroni correction with FDR (false discovery rate) methods.[8] Note further that some funds' payoff being identified as a "straddle payoff" might be false discoveries because of benchmark or variable misspecification or low R^2 values that lead to a high γ. However, at a minimum, the results suggest that we can correctly replicate funds' payoffs with the single call and put strategies. Moreover, we need not be particularly concerned about finding the perfect model that explains the cross-section of hedge fund returns to have the correct β and γ estimates. The rationale is that we know that false (or poor) identifications will be more likely identified as a straddle payoff because of a low ratio ($|\beta/\gamma|$), and our model is nevertheless able to accurately

[8] These results are, however, not reported for the sake of brevity.

replicate the payoffs of such strategies. The correction of the intercept is thus conditional on the payoff identification and provides a benchmark for those false identifications.[9]

Table 4: Distribution of the Replication Fit

This table report the cross-sectional distribution of the t-statistics. We report the number of hedge funds that fall within a payoff identification and provide their respective proportion in the sample. An examination of the minimum and maximum t-statistics are displayed with a Bonferroni correction of the p-values. A p-value higher than 10% suggests that we cannot statically reject the hypothesis that the payoff replication strategy is different from a fund's payoff at the 90% confidence level.

	Long	Short	Long	Short	Long	Short
	Single Call		Single Put		Straddle (Call & Put)	
# Fund	(497)	(19)	(7)	(324)	(1,204)	(1,227)
Proportion	15.20%	0.60%	0.20%	9.90%	36.70%	37.40%
Min t	-2.446	-1.377	-0.874	-2.529	-3.877	-2.682
Bonferroni p	1.000	1.000	1.000	1.000	0.504	1.000
Average t	0.009	0.286	-0.007	0.077	-0.014	-0.062
Max t	2.938	2.627	1.229	2.710	2.727	3.004
Bonferroni p	1.000	0.218	1.000	1.000	1.000	1.000
Number with t-stat						
t <-2.326	4	0	0	1	8	11
-2.326< t <-1.96	8	0	0	6	15	15
-1.96< t <-1.645	20	0	0	7	35	24
-1.645< t <0	220	6	3	130	552	595
0< t <1.645	210	11	4	163	547	534
1.645< t <1.96	21	0	0	13	29	37
1.96< t <2.326	8	1	0	3	13	9
2.326< t	6	1	0	1	5	2

To obtain further details in the assessment of the primary strategies' fit, we report in Table 5 the results for the categories defined in Joenväärä, Kosowski, and Tolonen (2016) of the average RMSE (eq. (20)) and AER (eq. (21)) in Panels A and B, respectively. Both measures suggest that our model produces, on average, a good quality of fit – the RMSE and AER are close to zero. We also report in Panel C the number of funds that falls in each primary strategy and option replication strategies. In total, we have 3,278 that have significant quadratic coefficients at the 10% confidence

[9]To mitigate the likelihood of false payoff discoveries, one could complement the model with traditional equity risk-factors, i.e., the factors of Fama and French (1993) (SMB, HML) or Carhart (1997) (UMD), to improve the R^2 of the model as in Fung and Hsieh (2011). However, due to the low degrees of freedom available in hedge fund samples, researchers generally seek to keep their models parsimonious. We did not include these factors for the same reason.

level, which represents approximately 30% of our sample (10,098 funds). A substantial number of hedge funds that exhibit a payoff resembling a short position in a put option on the market index are identified as Event Driven or Long/Short hedge funds. We report in the appendix the result of Table 5 when the option risk factors are added to regression model. Results and interpretations goes in the same direction.

Mitchell and Pulvino (2001) document that merger arbitrage strategies, a sub-category of Event Driven, indeed have a payoff resembling that of a short put option because this strategy takes a long position in the stock of the target company in the merger and a short position in the acquiring company. In bad economic conditions, this type of strategy will be more likely to fail and thus exhibit losses. In fact, writing put options may appear effective in a mean-variance framework, but this strategy performs poorly when we consider moments higher than the second order (DeRoon and Karehnke 2017). These types of strategies bear significant tail risks because writing a put option on the market index may severely impact fund performance when strong bearish trends affect the equity market (Agarwal and Naik 2004). Table 6 shows that funds with short put option payoffs have, on average, a negative skewness (-0.677) and positive kurtosis (6.596). Because these (extreme) returns are mostly captured by the third and fourth moments and may be ignored in traditional mean-variance frameworks, these last authors highlight that non-linear risk returns in hedge funds translate into significant loadings on the risk factor using the OTM put option.

Overall, the assessment of funds' identification payoffs seems in line with previous studies. We present our evidence by primary categories and attribute one option payoff to the highest proportion of funds that correspond to that option strategy.

CTA: Long straddle payoff, i.e., exhibits a trivial directional bet and has a similar payoff to straddle strategies (Fung and Hsieh 2004);

Event Driven: Short put or straddle payoff, i.e., strategies that are more likely to fail and exhibit consequent losses (Mitchell and Pulvino 2001).

Global Macro: Straddle payoff, i.e., market timers with a neutral bet on the benchmark (Fung and Hsieh 2001).

Long/Short: Single call payoff, i.e., a directional bet with timing abilities.

Table 5: Measures of Replication Fit by Primary Strategy

This table presents the average RMSE from eq (20) and AER from eq (21) in Panels A and B, respectively. Panel C reports the number of hedge funds that falls into a primary strategy, and Panel D reports the proportion of these funds in each primary strategy.

Primary Strategy	Long Single Call	Short Single Call	Long Single Put	Short Single Put	Long Straddle	Short Straddle	All Payoffs	Long Single Call	Short Single Call	Long Single Put	Short Single Put	Long Straddle	Short Straddle	All Payoffs
	Panel A: RMSE							Panel B: AER						
CTA	-0.0075	0.0073	-0.0137	0.0160	-0.0143	0.0188	-0.0050	0.0001	-0.0001	0.0002	0.0002	0.0000	0.0000	0.0000
Event Driven	-0.0053			0.0178	-0.0142	0.0161	0.0087	-0.0001			0.0000	0.0000	0.0000	0.0000
Global Macro	-0.0062	0.0102			-0.0171	0.0235	-0.0002	0.0001	0.0001			0.0000	0.0000	0.0000
Long/Short	-0.0084	0.0113	-0.0082	0.0231	-0.0189	0.0236	0.0057	0.0000	0.0000	-0.0004	-0.0001	0.0000	0.0000	0.0000
Market-Neutral	-0.0035	0.0070		0.0118	-0.0090	0.0116	0.0029	0.0001	0.0001		-0.0010	0.0000	0.0000	0.0000
Multi-Strategy	-0.0064		-0.0125	0.0148	-0.0149	0.0178	-0.0045	0.0000		0.0000	-0.0001	0.0000	0.0000	0.0000
Relative Value	-0.0061	0.0135	-0.0036	0.0252	-0.0114	0.0165	0.0061	-0.0001	-0.0001	0.0001	-0.0002	0.0000	0.0000	0.0000
Sector	-0.0080			0.0204	-0.0245	0.0358	0.0077	0.0001			0.0004	0.0000	0.0000	0.0001
Short Bias	-0.0148	0.0130	-0.0257	0.0194	-0.0132	0.0155	0.0087	0.0003	-0.0002	0.0003	-0.0001	0.0000	0.0000	0.0000
All Strategies	-0.0078	0.0113	-0.0147	0.0212	-0.0152	0.0196	0.0027	0.0000	-0.0001	0.0001	-0.0001	0.0000	0.0000	0.0000
	Panel C: # Observations							Panel D: Proportion of Funds by Primary Strategy						
CTA	21	1	2	9	255	93	381	5.5%	0.3%	0.5%	2.4%	66.9%	24.4%	11.6%
Event Driven	19			43	54	150	266	7.1%	0.0%	0.0%	16.2%	20.3%	56.4%	8.1%
Global Macro	7	3			51	37	98	7.1%	3.1%	0.0%	0.0%	52.0%	37.8%	3.0%
Long/Short	320	8	1	188	262	429	1208	26.5%	0.7%	0.1%	15.6%	21.7%	35.5%	36.9%
Market-Neutral	11	1		4	59	83	158	7.0%	0.6%	0.0%	2.5%	37.3%	52.5%	4.8%
Multi-Strategy	49		1	29	358	145	582	8.4%	0.0%	0.2%	5.0%	61.5%	24.9%	17.8%
Relative Value	38	1	1	22	137	234	433	8.8%	0.2%	0.2%	5.1%	31.6%	54.0%	13.2%
Sector	29			21	22	32	104	27.9%	0.0%	0.0%	20.2%	21.2%	30.8%	3.2%
Short Bias	3	5	2	8	6	24	48	6.3%	10.4%	4.2%	16.7%	12.5%	50.0%	1.5%
All Strategies	497	19	7	324	1204	1227	3278	15.2%	0.6%	0.2%	9.9%	36.7%	37.4%	100.0%

Market-Neutral: Short straddle payoff, i.e., a neutral bet on the market with the objective of profiting from mispricing and not from market timing (Chen and Liang 2007).

Multi-Strategy: Long straddle payoff, i.e., a neutral bet on the market with the objective of smoothing return volatility from strategy diversification.

Relative Value: Short straddle payoff, i.e., uncorrelated with the market, employing a convergence strategy on mispriced securities and likely to face strong fixed-income exposures during a market decline (Gatev, Goetzmann, and Rouwenhorst 2006; Chen and Liang 2007).

Sector: Mixed payoffs, i.e., this category is specific to HFR data and regroups a combination of directional and non-directional bets.

Short Bias: Short call, put or straddle, i.e., sell short overvalued securities and face substantial risk during good market conditions (Agarwal and Naik 2004).

3.2 Replication Strategies' Characteristics

In this section, we review the main characteristics of the selected options in the replication strategies. Table 7 displays the average values of the selected options to replicate a fund's performance. For instance, a fund with positive market timing skills (positive linear and quadratic terms) can be replicated by investing, on average, 11% of the strategy's capital in a call option with a moneyness of 1.07 and a maturity of 275 days ($\sim$ 9 months). While the moneyness of the selected options is fairly stable across the strategies, i.e., OTM call and put for single-instrument replications and ATM call and put for the straddle strategies, the maturity of the options are more flexible for single-instrument strategies, i.e., a larger standard deviation. For the straddle strategies, the selection of ATM options is consistent with the idea that the Gamma of the straddle is the highest for ATM options. Furthermore, our model forms straddle strategies by selecting a maturity of approximately 5 months ($\sim$ 150 days) and appears stable whether the strategies are long or short in the straddle. The five-month maturity is close to the quarterly expiration date for the options used in the look-back straddles of Fung and Hsieh (2001).

Market timers were originally identified as having a similar payoff as a long straddle strategy (Merton 1981). Fung and Hsieh (2004) use ATM options to construct the straddle. Although Siegmann and Lucas (2003) instead suggest using OTM options, the choice of moneyness for the

Table 6: Option-like Payoff Strategies: Descriptive Statistics

This table summarizes the descriptive statistics of the funds that are identified according to their option payoffs. The results are averaged for each payoff category. We report in Panel A the number of funds, the number of non-missing monthly observations, the mean, the standard deviation (STD), the skewness, the kurtosis and the Jarque-Bera coefficient to test the normality of returns. The significance of the parameter estimates are reported as performed: *, **, and *** and indicate statistical significance at the 0.1, 0.05 and 0.01 levels, respectively. The distribution of the returns is briefly reported with the minimum, 25th percentile (Q1), median, 75th percentile (Q3) and maximum. In Panel B, we display the descriptive statistics of the regression coefficients, that is, the alpha, beta and lambda. We also report the average ratio (beta/lambda), the adjusted R^2, the maximum drawdown (Max DD) and the level of the smoothing index of the funds.

Panel A: Descriptive Statistics of the Returns

	# Funds	# Monthly Obs	Mean	STD	Skew.	Kurt.	JB	Min.	Q1	Median	Q3	Max.
Long Call	497	110	0.075	0.189	-0.054	4.909	77***	-0.157	-0.025	0.007	0.037	0.171
Long Put	7	130	0.013	0.196	0.446	4.623	25***	-0.161	-0.032	-0.001	0.031	0.206
Short Call	19	85	0.001	0.2	0.093	4.51	24***	-0.155	-0.034	0.001	0.029	0.155
Short Put	324	115	0.085	0.197	-0.677	6.596	180***	-0.203	-0.021	0.01	0.039	0.166
Bottom Straddle	1204	94	0.081	0.166	0.31	6.163	169***	-0.124	-0.021	0.005	0.031	0.169
Top Straddle	1227	82	0.066	0.173	-0.787	10.151	915***	-0.187	-0.017	0.007	0.029	0.147
Unreplicated	7678	91	0.074	0.171	-0.13	6.515	293***	-0.15	-0.02	0.006	0.032	0.158

Panel B: Descriptive Statistics of the Regressions

	# Funds	Alpha	Beta	Lambda	Ratio	Adj R^2	Max DD	Smoothing
Long Call	497	-0.004	0.875	2.665	0.366	0.474	-0.358	0.675
Long Put	7	0.002	-0.736	2.603	-0.336	0.427	-0.462	0.855
Short Call	19	0.01	-0.854	-2.549	0.383	0.426	-0.44	0.746
Short Put	324	0.006	0.827	-2.756	-0.336	0.492	-0.395	0.675
Bottom Straddle	1204	-0.003	0.259	5.404	0.075	0.201	-0.247	0.716
Top Straddle	1227	0.009	0.395	-6.18	-0.083	0.293	-0.31	0.652
Unreplicated	7678	0.003	0.463	-0.03	-8.002	0.244	-0.299	0.671

Table 7: Selected Options: Descriptive Statistics

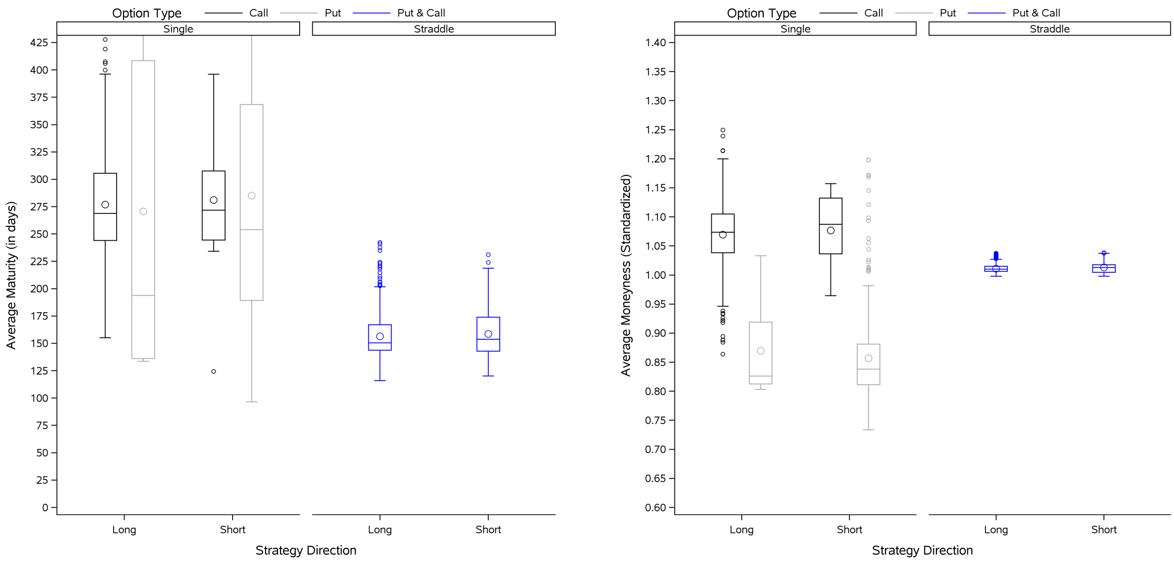
This table summarizes the average weight invested in the option-based strategy, the normalized Greeks (Delta, Gamma and Theta), and the moneyness and maturity according to the types of strategy involving options that replicate all possible patterns of the TM regression. Standard deviations of the average values are reported in parentheses.

		Long	Short	Long	Short	Long Straddle		Short Straddle	
Characteristics		Single Call		Single Put		Call	Put	Call	Put
Weight (w)	Mean	0.11	0.09	0.11	0.12	0.13	0.13	0.14	0.15
	STD	(0.07)	(0.08)	(0.04)	(0.08)	(0.13)	(0.15)	(0.17)	(0.19)
Delta (Δ)	Mean	10.92	11.07	-7.64	-8.62	16.76	-15.07	16.66	-14.97
	STD	(2.45)	(2.27)	(0.93)	(2.16)	(2.21)	(2.17)	(2.55)	(2.49)
Gamma (Γ)	Mean	73.3	76.01	46.29	62	211.86	192.47	210.37	191.07
	STD	(37.3)	(35.94)	(12.43)	(31.9)	(52.76)	(48.87)	(59.73)	(55.39)
Theta (Θ)	Mean	-0.11	-0.13	-0.15	-0.21	-0.21	-0.2	-0.21	-0.18
	STD	(0.05)	(0.05)	(0.04)	(0.14)	(0.02)	(0.03)	(0.02)	(0.04)
Moneyness (κ)	Mean	1.07	1.09	0.82	0.85	1.01	1.01	1.01	1.01
	STD	(0.05)	(0.06)	(0.04)	(0.08)	(0.01)	(0.01)	(0.01)	(0.01)
Maturity in days (τ)	Mean	275	269	328	291	153	153	158	158
	STD	(46)	(48)	(52)	(113)	(18)	(18)	(20)	(20)

Figure 5: Moneyness and Maturity of Options

This figure presents the distribution of the average maturity (in days) and moneyness of the selected options according to the types of strategies that replicate all possible patterns in the TM regression. The box plots for the call, put and straddle option strategies are depicted in black, gray and blue, respectively. The results are presented in days for the maturity (a) and in percentages for the moneyness (b). The boxes show the 5th percentile and 95th percentile of the distribution of the variables on the y-axis, and the mean of the distribution is represented by the dots inside the boxes. The dots outside the boxes are the outliers of the distribution.

(a) Maturity **(b)** Moneyness



Fung and Hsieh factors is clearly in line with our results. The danger with OTM options is that they rely on betting that the market will be volatile to make profits. If the market movement does not move in the same direction as the bet, than the time decay of the options (Theta, Θ) will quickly and strongly impact the intercept of the replication strategy, and in our model, the impact will be approximately 1.5 to 2 times stronger for replication strategies using a put rather than a call option. Figure 5 illustrates the distribution of the average maturity and moneyness of the selected options with respect to the strategy that the model attempts to replicate.

3.3 Alpha Adjustment

Managerial skill is by definition the part of the return in excess of any systematic sources of risk and attributed to the alpha of a multi-factor regression analysis (Agarwal, Mullally, and Naik 2015, p. 16). However, it is conceptually unclear whether the quadratic term of the TM model should be considered a systematic source of risk. The term can be viewed as a statistical artifact to measure the manager's exposure to the market movements. According to Fama (1972), who defined a fund manager's skills as consisting of both market timing and stock selection ability, it is clear that the combination of the intercept and the quadratic term ($\alpha_{TM} + \gamma Rm_t^2$) should naturally be regarded as skills. But, if we believe that the quadratic term (γRm_t^2) could easily be replicated by a passive strategy, then the only source of skill left in the equation is the intercept of the TM model (α_{TM}). As the replication model of Hübner (2016) satisfies the condition of passively replicating the linear and quadratic term of the TM model, the adjustment of the intercept (α_{TM}) should reflect a manager's true skill at security selection relative to a passive benchmark.

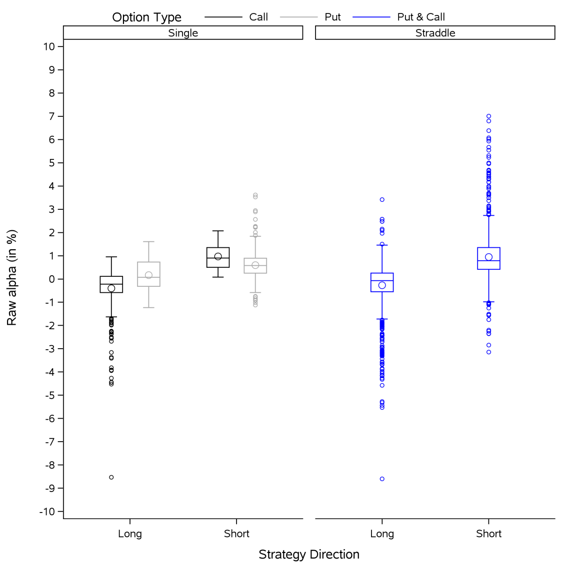
We illustrate in Figure 6 the distribution of the raw and adjusted alpha estimates from the original TM model with respect to the type of strategy the replication model attempts to replicate. Plot (a) displays the raw alphas, while Plot (b) displays the distribution of the adjusted alphas. In Plot (a), we see that a fund that times the market, namely, one with a positive quadratic term that is replicated by being long in a single call option, delivers, on average, a negative "naive" alpha ($\sim$ -0.40% per month). Conversely, a fund that resembles being in short a single put option delivers a positive "naive" alpha ($\sim$ 0.60% per month). However, while writing put options may appear successful in a mean-variance framework, it performs poorly when we consider moments higher than the second order (DeRoon and Karehnke 2017). In Plot (b), having the same alpha but adjusting the intercept from option-based replication strategy substantially changes the overall picture; the "dumb" alpha from writing put options shrinks from $\sim$ 0.60% to roughly -1.50% per month, while the alpha of a market timer is now raised from -0.40% to 0.40% per month.

A more granular analysis across hedge funds' primary strategies is provided in Table 8. The table presents, across strategies, the average raw alpha (Panel A) and the average alpha from the option replication strategies (Panel B). The adjusted alpha is simply the difference between Panel A and Panel B. Panel C reports the average adjusted R^2 of the model, and Panel D presents the average ratio $|\beta/\gamma|$ of the funds. We report in the appendix the results in Table 8 when the option

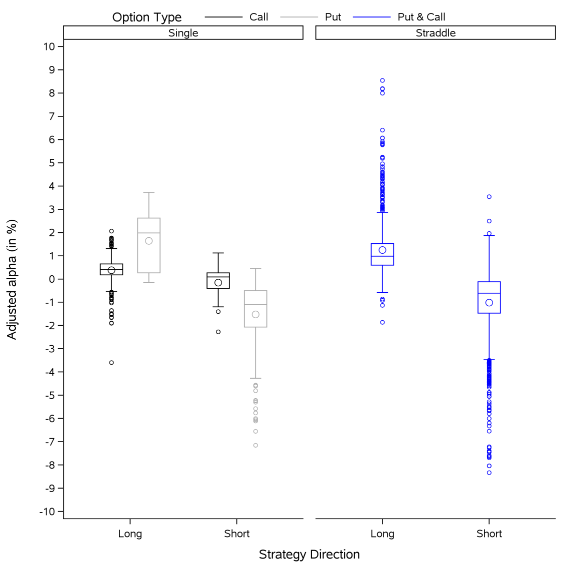
Figure 6: Raw and Adjusted Alphas

This figure shows the distribution of the raw (a) and adjusted (b) alpha estimates of hedge funds, α'_{TM} and $\pi^{\tau,\kappa}$ from eq (11), respectively. The regression model used in this analysis includes the TM variables and the instrumental variables that control for public information. The results are reported according to the types of strategies involving options that replicate all possible patterns of the regression model. The box plots for the call, put and straddle option strategies are depicted in black, gray and blue, respectively. The results are presented in percentages and on a monthly basis. The boxes show the 5th percentile and 95th percentile of the distribution of the variables on the y-axis, and the mean of the distribution is reported by the dots inside the boxes. The dots outside the boxes are the outliers of the distribution.

(a) Raw Alphas



(b) Adjusted Alphas



risk factors are added to regression model. The interpretations remain similar.

Kosowski, Naik, and Teo (2007) demonstrate, however, that assessing the performance of a fund based solely on the alpha coefficient of a regression model is misleading because the errors of the estimation are not considered in the performance evaluation. These errors lead to spurious outliers, which may be identified as good or bad performers, by chance. As a result, recent performance evaluations have been performed based on the normalization of the coefficient through the t-statistics ($t(\alpha)$) of the alpha and bootstrap methods. We explain in the next subsection Fama and French (2010)'s bootstrap test, in which the $t(\alpha)$ of a fund is considered to judge whether its performance is persistent or simply driven by luck.

3.3.1 Bootstrap Evaluation of Skills

This section evaluates the abnormal return for the actual funds and identifies whether the alpha correction from the option-based replication plays a significant role in understanding fund managers' skills. To perform this exercise, we employ the bootstrap procedure proposed by Fama and French (2010) to check whether the distribution of well and poorly performing funds remains the same before and after our alpha adjustment.[10] Fama and French (2010) compare the actual cross-section of mutual funds' alphas to a simulated cross-section of bootstrapped alpha in a world of zero true alpha (no timing or selection abilities). In this section, we transpose the procedure to our sample of hedge fund returns using the extensions of the TM regression models described in the prior sections.

Kosowski, Naik, and Teo (2007) emphasize two difficulties in evaluating the performance of hedge funds: first the difficulty of benchmarking dynamic hedge fund strategies and, second, the fact that adding alternative risk factors might reduce misspecifications in the model. Concerning the benchmark issue, we know that although the S&P 500 is probably not the most appropriate benchmark for evaluating the cross-section of hedge funds, it is nevertheless the most frequently used benchmark in literature. The interpretation of our results should thus not diverge from other studies based on the choice of this benchmark. Regarding the model specification, we complement the quadratic regression model of TM with option-based risk factors. Note that when a model of option risk factors is added to the TM model, we also re-estimate the linear and quadratic coefficients from equation (2) and re-identify the payoffs. In addition to improving the estimation of the regression

[10]Our bootstrap procedure is similar to that of Kosowski, Timmermann, and Wermers (2006), Chen and Liang (2007), Jiang, Yao, and Yu (2007), Kosowski, Naik, and Teo (2007), and Cao et al. (2013).

Table 8: Alpha Correction: Descriptive Statistics

This table decomposes the average alpha correction per primary strategy. Panel A reports the average raw alpha, while Panel B presents the average alpha from the option replication strategies per primary strategy. The adjusted alpha is simply the difference between Panel A and Panel B. In Panel C, we report the average adjusted R^2 of the regression model used to identify the option payoff of a fund. Finally, Panel D presents the average ratio $|\beta/\gamma|$ in each primary strategy.

Primary Strategy	Long Single Call	Short Single Call	Long Single Put	Short Single Put	Long Straddle	Short Straddle	All Payoffs	Long Single Call	Short Single Call	Long Single Put	Short Single Put	Long Straddle	Short Straddle	All Payoffs
	Panel A: Alpha							Panel B: Alpha Correction						
CTA	-0.0039	0.0098	0.0007	0.0041	-0.0019	0.0090	0.0008	-0.0075	0.0073	-0.0137	0.0160	-0.0143	0.0188	-0.0050
Event Driven	-0.0013			0.0063	-0.0037	0.0104	0.0060	-0.0053			0.0178	-0.0142	0.0161	0.0087
Global Macro	-0.0015	0.0122			-0.0025	0.0105	0.0029	-0.0062	0.0102			-0.0171	0.0235	-0.0002
Long/Short	-0.0043	0.0098	0.0161	0.0061	-0.0055	0.0090	0.0019	-0.0084	0.0113	-0.0082	0.0231	-0.0189	0.0236	0.0057
Market-Neutral	0.0023	0.0096		0.0050	-0.0011	0.0072	0.0037	-0.0035	0.0070		0.0118	-0.0090	0.0116	0.0029
Multi-Strategy	-0.0026		0.0073	0.0048	-0.0022	0.0096	0.0011	-0.0064		-0.0125	0.0148	-0.0149	0.0178	-0.0045
Relative Value	-0.0051	0.0177	0.0024	0.0053	0.0001	0.0090	0.0048	-0.0061	0.0135	-0.0036	0.0252	-0.0114	0.0165	0.0061
Sector	-0.0059			0.0072	-0.0074	0.0194	0.0042	-0.0080			0.0204	-0.0245	0.0358	0.0077
Short Bias	-0.0157	0.0065	-0.0077	0.0071	-0.0001	0.0099	0.0055	-0.0148	0.0130	-0.0257	0.0194	-0.0132	0.0155	0.0087
All Strategies	-0.0040	0.0097	0.0017	0.0060	-0.0027	0.0095	0.0026	-0.0078	0.0113	-0.0147	0.0212	-0.0152	0.0196	0.0027
	Panel C: R^2-adjusted							Panel D: Ratio $\|\beta/\gamma\|$						
CTA	0.5170	0.4229	0.2740	0.4531	0.1373	0.2264	0.1889	0.3540	0.3851	0.2383	0.3122	0.0556	0.0645	0.0821
Event Driven	0.3612			0.4598	0.2808	0.3044	0.3288	0.3282			0.3067	0.0928	0.0855	0.1401
Global Macro	0.3014	0.4197			0.1673	0.2862	0.2295	0.3421	0.6069			0.0684	0.0685	0.1045
Long/Short	0.4920	0.3072	0.4842	0.5054	0.2828	0.3293	0.3897	0.3740	0.2636	0.4341	0.3550	0.1142	0.0994	0.2165
Market-Neutral	0.4613	0.1615		0.6377	0.1550	0.1709	0.1969	0.3433	0.2131		0.6021	0.0740	0.0587	0.0990
Multi-Strategy	0.4959		0.3156	0.4614	0.1779	0.2957	0.2484	0.3849		0.3595	0.3273	0.0615	0.0795	0.1070
Relative Value	0.4136	0.3120	0.3111	0.5413	0.2261	0.3016	0.2998	0.3322	0.2921	0.2102	0.2518	0.0633	0.0705	0.1012
Sector	0.3903			0.4350	0.1837	0.2058	0.2989	0.3447			0.3120	0.1148	0.1003	0.2142
Short Bias	0.6104	0.6962	0.6669	0.4325	0.1586	0.2818	0.3712	0.2598	0.4931	0.4349	0.2784	0.1102	0.0775	0.1846
All Strategies	0.4739	0.4260	0.4275	0.4917	0.2007	0.2930	0.3072	0.3658	0.3834	0.3358	0.3363	0.0755	0.0831	0.1505

coefficients (Goetzmann, Ingersoll, and Ivković 2000), this method enables us to adapt the alpha correction for the option-like profiles of a fund. The alternative standard models include the option-based factors of Agarwal and Naik (2004) and the look-back straddle factors of Fung and Hsieh (2004). These models are standard asset pricing models used in the hedge fund industry that allow us to determine whether the alpha adjustment from our option-based replication strategy is either subsumed by or complementary to these widely accepted option risk factors. The rationale behind this test is that if our alpha correction is simply an alternative exposure to different risk-factors, then the correction should be captured by one of these models. Our evidence suggests, however, that the alpha adjustment is not composed of "exotic risk exposures" (Agarwal and Naik 2004) but is an isolated component (that arises from the flexibility of our model) that explains the skills of a fund manager. We describe the bootstrap procedure in the four following steps.

The first step consists in estimating the actual alphas of the hedge funds using a multi-factor model. In our application, we use the TM model augmented with conditional lagged instruments described in Section 2.3 and/or the option-based risk factors of Fung and Hsieh (2004) or Agarwal and Naik (2004):

$$R_t^i - Rf_t = \alpha^i + \beta^i Rm_t + \gamma^i Rm_t^2 + \sum_{l=1}^{L} \delta_l^i z_{l,t-1} Rm_t + \sum_{k=1}^{K} \beta_k^i OF_k + e_t^i \tag{22}$$

where R_t^i stands for the i^{th} hedge fund's return, and Rf_t is the risk-free rate (the one month T-bill from Ken French's website) at time t. $z_{l,t-1}$ denotes for the conditional lagged instruments, and OF_k stands for the option-based factors of Fung and Hsieh (2004) or of Agarwal and Naik (2004). We still consider the S&P 500 as a proxy for the market return (Rm_t). We also assume that $e_t^i \sim N(0, \sigma^2)$.

In the second step, we subtract the estimated α^i of each of the individual funds from its return (R_t^i) to construct a time series of zero-alpha returns, i.e., $(R_t^i - \alpha^i)$. As Cao et al. (2013, p. 499) note, this step ensures that the procedure generates "*hypothetical funds that, by construction, have the same factor loadings as the actual funds but have no timing ability*". In other words, the beta parameters remain unchanged. However, in our case, as the market timing ability is already captured by the quadratic terms, the only ability left in the model is the manager's skill at picking well performing stocks (security selection).

In the third step, we jointly[11] resample the zero-alpha returns with the factor returns (Rm_t and Rm_t^2). The joint resampling ensures that we capture the cross-sectional correlation between the fund returns in our sample and the explanatory variables. One run of the bootstrap works as follows: we randomly select a date from our sample of 239 monthly observations (from February 1996 to December 2015) and draw a selection, with replacement, of date observations of the same size as our original time frame (239 monthly observations). The time series is equivalent for the whole funds universe. We retain only funds with more than 36 observations in this run. As explained in Fama and French (2010), this procedure preserves the cross-sectional and time-series dependence across funds and explanatory variables. The bootstrap is composed of 1,000 runs (denoted b for bootstrapped) and estimates the alpha and t-statistic for each fund in a world in which the true alpha is zero:

$$(R_t^i - \alpha_t^i)_b = \hat{\alpha}_b^{i,0} + \hat{\beta}_b^i Rm_t + \hat{\gamma}_b^i Rm_t^2 + \sum_{l=1}^{L} \hat{\delta}_{l,b}^i z_{l,t-1} Rm_t + \sum_{k=1}^{K} \beta_{k,b}^i OF_k + e_{t,b}^i \tag{23}$$

In the fourth step, we average, across the 1,000 simulations, the alphas and their t-statistic ($t(\alpha)$) estimates at the same percentile to construct an empirical cumulative density function (CDF) of the cross-sectional zero alphas ($\hat{\alpha}_b^{i,0}$). Fama and French (2010) use the t-statistics of funds instead of their raw alphas to remove the influence of funds with short sample periods or high idiosyncratic risk – these funds being more likely to have alpha by chance. Thus far, the alpha corrections from our option-based strategies have not been integrated into the bootstrap. Because option-like strategies such as hedge funds exhibit non-linear payoffs, the evaluation of skills, which is associated with the intercept of a regression model, may be artificial. Indeed, the alpha of exotic investments with option-like payoffs from a typical linear regression is different from the traditional alpha of vanilla strategies (e.g., equities, bonds). The effect of skills for these exotic investments should thus be contingently adjusted for the non-linearities in their returns. Such adjustment is necessary because a quadratic model, such as the TM model, shifts (by construction) upward the alpha of a strategy that has a negative OLS coefficient on the quadratic term because the average squared market return is positive (DeRoon and Karehnke 2017). This is in line with the empirical studies of Coggin, Fabozzi, and Rahman (1993) and Jiang (2003), which report evidence of an artificial

[11] The bootstrap procedure is a random selection of monthly observations of all funds with replacement. The conditional resampling is performed to capture the cross-sectional correlation between portfolio returns constituting our sample. As in Harvey and Liu (2016), for example, the bootstrap preserves cross-sectional and time-series dependence.

negative correlation between the intercept and the quadratic coefficients. To do this, we repeat the operation from step one to step four and adjust the funds' returns by subtracting the alpha of our option-based replication strategies ($\alpha_i^{(\tau,\kappa)}$), that is, we replace R_t^i in equation (22) with ($R_t^i - \alpha_i^{(\tau,\kappa)}$).

Figure 7 illustrates the comparison of the simulated CDFs of $t(\alpha)$ for the raw and adjusted alpha frameworks (blue lines) and the CDFs of the actual $t(\alpha)$ estimates of funds (red dotted lines). The plots on the left are for the CDF of raw alpha and the plots on the right are for the CDF of the adjusted alpha.

Plots (a) and (b) are for the comparison the TM model complemented only with the conditional lagged instrumental variables. The CDF of the raw alphas presents a skewed $t(\alpha)$-distribution to the right, whereas the adjusted CDF has been shifted to the left. The consequence is that, under the adjusted framework, a larger proportion of alphas are found outside the 90% confidence interval (vertical gray dotted lines). Extreme and significant positive and negative alphas are more likely to be found under the adjusted model, as shown by comparing the left-hand and right-hand blue areas, which supports the evidence of fatter tails in the adjusted framework density. The results support that the adjustment from the passive option-based replication strategies identifies a larger proportion of poor performers in our sample and goes from approximately 5% to 15%. The alpha adjustment also tend to centralized the distribution near zero.

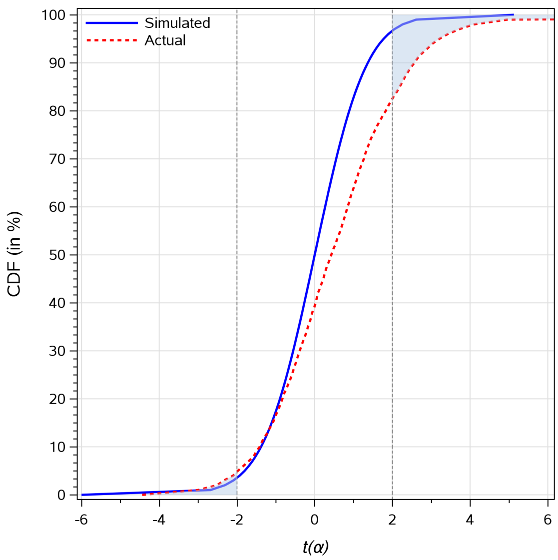
Plots (c) and (d) show the simulation results of the bootstrap methodology using the option-based factors of Fung and Hsieh (2004). Plot (c) presents evidence that a quadratic model exhibits a right-skewed distribution of the intercept. Adjusting the intercept for the degree of curvature in the quadratic model is presented in Plot (d); we observe an incremental improvement similar with the option-based factors of Fung and Hsieh (2004). This suggests that our alpha adjustment captures part, but not all, the residual information from the traditional look-back straddle strategies.

Plots (e) and (f) show the results of the bootstrap methodology using the option-based factors of Agarwal and Naik (2004). Overall, we see that the correction in our option-based replication model is complementary to the Agarwal and Naik (2004) factors. While widely accepted as explanatory variables in the hedge fund industry, one potential shortcoming of these option-based risk factors involves the pre-condition on the moneyness and maturity of the option, i.e., ATM and OTM with one-month maturity, which might not accurately reflect the dynamic nature of hedge funds' option-like trading strategies. To benchmark funds' performance at the individual level, the model should succeed at capturing the specific aspects of the manager's operations (Glosten and Jagannathan

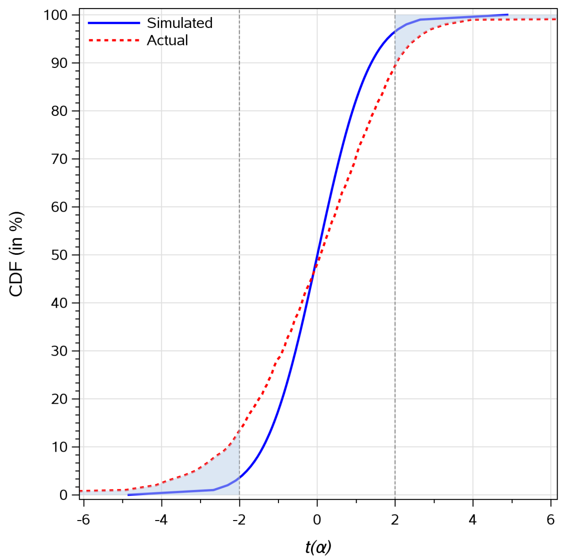
Figure 7: Cumulative Density Function of $t(\alpha)$

This figure illustrates the CDF of $t(\alpha)$ estimates on hedge funds with significant parameters from the TM model. The simulated CDF of the $t(\alpha)$ estimates for zero-alpha funds is represented by the blue line. The red dotted line is the CDF of the $t(\alpha)$ estimates for actual portfolios. The vertical gray dotted lines represent t-statistics at the usual 90% confidence level. For visualization purposes, the areas above this confidence level for the actual t-statistics are shaded. The aim of the figures is to compare the blue and red dotted lines at these 90% confidence levels. The sample period is from January 1996 to December 2015. Graphs on the left (right) show results for funds without (with) alpha correction from an option-based strategy. Plots (a) and (b) use as the factors of the TM model and conditional lagged instruments from Chen and Liang (2007), while Plots (c) and (d) complement this model with the option-based factors of Fung and Hsieh (2004, FH), and Plots (e) and (f) use the option-based factors of Agarwal and Naik (2004, AN).

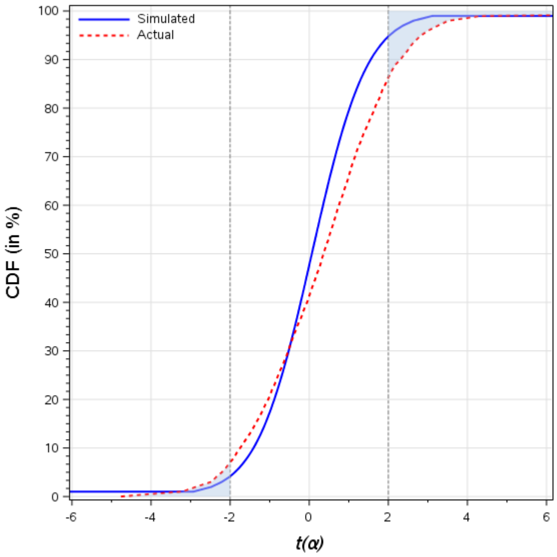
(a) Raw Alphas (TM)



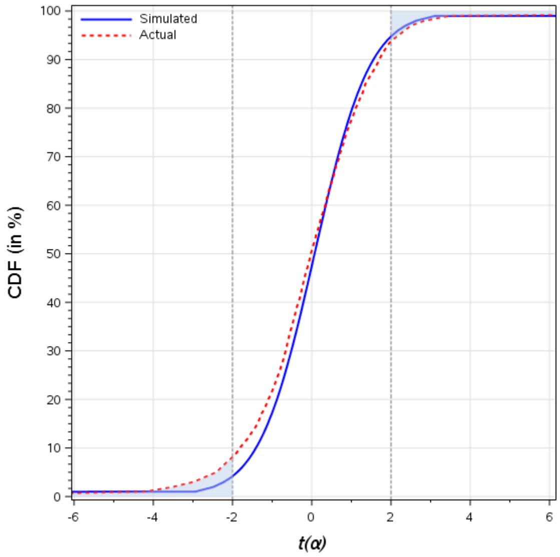
(b) Adjusted Alphas (TM)



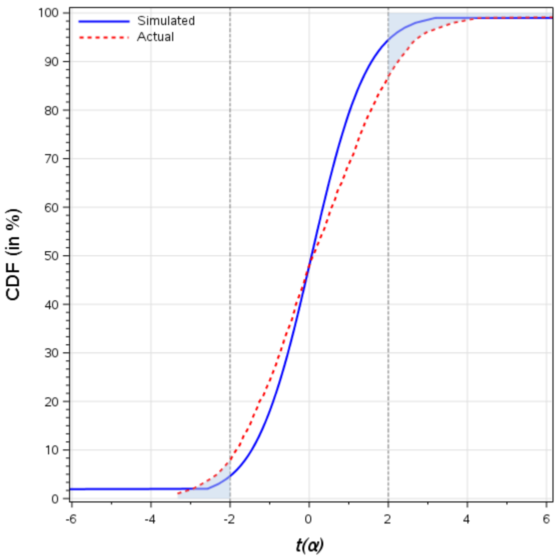
(c) Raw Alphas (FH)



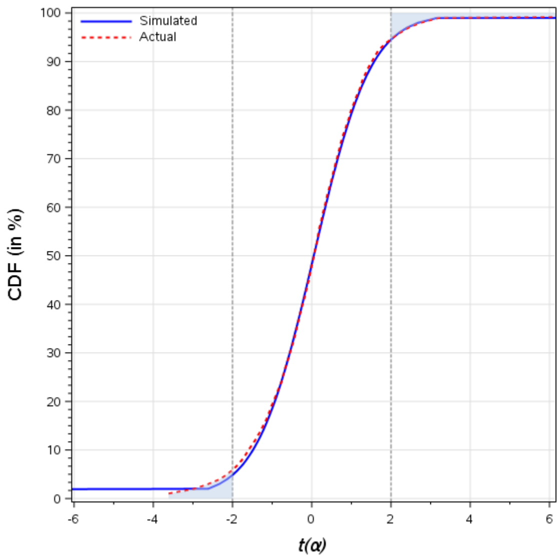
(d) Adjusted Alphas (FH)



(e) Raw Alphas (AN)



(f) Adjusted Alphas (AN)



1994). The model used in this paper is intended to fill this gap. Indeed, the distinction between the simulated and the actual distribution of adjusted alpha in Plot (f) is almost null.

According to the first paragraph in Fama and French (2010, p. 1915), "*active investment must also be a zero sum game-aggregate α is zero before costs*"; while hedge funds' returns are net of fees, the results suggest that our flexible adjustment of alpha based on the funds' level of gamma trading helps to better explain the selection skills of fund managers. From the last combination of factors and alphas adjustment, we cannot conclude that selection skills are present in our sub-sample of hedge funds. As Cochrane (2011, p. 1087) notes, "*Most active management and performance evaluation today just is not well described by the alpha–beta, information-systematic, selection-style split anymore. There is no "alpha". There is just beta you understand and beta you do not understand, and beta you are positioned to buy versus beta you are already exposed to and should sell*". This may suggest that the methodology used to construct the option factors of Agarwal and Naik (2004) should be modified to match our aggregate selection of options in order to capture the residual significant alphas from the cross-sectional distribution. Also, because we use net-of-fees returns, no significant alphas in the cross-section of hedge may simply suggests that fees collected by good market timers is compensation for their ability to anticipate market fluctuations.

In Table 9, we report these empirical distributions of the $t(\alpha)$ estimates for the simulated and actual estimates. Panel A presents the results for the models using the factors from the TM model and conditional lagged instruments from Chen and Liang (2007). Panels B and C complement the model in Panel A with the option-based factors from Fung and Hsieh (2004) and the option-based factors from Agarwal and Naik (2004), respectively. The last column of each panel is different from the table in Fama and French. In their paper, the authors consider "% < Act", which represents the fraction of $t(\alpha)$ estimates from the 1,000 simulations for which the estimates are lower than the actual $t(\alpha)$ for equivalent percentiles. In our paper, we are instead interested in "% < Sim", which we interpret as the fraction of $t(\alpha)$ estimates from the actual returns of the hedge fund sample that are lower than the average of the 1,000 simulations at the indicated percentiles. In other words, we examine how much of the funds have an alpha lower than the mean of the 1,000 simulated alphas at the 1st percentile and so forth. From this column, we can infer how many funds have a $t(\alpha)$ lower than some confidence level and whether our alpha correction helps to explain these residual alphas. For instance, in Panel A, we have in the column "% < Sim" of the raw alpha a value of 6.4% at the 5% confidence level and a value of 79.3% at the 95% confidence level. This suggests that the model leaves more than 10% of the funds with significant alphas (27.1% of the funds). For the adjusted alpha, the values are 16% and 86.2% for the same confidence levels (29.8% of the funds). Thus far, the alpha adjustment just seems to identify more funds with negative alphas. Panel B presents similar results and suggests that the option factors of Fung and Hsieh (2004) bring little additional information to our model. However, Panel C shows that the values for the raw alpha are 10.3% and 85.6% (24.7% of the funds) and 6% and 95% (11% of the funds) for the adjusted alpha at the 5th and 95th confidence levels, respectively. While the option factors of Agarwal and Naik (2004) centralized the distribution of $t(\alpha)$-estimates around zero, it fails to explain the residual significant alphas of the cross-sectional distribution of hedge funds. Our alpha adjustment fills this gap. We are thus fairly confident that the adjustment in our model improves on and is not captured by other standard, derivative-based risk factor models.

4 Robustness (Work in Progress)

4.1 Choice of Timing Ability Significance Levels

In this section, we review our results under different choices of significance levels for the linear and quadratic terms of the TM model. In summary, we use a significance level of 20% and despite the lower precision in the regression analysis and the larger number of funds considered, namely 4,626, representing approximately 42% of our sample, the interpretation of the results remains similar.

4.2 Alternative Payoff Identification

We compare the option payoff identification obtained by using the classic option-based factors of Agarwal and Naik (2004) with that of our quadratic model. The utility of the option risk factors of Agarwal and Naik (2004) resides in the combination of four strategies that use only one type of option and for which the direction of the trade (long or short) is endogenous to the sign of the option risk factors' loading from the OLS regression. However, Agarwal and Naik (2004) also note that the identification of significant factors should be addressed through a stepwise regression. A stepwise regression might be useful for ensuring model parsimony, but it also constrains the reproduction of a similar bootstrap test to that of Fama and French (2010) because the test requires that all funds have the same explanatory variables.

Table 9: Percentiles of $t(\alpha)$ Estimates for Actual and Simulated HF Returns

This table replicates Table III in Fama and French (2010, p. 1927) for our hedge fund sample. It shows values of $t(\alpha)$ at selected percentiles (Pct) of the distribution of $t(\alpha)$ estimates for actual (Act) hedge fund returns. The actual $t(\alpha)$ estimates are based on a 273 monthly observations. Sim is the average value of $t(\alpha)$ at the selected percentiles from the simulated fund returns. The column "% < Sim" represents the fraction of $t(\alpha)$ estimates from the actual returns of the hedge fund sample that are lower than the average of the 1,000 simulations at the indicated percentiles; this last column is thus different from the original Fama and French table. The period is from January 1996 to December 2015. The results are displayed for funds with and without alpha correction. Panel A presents the results when the model uses the factors from the TM model and conditional lagged instruments from Chen and Liang (2007), while Panel B complements this model with the option-based factors of Fung and Hsieh (2004, FH), and Panel C uses the option-based factors of Agarwal and Naik (2004, AN).

	Panel A: Treynor and Mazuy (1966)						Panel B: Fung and Hsieh (2004)						Panel C: Agarwal and Naik (2004)					
	Raw alpha			Adjusted alpha			Raw alpha			Adjusted alpha			Raw alpha			Adjusted alpha		
Pct	Sim	Act	%<Sim	Sim	Act	%<Sim	Sim	Act	%<Sim	Sim	Act	%<Sim	Sim	Act	%<Sim	Sim	Act	%<Sim
1	-2.679	-3.001	0.017	-2.663	-4.913	0.076	-2.935	-3.198	0.201	-2.939	-4.198	0.000	-2.714	-2.385	0.03	-48.381	-3.615	0.000
2	-2.312	-2.514	0.03	-2.301	-4.14	0.098	-2.471	-2.854	0.105	-2.477	-3.483	0.002	-2.341	-2.077	0.049	-2.618	-2.951	0.03
3	-2.09	-2.333	0.041	-2.089	-3.821	0.122	-2.214	-2.473	0.163	-2.218	-2.981	0.006	-2.115	-1.831	0.068	-2.334	-2.604	0.04
4	-1.93	-2.098	0.054	-1.933	-3.43	0.142	-2.024	-2.352	0.097	-2.029	-2.692	0.01	-1.949	-1.637	0.087	-2.132	-2.31	0.05
5	-1.802	-1.977	0.064	-1.808	-3.127	0.16	-1.881	-2.203	0.096	-1.884	-2.407	0.026	-1.82	-1.488	0.103	-1.979	-2.13	0.06
10	-1.381	-1.414	0.106	-1.388	-2.288	0.214	-1.41	-1.747	0.066	-1.411	-1.82	0.038	-1.389	-1.001	0.173	-1.485	-1.599	0.113
20	-0.894	-0.831	0.186	-0.9	-1.497	0.297	-0.883	-1.037	0.202	-0.881	-1.101	0.123	-0.89	-0.397	0.266	-0.933	-0.964	0.205
30	-0.553	-0.385	0.259	-0.555	-0.89	0.369	-0.52	-0.528	0.481	-0.518	-0.66	0.21	-0.542	-0.03	0.346	-0.556	-0.551	0.299
40	-0.266	0.024	0.326	-0.266	-0.397	0.43	-0.216	-0.054	0.811	-0.213	-0.341	0.23	-0.249	0.304	0.419	-0.241	-0.232	0.397
50	0.001	0.429	0.393	0.006	0.082	0.483	0.066	0.359	0.942	0.069	-0.027	0.295	0.024	0.59	0.486	0.05	0.053	0.498
60	0.269	0.846	0.465	0.277	0.518	0.546	0.349	0.751	0.971	0.353	0.34	0.493	0.296	0.889	0.54	0.341	0.319	0.607
70	0.554	1.267	0.527	0.567	0.979	0.611	0.654	1.158	0.986	0.658	0.695	0.598	0.59	1.256	0.603	0.655	0.632	0.707
80	0.89	1.831	0.61	0.907	1.467	0.682	1.02	1.656	0.996	1.023	1.105	0.657	0.942	1.686	0.677	1.03	0.994	0.808
90	1.368	2.566	0.725	1.389	2.037	0.787	1.554	2.297	0.995	1.556	1.702	0.728	1.452	2.314	0.782	1.574	1.516	0.907
95	1.775	3.209	0.793	1.799	2.546	0.862	2.032	2.825	0.992	2.031	2.183	0.716	1.912	2.879	0.856	2.062	2.059	0.95
96	1.898	3.426	0.812	1.923	2.701	0.881	2.179	3.009	0.992	2.177	2.338	0.721	2.053	3.076	0.876	2.213	2.237	0.958
97	2.05	3.717	0.831	2.079	2.916	0.905	2.369	3.251	0.993	2.366	2.499	0.676	2.235	3.279	0.899	2.406	2.444	0.969
98	2.262	4.089	0.862	2.289	3.282	0.93	2.634	3.506	0.992	2.633	2.83	0.732	2.492	3.646	0.927	2.681	2.737	0.978
99	2.613	4.955	0.905	2.647	3.963	0.955	3.118	4.327	0.992	3.11	3.456	0.816	2.95	4.406	0.96	3.162	3.209	0.989

In this paper, we use the following the regression model to identify a fund's option-like payoff using the factors of Agarwal and Naik (2004):

$$\begin{aligned}R_t^i - Rf_t = \alpha^i + \beta^i Rm_t + s^i SMB_t + h^i HML_t + m^i MOM_t \\ + \delta_1^i 10Y_t + \delta_2^i CredSpr + \delta_4^i MSCI_{em} \\ + \delta_5^i SPCa_t + \delta_6^i SPPa_t + \delta_7^i SPCo_t + \delta_8^i SPPo_t + e_t^i\end{aligned} \tag{24}$$

where Rm_t is the excess return of the Value-Weighted US index from CRSP, and SMB, HML and MOM are the equity risk factors of size, value and momentum obtained from Ken French's website. The 10Y is the month-end to month-end change in the US Federal Reserve's 10-year constant-maturity yield, CredSpr is the month-end to month-end change in the difference between Moody's Baa yield and the Federal Reserve's 10-year constant maturity yield, and $MSCI_{em}$ is the Morgan Stanley emerging market index, all three of which are obtained from David Hsieh's website. The option-based factors are written on the S&P 500 index with an ATM call option (SPCa), an ATM put option (SPPa), an OTM call option (SPCo) and an OTM put option strategy (SPPo).

To identify a fund's option payoff, we consider the sign and significance level of the loadings on the option risk factors. For instance, a positive (negative) and significant (p-value of 10%) loading on the call option strategies (δ_5 and δ_7) will be classified as a "Long Call" ("Short Call"). The approach is similar for a put option. If these call and put strategies are both significant and have the same sign, then the payoff will be considered a "Long Straddle" when the sign of the loadings is positive and as a "Short Straddle" when the sign of the loadings is negative. If more than three strategies are significant, then we classify this as a "Complex Payoff."

Panel A of Table 10 presents the number of funds identified with one type of option payoff when the regression involves a stepwise procedure to select dominant risk factors. We see that approximately 3,000 funds fall into the same categories as ours. These results indicate that, with this method, more funds are identified as using "Short Call" and "Long Put" strategies and suggest that a larger proportion of funds would be used as a market insurance strategy. Moreover, strategies designed to have a neutral bet on the market (Global Macro and Market-Neutral) appear to have a directional bet on the market, which appears paradoxical. In Panel B, we report the number of funds with significant alpha across the range of primary strategies and option payoff classifications. On average, 34.51% of the funds have a significant intercept. The "Long Straddle" classification (good market timers) have the highest number (68.75%) of funds with significant alphas.[12] Panels C and D report the same analysis when the regression involves a regular OLS procedure, i.e., no sequential selection of the variables. Overall, we see that most of funds have a "Complex Payoff," such that more than two option risk factors load significantly and make the identification process more difficult. Only 302 funds have a simple payoff identification, and 2,117 funds are classified as complex. On aggregate, the number of funds with option-like payoffs decreases from 3,428 to 2,419, as does the proportion of funds with a significant alpha (from 34.51% to 26.46%). Although this last approach is not suggested by Agarwal and Naik (2004) , proceeding with testing the cross-sectional distribution of alphas among hedge funds will remain a complex exercise with a stepwise regression. We believe that the risk factors of Agarwal and Naik (2004) are important control variables to capture the non-linearities of hedge fund returns but that the identification of option payoffs is simpler with a quadratic model and the relationship between the linear and quadratic term (the ratio $|\beta/\gamma|$).

5 Conclusion

This paper establishes a benchmark to assess the timing skills of fund managers. Our model is intended to adjust the fund managers' returns by the alpha of a passive option-based strategy that replicates the non-linearity in the fund returns. Fama (1972) defined a fund manager's skills as both market timing and stock selection ability, such that the combination of the intercept and the quadratic term ($\alpha_{TM} + \gamma b^2$) captures these skills. However, when assuming that the quadratic term (γb^2) could be replicated by a passive strategy, the only source of skill left in the equation is the intercept (α_{TM}), which thus represents the security selection skill of a manager. Our study follows this assumption and employs the replication model of Hübner (2016) to satisfy the condition of passively replicating the linear and quadratic terms of the market timing model – the Treynor and Mazuy (1966, TM) model. The "cost" of the replication serves as a basis for adjusting the intercept (α) of the TM model and should reflect the true skill that a manager demonstrates relative to a passive benchmark with equivalent convexity/concavity.

After adjusting the alpha of the managers with that of the replication strategy, we simply assess the systematic sources of fund returns through traditional multi-factor models. Overall, the alpha

[12]These alphas are, on average, positive (t-stat of 4.00). For parsimony, these results are not reported but are available upon request.

Table 10: Payoff Identification by Primary Strategy

This table presents the payoff identification using the option-based risk factors of Agarwal and Naik (2004). Panel A reports the number of hedge funds that fall into an option payoff by primary strategy from a stepwise regression. Panel B reports the proportion of these funds with a significant intercept. Panel C reports the number of hedge funds that fall into an option payoff by primary strategy from a regular OLS regression. Panel D shows the proportion of the funds from Panel C with a significant intercept. The threshold for parameter significance is set to 10%.

Primary Strategy	Long Single Call	Short Single Call	Long Single Put	Short Single Put	Long Straddle	Short Straddle	Complex Payoff	All Payoffs	Long Single Call	Short Single Call	Long Single Put	Short Single Put	Long Straddle	Short Straddle	Complex Payoff	All Payoffs
	Panel A: # Observation (Stepwise)								Panel B: Proportion of Significant Alpha (Stepwise)							
CTA	139	36	70	46	32	2	33	358	0.4029	0.1667	0.1714	0.1739	0.8125	0.0000	0.3636	0.3352
Event Driven	71	48	38	95	1	7	35	295	0.4085	0.1458	0.4474	0.3158	1.0000	0.2857	0.3143	0.3288
Global Macro	26	20	26	17	6	9	11	115	0.4231	0.4000	0.5000	0.0588	0.5000	0.1111	0.3636	0.3565
Long/Short	403	196	299	227	39	14	159	1337	0.3623	0.2347	0.2742	0.2115	0.5128	0.5000	0.3836	0.3067
Market-Neutral	46	22	34	31	1	6	19	159	0.3043	0.3182	0.3529	0.2258	1.0000	0.5000	0.4211	0.3270
Multi-Strategy	236	64	90	87	42	11	65	595	0.4619	0.2969	0.4778	0.4023	0.7381	0.4545	0.5077	0.4622
Relative Value	58	106	61	94	6	16	59	400	0.3276	0.1981	0.5410	0.3085	0.8333	0.4375	0.4407	0.3500
Sector	31	20	26	13		2	20	112	0.2258	0.2000	0.3077	0.3846		0.0000	0.4000	0.2857
Short Bias	11	11	6	11	1	3	14	57	0.5455	0.1818	0.1667	0.2727	1.0000	0.0000	0.2143	0.2807
All Strategies	1021	523	650	621	128	70	415	3428	0.3888	0.2294	0.3400	0.2673	0.6875	0.3571	0.4000	0.3451
	Panel C: # Observation (regular-OLS)								Panel D: Proportion of Significant Alpha (regular-OLS)							
CTA	16	9	3	2	1		228	259	0.3750	0.0000	0.3333	0.5000	0.0000		0.2061	0.2124
Event Driven	7	1	2	9			200	219	0.1429	0.0000	1.0000	0.3333			0.2400	0.2466
Global Macro	4	1	3	1			56	65	0.7500	0.0000	0.3333	1.0000			0.1964	0.2462
Long/Short	48	31	35	19			806	939	0.2292	0.2258	0.3429	0.2105			0.2184	0.2236
Market-Neutral	4	1	8	5			83	101	0.2500	0.0000	0.3750	0.4000			0.3012	0.3069
Multi-Strategy	32	3	6	5			317	363	0.3750	0.0000	0.3333	0.4000			0.3691	0.3664
Relative Value	11	10	5	3			326	355	0.4545	0.2000	0.6000	0.0000			0.3313	0.3324
Sector	3	3	3	2			62	73	0.0000	0.3333	0.0000	0.5000			0.1935	0.1918
Short Bias	1	1	2	2			39	45	1.0000	0.0000	0.5000	0.0000			0.1795	0.2000
All Strategies	126	60	67	48	1	0	2117	2419	0.3175	0.1667	0.3731	0.2917	0.0000	NA	0.2603	0.2646

adjustment from our model delivers an interesting picture of the cross-sectional skills in our hedge fund sample (a merged sample of HFR and Morningstar): the alpha of funds with a similar payoff as a short put options strategy shrinks from approximately 0.60% to approximately -1.50% per month, while the alpha from market timers increases from approximately -0.40% to 0.40% per month. After combining the option-based factors of Agarwal and Naik (2004) with our alpha adjustments, we cannot conclude that selection skills are present in our hedge fund sample. Our interpretations are based on net-of-fees returns and might suggest that fees collected by good market timers are compensation for their ability to anticipate market fluctuations.

This research contributes to the literature on the gamma trading in hedge funds' trades and their market timing skills because it first sets a benchmark for replicating the non-linear nature of the performance of hedge funds, and it does so by applying a flexible approach that uses tradable options from OptionMetrics. Second, the adjustment in our model improves on and is not captured by other standard, derivative-based risk factors models. Third, the approach frees us to make more accurate inferences in comparing non-linear strategies with "skilled" versus "dumb" alpha. Indeed, the algebra behind a quadratic equation leaves a positive (negative) intercept when the quadratic coefficient is negative (positive), such that a positive market timer will have, on average, negative alpha while a strategy that shorts naked put options will have, on average, positive alpha by construction (see, for instance, Jurek and Stafford 2015). Adjusting for this mechanical effect leaves us with a more accurate evaluation of the skills available in the hedge fund industry. Overall, we categorize the payoffs of approximately 30% of our hedge fund sample into three main categories: directional with market timing skills (long-short hedge funds), non-directional with market timing (multi-strategy, CTAs), and non-directional/convergence bets (relative value, market-neutral). We find positive adjustments for market timers with directional bets and non-directional bets (long call or straddle payoffs) but negative adjustments for negative timers with convergence bets (top straddle payoffs). We demonstrate that the alpha adjustment is strongly dependent on the curvature of the payoff – i.e., the ratio β/γ.

We hope this study can improve our understanding of the non-linearites in hedge fund returns and contribute to the development of a new set of option-based risk factors that more accurately capture the dynamic patterns of hedge funds, which is a topic we hope to pursue in future research.

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Appendices

A Hedge Fund Database Treatments

The treatments applied to merge our databases (Morningstar and HFR) regroup the following conditions for both databases, which contain monthly net-of-fees returns and assets under management for the period from January 1974 to December 2015;

1. We focus on the post-1994 period because prior to this date, the coverage of defunct funds is incomplete. In our paper, we focus on 1996 onward to fit the condition imposed by the OptionMetrics database, which only starts in January 1996.

2. In Joenväärä, Kosowski, and Tolonen (2016), the data for raw returns and AuM observations are denominated in several different currencies and the authors convert returns and AuM observations that are not denominated in USD to USD using end-of-month spot rates. In this paper, however, we only use funds denominated in USD to be in line with the benchmark used in our analysis (the S&P 500).

3. We include only funds that report net-of-fee returns on a monthly basis.

4. We remove very large or small returns to eliminate a possible source of error by truncating returns between the limits of -90% and 300%.

5. We exclude the first twelve observations of each hedge fund to reduce the issues of backfill bias (Fung and Hsieh 2001; Bali, Brown, and Caglayan 2014).

6. We exclude hedge funds with track records shorter than 36 months (to address survivorship bias) as in (Bali, Brown, and Caglayan 2014; Patton and Ramadorai 2013).

B Hedge Fund Classifications

Table 1: Primary Categories

This table presents the mapping of the categories used in Joenväärä, Kosowski, and Tolonen (2016) to standardize the groups between the main hedge fund data providers.

Primary Strategies	**Strategy 1**	**Strategy 2**	**Strategy 3**	**Strategy 4**	**Strategy 5**
CTA	Managed Futures	Fundamental (Agricultural, Currency, Diversified, Energy, Financials, Metals, Interest Rates)	Currency (Discretionary, Systematic)	Systematic Futures	Commodity (Agriculture, Energy, Metals, Multi)
Emerging Markets	Emerging Markets	Emerging Markets (Asia, Eastern Europe/CIS, Latin America, Mena, Global)	Long/Short Equity (China, Emerging Markets, Europe)		
Event Driven	Activists	Distressed Securities	Fund Timing	Merger Arbitrage	
Fund of Funds		Fund of Funds (Debt, Equity, Event, Macro, Systematic, Multi-Strategy, Other, Relative Value)	Investable Index		
Global Macro	Macro	Discretionary	Fundamental Interest Rates	Stock Index, Stock Index Arbitrage	Stock Index, Arbitrage
Long Only	Equity Long Only	Mutual Funds	ETFs	Bottom-Up	Distressed Debt, Diversified Debt
Long/Short	Long/Short Equity Hedge	Long/Short Equities, Equity Long/Short, Long/Short Equity (Asia/Pacific, Global, U.S. U.S. Small Cap)	Equity Long-Bias	Equity Hedge	Equity 130-30
Market-Neutral	Equity Market Neutral	Statistical Arbitrage	Market Neutral	Credit Market Neutral	
Multi-Strategy	Multi-Strategy	Systematic Diversified	Balanced (Stocks & Bonds)	Multi-Advisor	
Relative Value	Convertible Arbitrage, Arbitrage, Diversified Arbitrage, Credit Arbitrage	Fixed income (Arbitrage, Debt, Capital Structure, Asset-Backed Loans, Collateralized Debt Obligations, Convertible Bonds, Diversified, High Yield, Mortgage Backed, Insurance-Linked Securities, Long-Only Credit, Sovereign, Corporate)	Options Strategy, Stock Index Option Strategies, Volatility Trading	Tail Risk, Yield Alternatives	Fixed Income Long/Short Credit, Long/Short Debt
Sector	Sector Energy	Sector (Basic Materials, Health care, Energy, Environment, Farming, Financial, Bio-tech, Metals, Mining, Miscellaneous, Natural Resources, Real-Estate, Technology)			
Short Bias	Dedicated Short Bias	Short Bias	Equity Dedicated Short	Equity Short Bias	Equity Short Bias Opportunistic

C Tables 5 and 8 with Fung and Hsieh (2004) Factors

Table 5: Measures of Replication Fit by Primary Strategy – Fung and Hsieh (2004) factors

This table presents the average RMSE from eq (20) and AER from eq (21) in Panels A and B, respectively. Panel C reports the number of hedge funds that fall into a primary strategy, and Panel D reports the proportion of these funds according to each primary strategy.

Primary Strategy	Long Single Call	Short Single Call	Long Single Put	Short Single Put	Long Straddle	Short Straddle	All Payoffs	Long Single Call	Short Single Call	Long Single Put	Short Single Put	Long Straddle	Short Straddle	All Payoffs
	Panel A: RMSE							Panel B: AER						
CTA	0.0010	0.0006	0.0015	0.0012	0.0000	0.0000	0.0001	-0.0001	-0.0001	0.0005	-0.0001	0.0000	0.0000	0.0000
Event Driven	0.0008		0.0002	0.0008	0.0000	0.0000	0.0002	0.0000		0.0000	0.0000	0.0000	0.0000	0.0000
Global Macro	0.0010	0.0014		0.0012	0.0000	0.0000	0.0001	0.0000	-0.0005		-0.0006	0.0000	0.0000	0.0000
Long/Short	0.0014	0.0006	0.0010	0.0013	0.0000	0.0000	0.0005	0.0000	-0.0001	-0.0001	0.0000	0.0000	0.0000	0.0000
Market-Neutral	0.0006	0.0007		0.0012	0.0000	0.0000	0.0001	-0.0001	0.0002		-0.0002	0.0000	0.0000	0.0000
Multi-Strategy	0.0010	0.0005		0.0016	0.0000	0.0000	0.0002	0.0000	0.0000		0.0001	0.0000	0.0000	0.0000
Relative Value	0.0009	0.0002		0.0013	0.0000	0.0000	0.0001	-0.0001	0.0000		-0.0002	0.0000	0.0000	0.0000
Sector	0.0013			0.0017	0.0000	0.0000	0.0007	0.0001			0.0000	0.0000	0.0000	0.0000
Short Bias	0.0012	0.0015	0.0013	0.0006	0.0000	0.0000	0.0004	0.0002	0.0001	-0.0006	-0.0001	0.0000	0.0000	0.0000
All Strategies	0.0012	0.0009	0.0011	0.0013	0.0000	0.0000	0.0003	0.0000	-0.0001	-0.0002	0.0000	0.0000	0.0000	0.0000
	Panel C: # Obs							Panel D: Proportion of Funds by Primary Strategy						
CTA	24	1	1	13	191	115	345	7.0%	0.3%	0.3%	3.8%	55.4%	33.3%	10.8%
Event Driven	26		1	41	52	152	272	9.6%	0.0%	0.4%	15.1%	19.1%	55.9%	8.5%
Global Macro	9	3		1	40	44	97	9.3%	3.1%	0.0%	1.0%	41.2%	45.4%	3.0%
Long/Short	278	6	1	195	275	438	1193	23.3%	0.5%	0.1%	16.3%	23.1%	36.7%	37.3%
Market-Neutral	10	1		6	59	94	170	5.9%	0.6%	0.0%	3.5%	34.7%	55.3%	5.3%
Multi-Strategy	64	3		30	280	158	535	12.0%	0.6%	0.0%	5.6%	52.3%	29.5%	16.7%
Relative Value	31	1		22	161	224	439	7.1%	0.2%	0.0%	5.0%	36.7%	51.0%	13.7%
Sector	25			25	17	33	100	25.0%	0.0%	0.0%	25.0%	17.0%	33.0%	3.1%
Short Bias	3	5	3	7	9	19	46	6.5%	10.9%	6.5%	15.2%	19.6%	41.3%	1.4%
All Strategies	470	20	6	340	1084	1277	3197	14.7%	0.6%	0.2%	10.6%	33.9%	39.9%	100.0%

Table 8: Alpha Correction Descriptive Statistics – Fung and Hsieh (2004) factors

This table decomposes the average alpha correction per primary strategy. We report in Panel A the average raw alpha, while Panel B presents the average alpha from the option replication strategies per primary strategy. The adjusted alpha is simply the difference between Panel A and Panel B. In Panel C, we report the average adjusted R^2 of the regression model used to identify the option payoff of a fund. Finally, Panel D presents the average ratio $|\beta/\gamma|$ in each primary strategy.

Primary Strategy	Long Single Call	Short Single Call	Long Single Put	Short Single Put	Long Straddle	Short Straddle	All Payoffs	Long Single Call	Short Single Call	Long Single Put	Short Single Put	Long Straddle	Short Straddle	All Payoffs
	Panel A: Alpha							Panel B: Alpha Correction						
CTA	-0.0020	0.0101	0.0011	0.0051	-0.0021	0.0088	0.0019	-0.0069	0.0079	-0.0259	0.0199	-0.0136	0.0170	-0.0017
Event Driven	-0.0004		0.0004	0.0067	-0.0047	0.0106	0.0060	-0.0044		-0.0003	0.0167	-0.0154	0.0160	0.0081
Global Macro	-0.0025	0.0122		0.0122	-0.0016	0.0107	0.0044	-0.0062	0.0111		0.0180	-0.0193	0.0212	0.0016
Long/Short	-0.0047	0.0051	0.0165	0.0069	-0.0064	0.0094	0.0021	-0.0087	0.0058	-0.0079	0.0219	-0.0188	0.0239	0.0060
Market-Neutral	0.0010	0.0088		0.0053	-0.0020	0.0066	0.0033	-0.0028	0.0075		0.0110	-0.0090	0.0117	0.0036
Multi-Strategy	-0.0013	0.0048		0.0039	-0.0013	0.0103	0.0025	-0.0055	0.0087		0.0133	-0.0140	0.0181	-0.0018
Relative Value	-0.0047	0.0031		0.0063	-0.0004	0.0093	0.0046	-0.0068	0.0018		0.0248	-0.0110	0.0170	0.0054
Sector	-0.0073			0.0113	-0.0072	0.0236	0.0076	-0.0090			0.0338	-0.0282	0.0448	0.0162
Short Bias	-0.0086	0.0064	0.0015	0.0051	-0.0048	0.0096	0.0041	-0.0146	0.0131	-0.0019	0.0246	-0.0144	0.0147	0.0074
All Strategies	-0.0038	0.0068	0.0038	0.0068	-0.0029	0.0098	0.0031	-0.0077	0.0089	-0.0066	0.0213	-0.0149	0.0198	0.0040
	Panel C: R^2-adjusted							Panel D: Ratio $|\beta/\gamma|$						
CTA	0.4854	0.4338	0.3679	0.3657	0.2165	0.2284	0.2459	0.3121	0.3163	0.2123	0.2735	0.0722	0.0626	0.0944
Event Driven	0.3624		0.1275	0.4616	0.3180	0.3038	0.3353	0.3307		0.2677	0.3152	0.1035	0.0906	0.1505
Global Macro	0.2764	0.4178		0.4205	0.2065	0.2848	0.2572	0.3440	0.4974		0.2492	0.0666	0.0715	0.1098
Long/Short	0.5196	0.3665	0.4767	0.4844	0.3059	0.3257	0.3926	0.3826	0.3342	0.4466	0.3470	0.1083	0.0982	0.2089
Market-Neutral	0.4594	0.1960		0.5110	0.1637	0.1653	0.1945	0.3714	0.2202		0.4628	0.0639	0.0568	0.0930
Multi-Strategy	0.4687	0.3979		0.4700	0.2486	0.3082	0.3058	0.4123	0.2533		0.3486	0.0794	0.0828	0.1363
Relative Value	0.4613	0.6175		0.4582	0.2400	0.3153	0.3059	0.3481	0.2726		0.2417	0.0595	0.0652	0.0924
Sector	0.3842			0.4595	0.1917	0.2074	0.3120	0.3294			0.2923	0.1128	0.0957	0.2062
Short Bias	0.4256	0.7251	0.5657	0.4833	0.3108	0.3231	0.4113	0.2616	0.5150	0.4997	0.2774	0.1104	0.0733	0.1997
All Strategies	0.4846	0.4760	0.4449	0.4726	0.2530	0.2941	0.3285	0.3733	0.3821	0.4043	0.3300	0.0831	0.0820	0.1541

D Tables 5 and 8 with Agarwal and Naik (2004) Factors

Table 5: Measures of Replication Fit by Primary Strategy – Agarwal and Naik (2004) factors

This table presents the average RMSE from eq (20) and AER from eq (21) in Panels A and B, respectively. Panel C reports the number of hedge funds that fall into a primary strategy, and Panel D reports the proportion of these funds according to each primary strategy.

Primary Strategy	Long Single Call	Short Single Call	Long Single Put	Short Single Put	Long Straddle	Short Straddle	All Payoffs	Long Single Call	Short Single Call	Long Single Put	Short Single Put	Long Straddle	Short Straddle	All Payoffs
	Panel A: RMSE							Panel B: AER						
CTA	0.0012	0.0008	0.0004	0.0025	0.0000	0.0000	0.0003	0.0000	0.0000	-0.0001	-0.0001	0.0000	0.0000	0.0000
Event Driven	0.0011			0.0010	0.0000	0.0000	0.0003	0.0001			-0.0001	0.0000	0.0000	0.0000
Global Macro	0.0012	0.0008	0.0025	0.0006	0.0000	0.0000	0.0001	0.0000	0.0002	-0.0009	-0.0005	0.0000	0.0000	0.0000
Long/Short	0.0016	0.0016	0.0008	0.0014	0.0000	0.0000	0.0006	0.0000	-0.0004	-0.0001	0.0000	0.0000	0.0000	0.0000
Market-Neutral	0.0008	0.0010		0.0032	0.0000	0.0000	0.0002	0.0001	-0.0005		-0.0015	0.0000	0.0000	-0.0001
Multi-Strategy	0.0014	0.0005		0.0012	0.0000	0.0000	0.0003	-0.0001	0.0001		0.0001	0.0000	0.0000	0.0000
Relative Value	0.0010	0.0006	0.0006	0.0012	0.0000	0.0000	0.0001	0.0000	-0.0001	0.0000	-0.0003	0.0000	0.0000	0.0000
Sector	0.0023			0.0012	0.0000	0.0000	0.0008	0.0002			-0.0003	0.0000	0.0000	0.0000
Short Bias	0.0024	0.0024	0.0003	0.0010	0.0000	0.0000	0.0005	0.0010	0.0007	-0.0001	-0.0002	0.0000	0.0000	0.0001
All Strategies	0.0015	0.0015	0.0009	0.0014	0.0000	0.0000	0.0004	0.0000	0.0000	-0.0002	-0.0001	0.0000	0.0000	0.0000
	Panel C: # Obs							Panel D: Proportion of Funds by Primary Strategy						
CTA	29	3	1	16	161	102	312	9.3%	1.0%	0.3%	5.1%	51.6%	32.7%	9.6%
Event Driven	40			35	67	141	283	14.1%	0.0%	0.0%	12.4%	23.7%	49.8%	8.7%
Global Macro	5	3	1	2	36	36	83	6.0%	3.6%	1.2%	2.4%	43.4%	43.4%	2.6%
Long/Short	345	10	1	98	412	411	1277	27.0%	0.8%	0.1%	7.7%	32.3%	32.2%	39.3%
Market-Neutral	20	2		6	64	83	175	11.4%	1.1%	0.0%	3.4%	36.6%	47.4%	5.4%
Multi-Strategy	72	2		33	269	145	521	13.8%	0.4%	0.0%	6.3%	51.6%	27.8%	16.0%
Relative Value	31	2	1	27	206	190	457	6.8%	0.4%	0.2%	5.9%	45.1%	41.6%	14.1%
Sector	26			9	34	26	95	27.4%	0.0%	0.0%	9.5%	35.8%	27.4%	2.9%
Short Bias	2	7	1	3	10	25	48	4.2%	14.6%	2.1%	6.3%	20.8%	52.1%	1.5%
All Strategies	570	29	5	229	1259	1159	3251	17.5%	0.9%	0.2%	7.0%	38.7%	35.7%	100.0%

Table 8: Alpha Correction Descriptive Statistics – Agarwal and Naik (2004) factors

This table decomposes the average alpha correction per primary strategy. We report in Panel A the average raw alpha, while Panel B presents the average alpha from the option replication strategies per primary strategy. The adjusted alpha is simply the difference between Panel A and Panel B. In Panel C, we report the average adjusted R^2 of the regression model used to identify the option payoff of a fund. Finally, Panel D presents the average ratio $\left|\beta/\gamma\right|$ in each primary strategy.

Primary Strategy	Long Single Call	Short Single Call	Long Single Put	Short Single Put	Long Straddle	Short Straddle	All Payoffs	Long Single Call	Short Single Call	Long Single Put	Short Single Put	Long Straddle	Short Straddle	All Payoffs
	Panel A: Alpha							Panel B: Alpha Correction						
CTA	-0.0051	0.0091	0.0031	0.0037	-0.0058	0.0126	0.0010	-0.0080	0.0055	-0.0173	0.0494	-0.0234	0.0255	-0.0019
Event Driven	-0.0024			0.0069	-0.0079	0.0152	0.0062	-0.0059			0.0171	-0.0177	0.0214	0.0078
Global Macro	-0.0011	0.0088	0.0068	0.0072	-0.0080	0.0118	0.0022	-0.0090	0.0083	-0.0349	0.0275	-0.0227	0.0242	0.0007
Long/Short	-0.0067	0.0160	0.0162	0.0078	-0.0116	0.0167	0.0006	-0.0102	0.0153	-0.0091	0.0224	-0.0255	0.0338	0.0017
Market-Neutral	-0.0014	0.0095		0.0064	-0.0059	0.0103	0.0029	-0.0054	0.0103		0.0181	-0.0157	0.0132	0.0006
Multi-Strategy	-0.0045	0.0128		0.0055	-0.0081	0.0126	-0.0009	-0.0085	0.0067		0.0210	-0.0223	0.0226	-0.0050
Relative Value	-0.0049	0.0107	0.0060	0.0060	-0.0068	0.0132	0.0025	-0.0062	0.0104	-0.0147	0.0232	-0.0187	0.0244	0.0027
Sector	-0.0112			0.0105	-0.0145	0.0282	0.0004	-0.0143			0.0214	-0.0267	0.0409	-0.0003
Short Bias	-0.0198	0.0163	-0.0053	0.0102	-0.0137	0.0122	0.0056	-0.0229	0.0196	-0.0106	0.0256	-0.0328	0.0180	0.0058
All Strategies	-0.0059	0.0136	0.0053	0.0069	-0.0088	0.0146	0.0014	-0.0094	0.0133	-0.0173	0.0233	-0.0225	0.0267	0.0009
	Panel C: R^2-adjusted							Panel D: Ratio $\left|\beta/\gamma\right|$						
CTA	0.3247	0.2145	0.3532	0.2751	0.1725	0.1854	0.1971	0.3346	0.4682	0.3745	0.2818	0.0781	0.0809	0.1180
Event Driven	0.4239			0.4351	0.3106	0.3093	0.3413	0.3330			0.3373	0.1070	0.0847	0.1563
Global Macro	0.2791	0.1702	0.2254	0.2019	0.2103	0.2711	0.2394	0.2592	0.3223	0.2802	0.3609	0.0583	0.0769	0.0980
Long/Short	0.5014	0.3963	0.4741	0.4887	0.3412	0.3261	0.3915	0.3792	0.3205	0.3943	0.3662	0.0965	0.0841	0.1916
Market-Neutral	0.3242	0.2067		0.5782	0.1564	0.1609	0.1927	0.3252	0.2603		0.4596	0.0815	0.0744	0.1210
Multi-Strategy	0.4139	0.2924		0.4283	0.2221	0.2765	0.2771	0.3604	0.2963		0.2979	0.0758	0.0794	0.1310
Relative Value	0.3393	0.4719	0.3513	0.4360	0.2219	0.3362	0.2914	0.3235	0.2296	0.3093	0.3019	0.0779	0.0775	0.1088
Sector	0.4152			0.3801	0.2963	0.3308	0.3462	0.3370			0.4321	0.1040	0.0956	0.1966
Short Bias	0.5665	0.6761	0.5349	0.4399	0.4511	0.3285	0.4259	0.2507	0.3832	0.3459	0.3009	0.0775	0.0710	0.1455
All Strategies	0.4552	0.4066	0.3878	0.4456	0.2596	0.2937	0.3207	0.3630	0.3390	0.3408	0.3426	0.0854	0.0813	0.1534