Gamma Trading Skills in Hedge Funds*

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Abstract

Decomposing the gamma trading, timing and managerial stock-picking skills of individual hedge funds is a central challenge in the active management industry. However a systematic negative bias, attributed to the implied cost of options, blurs the evaluation of the selectivity and market timing skills from traditional market timing models. Simple option strategies, one call and one put, fitted on the time-varying coefficients of these models capture the implied cost. We show that incorporating this cost allows us to categorize groups of hedge funds in a way that correlates positively with future returns. Our model offers a flexible tool to benchmark the nonlinear payoff of individual hedge funds and reveals that managers who are skilled at timing the market share similar information for picking stocks. We conclude that the relationship between the selectivity and market timing skills is not constrained to be negatively correlated.

Keywords: Derivatives, Hedge Funds, Portfolio Management.

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Introduction

Because option-like strategies such as those of hedge funds exhibit a non-linear payoff, an evaluation of skills, which is associated with the intercept of a regression model, may be artificial.[1] 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., passive equity and bond strategies). The role of skills in these exotic investments should thus be contingently adjusted for the non-linearities in their payoffs. 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).

The use of a quadratic model, such as the Treynor and Mazuy (1966) model to assess market timing skills, shifts upward (by construction) 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 confirmed in our data: funds with a positive OLS coefficient on the quadratic term deliver, on average, a negative alpha (between -0.22% and -0.06% per month), while funds with a negative OLS coefficient on the quadratic term show, on average, a large positive alpha of between 1.09% and 1.18% per month. Funds with a negative quadratic term have a payoff resembling that of a short put option and perform well in mean-variance frameworks. This is because such frameworks fail to capture the left-tail risks of portfolios with non-linear payoffs (Agarwal and Naik 2004). While the Treynor and Mazuy (1966, TM) market timing model has an option-based motivation, it assumes that the cost of the option is free (Jagannathan and Korajczyk 1986). For that reason, the literature has designed option-based factors, which substitute for or complement market timing models, to capture the convex or concave nature of hedge funds' trades.[2] Despite the explanatory power provided by these factors, the methodologies used to construct them may lack flexibility when choosing the right type of options to trade as a result of the highly opportunistic

[1] See, among others, Jagannathan and Korajczyk (1986), Coggin, Fabozzi, and Rahman (1993), Bollen and Busse (2001), and Jiang (2003) for explanations of the negative artificial bias present in market timing models and Fung and Hsieh (2001), Mitchell and Pulvino (2001), Titman and Tiu (2011), and Hübner, Lambert, and Papageorgiou (2015) for evidence on the option-like payoffs displayed in the hedge fund industry.

[2] Among others, Fung and Hsieh (2001), Agarwal and Naik (2004), Fung and Hsieh (2004), and Jurek and Stafford (2015) provide option-based risk factors, while Agarwal, Arisoy, and Naik (2017) write an exhaustive literature review on these strategies.

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.[3]

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 and the cost of options implied in market timing models, 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 by 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 alpha adjustment with their market timing skills, simple portfolio sorts on hedge funds reveal a positive monotonic relationship between our Adjusted-Skill Index and future returns. These results are maintained until twelve months after portfolio formation.

To achieve these objectives, we build on the option-based replication model of Hübner (2016). We generalized the model in a time-varying framework in which almost all types of payoffs – even when funds do not exhibit market timing – can be synthetically replicated using only two options,

[3]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*".

i.e., one call and one put.[4]

The model defines the option features ("the Greeks") that would match the non-linear payoffs captured by the linear and quadratic coefficients of the TM model. The model works well because the Greeks of the option – i.e., Δ and Γ – can be used to match the linear and quadratic terms of the TM model – i.e., β and γ. The option-based replication strategy is intended to be passive, such that the alpha from this strategy can be viewed as a benchmark for the replicated fund performance. The benchmark sets up the cost of options implied in market timing models; the performance of the fund is thus redefined as the outperformance with respect to the alpha of the benchmark.

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 almost the entire cross-section of hedge funds in our sample (95%). The categories are the following: directional with market timing skills (e.g., long-short and short bias hedge funds), non-directional with market timing (e.g., multi-strategy, global macro, CTAs), and non-directional with convergence bets (event driven, relative value, market-neutral). Second, we reveal the impact of these non-linear payoffs on managerial skills. We find strong positive adjusted alpha for market timers with directional bets (between 0.63% and 3.81% per month) and non-directional bets ($\sim$ 3.03% per month) but negative adjustments for negative timers with directional bets (between -0.06% and -3.49% per month) and convergence bets (top straddles, approximately -1.85% per month). The adjustments strongly depend on the curvature of the payoff.

The remainder 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 gamma skills in the cross-section of hedge funds, quantifies the cost of option implied in market timing model and analyzes the consequences of adjusting a manager's alpha by this cost. Section 4 shows how an indicator of skills between selectivity and timing can be constructed to group funds into portfolios and correlate positively with future return. Section 5 provides robustness tests on

[4] We empirically have approximately 95% of the observations for funds with a minimum of 36 observations that have an option-based replication at each time period t. Our sample comprises 632,154 observations, of which 616,497 have an option-based replication. The other 15,657 observations display a $\beta \approx 0$ and $\gamma \approx 0$ and thus we do not consider them in our analysis.

the selection of the market timing model as well as model misspecifications. Section 6 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 revisited

The model of Treynor and Mazuy (1966) is one of the classical return-based models used to detect fund convexity from market timing skills. This quadratic model takes the following form:

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

where γ represents the coefficient of timing ability. Market timing skills are attributed to the fund manager in case of positive convexity, i.e. positive gamma.

Empirical evidence shows several issues of the TM model (Kryzanowski, Lalancette, and To 1997; Becker et al. 1999; Bollen and Busse 2004; Comer, Larrymore, and Rodriguez 2009). Avramov et al. (2011) highlight the need to use conditional information to evaluate managers' market timing skills.

To address one of these limits, Chen and Liang (2007) condition the exposure to the benchmark on five lagged instruments which proxy for "public information.". Following (e.g., Ferson and Schadt 1996; Becker et al. 1999; Graham and Harvey 1996; Ferson and Siegel 2001; Jiang 2003), they use macro-economic variables that provide future information about the current economic conditions of the market. . The variables used 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), we can compare the unconditional and conditional market timing models as follows:

$$
\begin{aligned}
R_{i,t} &= \alpha_{TM} + \beta_u Rm_t + \gamma_u Rm_t^2 + e_{i,t} \\
&= \alpha_{TM} + \beta_c Rm_t + \gamma_c Rm_t^2 + \sum_{l=1}^{L} \delta_l (z_{l,t-1} Rm_t) + e_{i,t}
\end{aligned} \tag{2}
$$

with $z_{l,t-1}$ being the demeaned (over the fund period) series of the lagged instruments Z_l. The variables are standardized (mean = 0, standard deviation = 1) to capture the "surprise" component rather than the absolute levels of these variables.[5] The fund's time-varying beta annotated as β^* is made equal to $\beta_c + \sum_{l=1}^{L} \delta_l z_{l,t-1}$.

To capture within-month risk exposure for hedge funds, Patton and Ramadorai (2013) construct monthly estimates of macro-economic variables – the same $z_{l,t-1}$ as in the previous paragraph – by aggregating their daily innovations to capture intra-month variations. Using intra-period trading is supported by Goetzmann, Ingersoll, and Ivković (2000) and Pfleiderer and Bhattacharya (1983), who report that the artificial negative correlation between timing and selectivity skills could simply come from intra-period trading. To construct these variables, we use the the daily log market returns of the S&P 500 and the logarithmic values of the daily macro-economic variables previously mentioned. The macro-economic variables are also standardized with mean 0 and standard deviation 1 over the month analyzed. Formally, we compute the monthly aggregation of the daily variables conditional on the daily log market return as follows:

$$
z_t^* Rm_t = \sum_{d \in M(t)} z_{d-1} \log(Rm_d) \tag{3}
$$

where $M(t)$ is the number of days in month t.

The formal definition of the OLS regression thus becomes

$$
\begin{aligned}
R_{i,t} &= \alpha_{TM} + \beta_c Rm_t + \gamma_c Rm_t^2 + \sum_{l=1}^{L} \delta_l (z_{l,t-1} Rm_t) + \sum_{l=1}^{L} \Delta_l (z_{l,t-1}^* Rm_t) + e_{i,t} \\
&= \alpha_{TM} + \beta^* Rm_t + \gamma_c Rm_t^2 + e_{i,t}
\end{aligned} \tag{4}
$$

[5] We de-trend the instrumental variables Z_{t1} from their mean level such that the loading coefficients can be interpreted as the average level of risk exposure (Patton and Ramadorai 2013).

The conditional beta of a fund manager is now equal to $\beta^* = \beta_c + \sum_{l=1}^{L} \delta_l z_{l,t-1} + \sum_{l=1}^{L} \Delta_l z^*_{l,t-1}$, while the term γ_c reflects private market timing skills. For simplicity, we refer in the remainder of the paper to the coefficients β^* as β and γ_c as γ.

Finally, at this stage, our model assumes constant values for these four coefficients. However, hedge fund managers being active investors, their market timing skills may change over time.To capture the dynamic allocation behavior of fund managers, we estimate the model using rolling-window regressions with a minimum of 36 and a maximum of 60 available months.[6]

In the next section, we detail the generalized 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), our derivative-based framework is focused on the timing component from market returns.[7] 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), our 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 extended TM model at the individual fund level. To achieve this objective, we start by normalizing the option Greeks from OptionMetrics according to the underlying stock price and the price of the option. The normalization relies on the Taylor expansion of the option value (V). The option can take the form of either a call or a put option. From the Taylor series expansion, the approximation of the option value (V) on a security with price S at time t is obtained by,

$$dV \approx \frac{\partial V}{\partial S} dS + \frac{1}{2} \frac{\partial^2 V}{\partial S^2} (dS)^2 + \frac{\partial V}{\partial t} dt + o(t) \tag{5}$$

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 $\frac{\partial V}{\partial t}$

[6]Chen and Liang (2007) also use rolling regressions with fixed windows of 36 months to analyze the time variation in hedge funds timing ability.

[7]A growing stream of literature has investigated the ability of hedge funds to anticipate the variations in 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 indicate that the ability to time these variables can be identified as a source of superior hedge fund performance. Evidence indicates that a sub-sample of these funds exhibits such timing abilities even after accounting for option-based risk factors.

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) and the interest rate (r) are constant. Moreover, controlling for the monthly and intra-month values of both 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 (5) we obtain

$$dV \approx \Delta_v dS + \frac{1}{2}\Gamma_v (dS)^2 + \Theta_v dt + o(t) \tag{6}$$

Writing equation (6) in discrete time yields

$$V_t - V_{t-\Delta t} = \Delta_v (S_t - S_{t-\Delta t}) + \frac{1}{2}\Gamma_v (S_t - S_{t-\Delta t})^2 + \Theta_v \Delta t \tag{7}$$

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:

$$R_t^v = \underbrace{\frac{M_{t-\Delta t}}{V_{t-\Delta t}}\Delta_v}_{\text{(1) Normalized Delta}} Rm_t + \frac{1}{2} \underbrace{\frac{M_{t-\Delta t}^2}{V_{t-\Delta t}}\Gamma_v}_{\text{(2) Normalized Gamma}} Rm_t^2 + \underbrace{\frac{\Theta_v}{V_{t-\Delta t}}}_{\text{(3) Normalized Theta}} \Delta t \tag{8}$$

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.[8] 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:

$$R_t^v = \Delta_v Rm_t + \frac{1}{2}\Gamma_v Rm_t^2 + \Theta_v \Delta t \tag{9}$$

with R_t^v being the return of the option over the interval Δt (1-month), Δ_v, Γ_v, and Θ_v being the normalized Delta, Gamma and Theta of the option, respectively, and Rm_t being the return of the

[8] 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 convert the value to a monthly basis.

underlying stock index (S&P 500) at time t.

1.3 Option-Based Replication

We generalize the model of Hübner (2016) to replicate fund return payoff. We use a time-varying framework so that a fund can exhibit some nonlinearities in t but none in $t+1$. To perform this exercise, we simply use the combination of two options: one call and one put. The process can then be described in two steps.

The first step consists in finding, in each period, the *call* and *put* options with the closest match to the following ratio: $\Delta^c_{\tau,\kappa}/\Gamma^c_{\tau,\kappa} = -\Delta^p_{\tau,\kappa}/\Gamma^p_{\tau,\kappa}$. This identity ensure similar convexity for the options such that $\gamma = \gamma^c + \gamma^p$, where $\beta^c/\gamma^c = -\beta^p/\gamma^p$ and c and p are the subscript for the call and put option, respectively.

The closest match attributes one call and one put option with maturity (τ) and moneyness (κ) to each monthly return observation of a fund. Compared to classical option-based factors, our model does not pre-define the choice of the maturity of the option. Concerning the moneyness, funds with either a non-directional bet ($\beta \approx 0$) or no private timing skills ($\gamma \approx 0$) will be replicated with ATM options, whereas funds that do not satisfy these conditions will have complete freedom in the choice of option moneyness. This specification makes our framework very flexible in the selection of the correct type of option for replication purposes.

The formal description of the option-based replication strategy is given by,

$$\begin{aligned} R^{\tau,\kappa}_t &= w^c_{\tau,\kappa} R^c_t + w^p_{\tau,\kappa} R^p_t + (1 - w^c_{\tau,\kappa} - w^p_{\tau,\kappa}) Rf_t + o(\Delta t) \\ &= w^c_{\tau,\kappa}(\Delta^c_{\tau,\kappa} Rm_t + \frac{1}{2}\Gamma^c_{\tau,\kappa} Rm^2_t + \Theta^c_{\tau,\kappa}) \\ &+ w^p_{\tau,\kappa}(\Delta^p_{\tau,\kappa} Rm_t + \frac{1}{2}\Gamma^p_{\tau,\kappa} Rm^2_t + \Theta^p_{\tau,\kappa}) \\ &+ (1 - w^c_{\tau,\kappa} - w^p_{\tau,\kappa}) Rf_t + o(\Delta t) \end{aligned} \tag{10}$$

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 Rf is the monthly risk-free rate from Kenneth French's website. The superscripts c and p denote call and put options, respectively.

Note that the replication strategy has budget constraints that are satisfied by solving for the exposures $w^c_{\tau,\kappa}$ and $w^p_{\tau,\kappa}$ to the selected options and allocating a proportion $(1 - w^c_{\tau,\kappa} - w^p_{\tau,\kappa})$ to the risk-free rate.

The second step consists in solving for the weights ($w^c_{\tau,\kappa}$ and $w^p_{\tau,\kappa}$) that are attributed to the selected call and put options with the equivalent maturity (τ) but potentially different moneyness (κ). The weights should satisfy the following conditions:

$$\begin{cases} \beta = w^c_{\tau,\kappa}\Delta^c_{\tau,\kappa} + w^p_{\tau,\kappa}\Delta^p_{\tau,\kappa} \\ \gamma = \frac{1}{2}(w^c_{\tau,\kappa}\Gamma^c_{\tau,\kappa} + w^p_{\tau,\kappa}\Gamma^p_{\tau,\kappa}) \end{cases} \tag{11}$$

And the weights can be obtained through traditional nonlinear optimizations or more simply through a closed form solution as follow:

$$\begin{pmatrix} w^c_{\tau,\kappa} \\ w^p_{\tau,\kappa} \end{pmatrix} = \begin{bmatrix} \frac{\Gamma^p_{\tau,\kappa}}{\Delta^c_{\tau,\kappa}\Gamma^p_{\tau,\kappa} - \Delta^p_{\tau,\kappa}\Gamma^c_{\tau,\kappa}} & \frac{-2\Delta^p_{\tau,\kappa}}{\Delta^c_{\tau,\kappa}\Gamma^p_{\tau,\kappa} - \Delta^p_{\tau,\kappa}\Gamma^c_{\tau,\kappa}} \\ \frac{-\Gamma^c_{\tau,\kappa}}{\Delta^c_{\tau,\kappa}\Gamma^p_{\tau,\kappa} - \Delta^p_{\tau,\kappa}\Gamma^c_{\tau,\kappa}} & \frac{2\Delta^c_{\tau,\kappa}}{\Delta^c_{\tau,\kappa}\Gamma^p_{\tau,\kappa} - \Delta^p_{\tau,\kappa}\Gamma^c_{\tau,\kappa}} \end{bmatrix} \begin{pmatrix} \beta \\ \gamma \end{pmatrix} \tag{12}$$

The linear and quadratic terms $\beta Rm_t + \gamma Rm_t^2$ are thus equal to
$(w^c_{\tau,\kappa}\Delta^c_{\tau,\kappa} + w^p_{\tau,\kappa}\Delta^p_{\tau,\kappa})Rm_t + \frac{1}{2}(w^c_{\tau,\kappa}\Gamma^c_{\tau,\kappa} + w^p_{\tau,\kappa}\Gamma^p_{\tau,\kappa})Rm_t^2$.

The intercept (hereafter, alpha) of the passive strategies composed of one call and one put option is given by,

$$\alpha^{\tau,\kappa} = w^c_{\tau,\kappa}\Theta^c_{\tau,\kappa} + w^p_{\tau,\kappa}\Theta^p_{\tau,\kappa} + (1 - w^c_{\tau,\kappa} - w^p_{\tau,\kappa})Rf_t \tag{13}$$

Because this alpha comes from a purely passive strategy, it can be viewed as the cost of implementing the same timing strategy as the fund manager when her access is limited to a set of options on a benchmark and a risk-free. Subtracting the alpha ($\alpha^{\tau,\kappa}$) of the option strategy from the alpha (α_{TM}) of the manager should control for the cost of the option implied in market timing models.[9] The adjusted-α of the fund is now defined as

$$\begin{aligned} \pi^{\tau,\kappa} &= \alpha'_{TM} - \alpha^{\tau,\kappa} \\ &= \alpha'_{TM} - w^c_{\tau,\kappa}\Theta^c_{\tau,\kappa} - w^p_{\tau,\kappa}\Theta^p_{\tau,\kappa} - (1 - w^c_{\tau,\kappa} - w^p_{\tau,\kappa})Rf_t \end{aligned} \tag{14}$$

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

[9] See Bollen and Busse (2004) for a discussion on the alpha of the quadratic market timing model and Jiang (2003) and Ferruz, Muñoz, and Vargas (2010) for a discussion on the cost of the option implied in market timing models.

Or equivalently,

$$\pi^{\tau,\kappa} = \alpha_{TM} - w^c_{\tau,\kappa}\Theta^c_{\tau,\kappa} - w^p_{\tau,\kappa}\Theta^p_{\tau,\kappa} - (\beta - w^c_{\tau,\kappa} - w^p_{\tau,\kappa})Rf_t \tag{15}$$

Table 1 summarizes the model procedures to replicate a fund's payoff. The first column reports the paper notation for the fund classification; the second column shows the direction of the fund, denoted by β; the third column indicates whether the replicated fund has gamma trading skills (γ); the sixth column is informative about the regression characteristics used to classify the replicated fund. We choose $-\beta/2\gamma$ because the value is equal to the inflection point (vertex) of the quadratic model and by consequence, contains key information about the nonlinear characteristics of a fund's returns; and the last column describes the type of option-based strategy used to replicate the fund payoff.

Note that when a fund does not exhibit γ skills, then the conditions of equation (11) become

$$\begin{cases} \beta = w^c_{\tau,\kappa}\Delta^c_{\tau,\kappa} + w^p_{\tau,\kappa}\Delta^p_{\tau,\kappa} \\ w^c_{\tau,\kappa} = -w^p_{\tau,\kappa} \end{cases} \tag{16}$$

These new conditions ensure that the replication of a directional fund with no γ skills is simply a synthetic replication of the fund. For example, a fund with positive β and no γ will be replicated by buying an amount $w^c_{\tau,\kappa}$ of a call and shorting an equivalent amount $w^p_{\tau,\kappa}$ in a put. These options are ATM and have equivalent maturity.

1.4 Implied Cost of Option Trading

This section illustrates the implementation of the option-based replication strategies in a controlled environment. We present an hypothetical *Perfect Market Timer* fund as in the works of Hasanhodzic and Lo (2007) and Chen and Liang (2007), which the authors refers to as "Capital Multiplication Partners," to show the option-like payoffs that such a perfect timer would exhibit. The performance of the Capital Multiplication Partners fund is constructed by being invested in the market when the market returns are higher than the risk-free and in the risk-free rate when market returns are lower than the risk-free. The mathematical expression to obtain the performance of this fund is simply max(Rm, Rf). When the TM model is applied on this fund, the β and γ coefficients

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 with the Newey-West adjustment for standard errors and apply a lag of t=3 for the linear and quadratic parameters. This table presents the payoff identifications to apply the option-based replication strategies. The notation Rm^- stands for the minimum value of the market return, while Rm^+ represents the maximum value of the market return over the analyzed period. The notation β^+ refers to a positive beta coefficient, while β^- denotes a negative beta coefficient. The notations are similar for the sign of the gamma (γ) coefficient.

Paper	Classification		Characteristics			Replication
Notation	Direction	Gamma Skills	β	γ	ratio $(-\beta/2\gamma)$	Strategy
β^+	Long	None	> 0	≈ 0	None	Long Call + Short Put
β^-	Short	None	< 0	≈ 0	None	Short Call + Long Put
$[\beta^+, \gamma^+]$	Long	Positive	> 0	> 0	$\notin [Rm^-, Rm^+]$	Long Strangle
$[\beta^-, \gamma^+]$	Short	Positive	< 0	> 0	$\notin [Rm^-, Rm^+]$	Long Strangle
$[\beta^+, \gamma^-]$	Long	Negative	> 0	< 0	$\notin [Rm^-, Rm^+]$	Short Strangle
$[\beta^-, \gamma^-]$	Short	Negative	< 0	< 0	$\notin [Rm^-, Rm^+]$	Short Strangle
γ^+	Neutral	Positive	≈ 0	> 0	$\in [Rm^-, Rm^+]$	Long Straddle
γ^-	Neutral	Negative	≈ 0	< 0	$\in [Rm^-, Rm^+]$	Short Straddle

are both significant and positive and the fund payoff resembles that of a long call. In our framework, the model would replicate that payoff through a strangle strategy with low weight invested in the put option and high weight invested in the call option.

As Fama and French (2010, p. 1915) write, "*Active investment must also be a zero sum game-aggregate is zero before costs*," so for one type of payoff, there should be a counterparty. The counterparty for the Capital Multiplication Partners fund is given by min(Rm, Rf) and has a payoff equivalent to a short call option. We also provide four other types of fund payoff that can be replicated in our framework: (i) a long put payoff (max(-Rm,-Rf)), (ii) a short put payoff (min(-Rm, -Rf)), (iii) a perfect neutral timer through a long straddle payoff (max(-Rm,Rm)), and (iv) a worst neutral timer through a short straddle payoff (min(-Rm,Rm)).

Figure 1 illustrates the payoffs of hypothetical funds with, by design, no security selection skills but market timing skills. The alpha correction provided by our replication model is illustrated by the vertical black line. The alpha correction can be interpreted as the cost of implementing the timing strategy through a range of options listed on the benchmark. We review in Section 3.3 the implication of this alpha adjustment for the negative correlation bias between the α and γ coefficients present in the quadratic model. We also check whether this artificial effect applies to our framework.

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 the HFR and Morningstar databases for our hedge fund sample.

2 Data

2.1 Options and Greeks

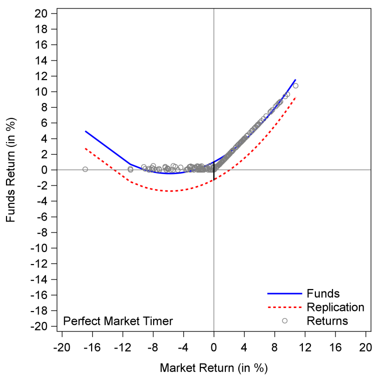
OptionMetrics provides data on the historical price, implied volatility and Greeks for the US equity and index options markets. We restrict our use of OptionMetrics data to the Standard and Poor's (S&P) 500 composite index (ID 108105) and retrieve options with a standard settlement date, that is, where 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).[10] We only retain observations from the first day of each month for which the open interest

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

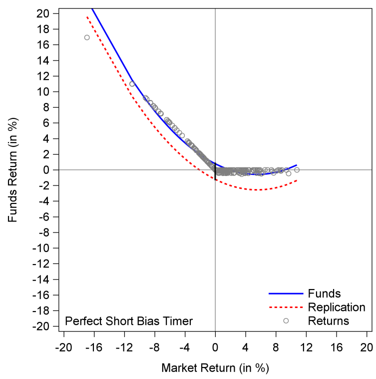
Figure 1

This figure illustrates the cost of replication using options for six hypothetical fund managers with significantly good or bad market timing skill. The fund payoff is illustrated by the blue line, while the option-based replication payoff is given by the red dotted line. The cost of replication is equivalent to the alpha from the option-based strategy and highlighted by the vertical black line. The empty circles refers to the hypothetical fund returns.

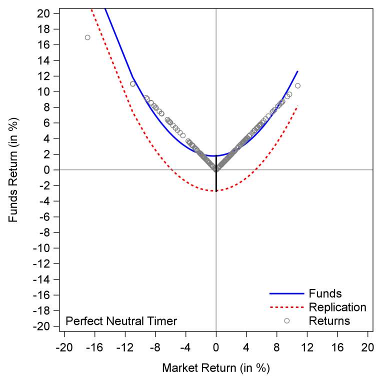
(a) Max(Rm,Rf)



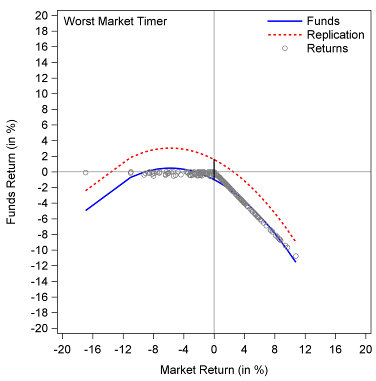
(b) Max(-Rm,-Rf)



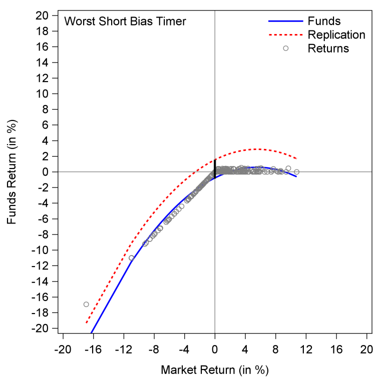
(c) Max(-Rm,Rm)



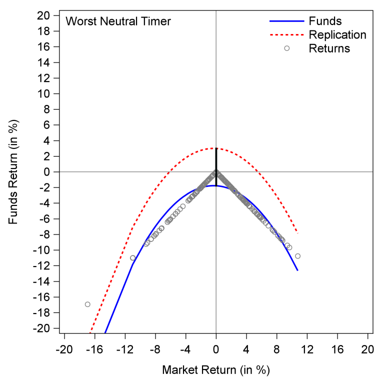
(d) Min(Rm,Rf)



(e) Min(-Rm,-Rf)



(f) Min(-Rm,Rm)



(volume) is greater than zero and that have valid implied volatility and Delta values. The 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 matching[11] 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 yields 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.

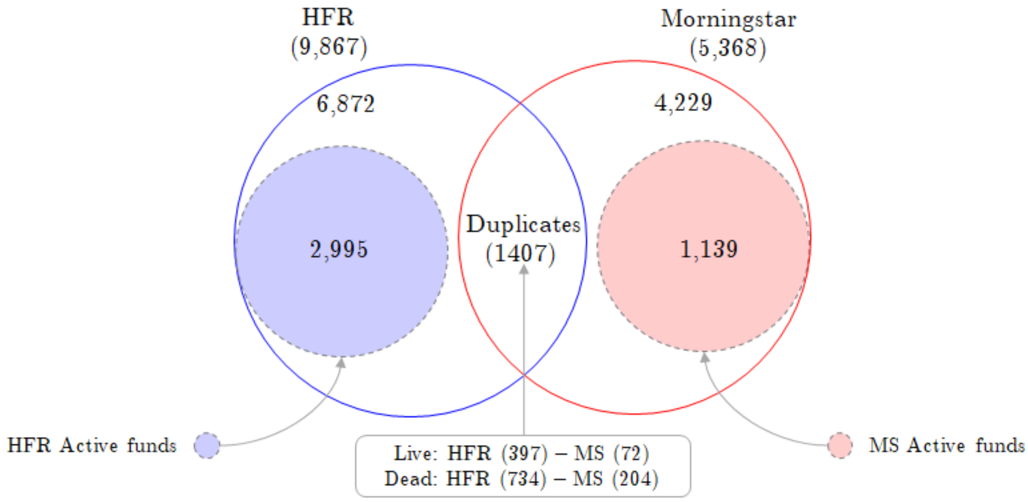
Figure 2 illustrates that the number of alive and dead funds that are specific to each database after treatments is equal to 6,872 and 2,995 for HFR and to 4,229 and 1,139 for Morningstar, respectively. We record 1,407 duplicates between HFR and Morningstar. For these funds, we select the fund from the provider that reports the most observations – generally HFR in our sample: 397 alive funds are attributed to HFR, 72 alive funds are attributed to Morningstar, 734 dead funds are attributed to HFR, and 204 dead funds are attributed to Morningstar.

Because each database reports different hedge fund 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

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

Figure 2: 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.



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.[12] 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

[12]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: Fund 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	

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) propose the following model of return smoothing:

$$R_t^0 = \theta_0 R_t + \theta_1 R_{t-1} + ... + \theta_k R_{t-k} \tag{17}$$

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 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:

$$R_t = \frac{R_t^0 - \hat{\theta}_0 R_t - \hat{\theta}_1 R_{t-1} - ... - \hat{\theta}_k R_{t-k}}{\hat{\theta}_0} \tag{18}$$

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. 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 the smoothing index to filter the duplicates in our database (as described in the previous section). The smoothing index is computed as follows:

$$\xi = \sum_{j=0}^{k} \theta_j^2 \in [0, 1] \tag{19}$$

where θ_j are the parameters from the MA process estimated in equation (17). The smoothing index is often compared to the Herfindhal index, as it yields 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 Other 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 the short-term interest rate (PTFSIR) and on the stock market (PTFSSTK).[13] Panel C reports the instrumental variables estimated on a monthly basis as 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).

3 Gamma Skills in The Cross-Section of Hedge Funds

This section presents four contributions to the current literature on hedge funds. First, we report the time-varying option-like identification of a fund through the indications from Table 1 and summarize the option-like characteristics of hedge funds strategies. Second, we quantify the alpha of the option replication strategies, which is a function of the leverage, time decay (theta), and the risk-free rate and should be regarded as the cost of the option for implementing the timing strategy.

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

Table 3: Monthly 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 the 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

Third, we evaluate the cost of options implied in the TM market timing model across our hedge fund sample and present evidence of the artificial negative relationship between the intercept and the quadratic term in market timing models. We demonstrate that our replication framework is free from this systematic bias.

3.1 Time-Varying Option-Like Payoff

Kacperczyk, Van Nieuwerburgh, and Veldkamp (2014, p. 1458) support that "*time variation in fund manager skill is a useful piece of evidence in the quest to understand fund behavior.*" Common market timing frameworks, such as that of Treynor and Mazuy (1966), assume the coefficients of the model to be constant (Jagannathan and Korajczyk 1986). Two caveats are in order. First, the model provides no information about the dynamic behavior of the manager on his strategy allocation. Second, risk is assumed to be stationary over time. Bollen and Whaley (2009) circumvent this issue by using changepoint regressions that capture significant shifts in fund managers' risk exposure. In their study, the amount of shifts is however reduced to only one significant change in risk exposure. Instead, we favor the use of rolling-window regressions to capture more than one change in option-like behavior by fund managers. We impose a minimum of 36 up to a maximum of 60 available months to perform the regression established in equation (4).

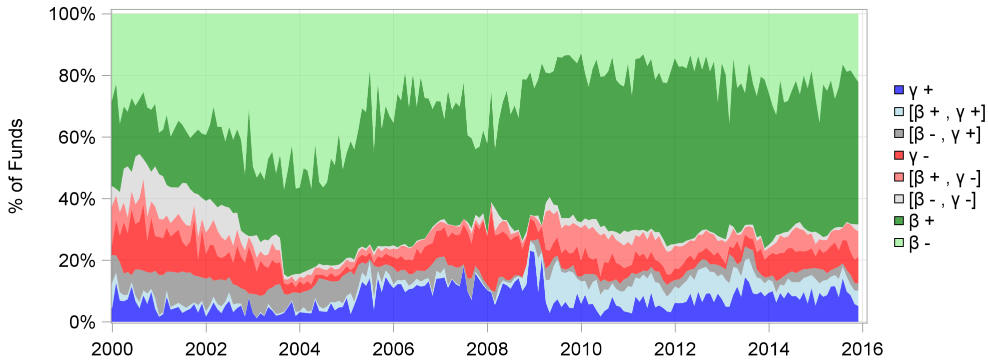
Figure 3 illustrates the identification of option-like payoffs for the cross-section of hedge funds over time. The benefit of our method resides in the fact that even a fund without significant gamma skills (γ) will be replicated through a synthetic replication using one ATM call and ATM put on the underlying benchmark (S&P 500). This number of synthetic replications, reported in green colors, is large in our sample and varies from 45% in 2001 up to roughly 80% in 2004. These synthetic linear replications are nevertheless important in the time-varying framework since funds can exhibit only a linear bet in time period t while showing private market timing skills in t+1. As our sample is composed of approximately 11,000 funds, the model covers almost 95% of the observations for funds with a minimum of 36 observations that have an option-based replication at each time period t.[14]

We now turn to the analysis of the persistence of the option-like payoffs identified in hedge funds. Similar to Fama and French (2007) on individual stocks and Chen, Cliff, and Zhao (2017) on hedge funds, we consider the transition of a fund's classification between time period t to $t+1$. The results

[14]Our sample comprises 632,154 observations, of which 616,497 have an option-based replication. The other 15,657 observations display a $\beta \approx 0$ and $\gamma \approx 0$ and thus we do not consider them in our analysis.

Figure 3: Time-Varying Option-Like Payoff

This figure illustrates the identification of option-like payoffs for our cross-sectional hedge fund sample over time. The classification of the funds follows the guidelines in Table 1. These guidelines are conducted on the linear (β) and non-linear (γ) terms from the regression presented in equation (4). The sample period illustrated in the figure ranges from January 2000 to December 2016.



can be interpreted as the empirical probability that one fund classified with only gamma skill in period t becomes to a fund with persistent gamma skill and a significant bet on the market in $t+1$. Table 4 shows that this empirical probability is approximately 13%. Analyzing the transition of funds is important because it also reveals the dynamic behavior of a fund manager of changing the optional features of his strategy conditional on the fund survival. Panel A shows that it is very unlikely (close to 0%) that a fund with positive γ coefficient exhibits negative coefficient over the next month regardless of whether the fund has a directional bet on the market (β), and vice versa. It is also unlikely that a fund with only a linear bet on the market demonstrates positive market timing skills over the next month ($\sim 3.5\%$). While these probabilities slightly increase from Panel B to Panel D, results indicate the same direction of transitions over the next 3, 6 and 12 months. For instance, funds with gamma skill (γ^+) tend to remain in their states only for a short period of time – one to three months – and may suggest that neutral allocation w.r.t the market is just a temporary state rather than a long-term strategy. Finally, we find some evidence that funds with positive market timing skills ($[\beta^+, \gamma^+]$, $[\beta^-, \gamma^+]$, and γ^+) are less likely to stop reporting over the subsequent periods compared to funds with negative market timing skills (on average, $\sim 1.8\%$ against 2.8%), and this probability increases linearly as we increase the time period (on average, $\sim 18\%$ against 21% in Panel D).

Table 4: Transition Matrix

This table reports the transition probabilities between the option-like payoff identifications in the cross-section of hedge funds. We form the transition across groups from the current month to the next 1, 3, 6, and 12 months. The last column of the table reports the empirical probability that a fund leaves our sample for reporting purposes (intentionally or unintentionally, i.e., dead funds).

	β^+	$[\beta^+,\gamma^+]$	$[\beta^+,\gamma^-]$	β^-	$[\beta^-,\gamma^+]$	$[\beta^-,\gamma^-]$	γ^+	γ^-	Out	β^+	$[\beta^+,\gamma^+]$	$[\beta^+,\gamma^-]$	β^-	$[\beta^-,\gamma^+]$	$[\beta^-,\gamma^-]$	γ^+	γ^-	Out
	Panel A: Next month									Panel B: Next 3 months								
β^+	72.7%	1.6%	1.7%	19.1%	0.4%	0.2%	1.5%	1.1%	1.9%	66.0%	2.3%	2.3%	18.9%	0.6%	0.3%	2.4%	1.8%	5.4%
$[\beta^+,\gamma^+]$	15.9%	51.2%	0.0%	2.5%	4.9%	0.0%	23.8%	0.0%	1.7%	22.2%	42.1%	0.2%	3.6%	4.3%	0.0%	22.7%	0.1%	4.9%
$[\beta^+,\gamma^-]$	13.9%	0.0%	55.6%	2.5%	0.0%	3.5%	0.0%	22.0%	2.5%	18.9%	0.1%	46.3%	3.6%	0.0%	3.3%	0.0%	20.6%	7.2%
β^-	29.9%	0.3%	0.4%	61.6%	1.4%	1.0%	1.7%	1.7%	1.9%	30.8%	0.6%	0.7%	54.4%	2.1%	1.3%	2.8%	2.5%	4.8%
$[\beta^-,\gamma^+]$	3.7%	5.0%	0.0%	10.9%	47.0%	0.0%	31.4%	0.0%	2.1%	5.8%	5.5%	0.0%	16.4%	39.3%	0.0%	28.4%	0.1%	4.5%
$[\beta^-,\gamma^-]$	3.7%	0.0%	7.6%	14.2%	0.0%	41.3%	0.0%	29.8%	3.3%	7.3%	0.1%	7.8%	18.2%	0.0%	33.6%	0.1%	26.5%	6.5%
γ^+	8.0%	13.5%	0.0%	5.4%	14.2%	0.0%	57.3%	0.0%	1.6%	12.8%	12.0%	0.1%	9.3%	13.3%	0.0%	47.6%	0.1%	4.8%
γ^-	7.0%	0.0%	16.2%	6.7%	0.0%	9.9%	0.0%	57.5%	2.7%	11.8%	0.1%	14.9%	11.1%	0.0%	8.7%	0.1%	46.6%	6.6%
	Panel C: Next 6 months									Panel D: Next 12 months								
β^+	59.8%	2.9%	2.7%	17.5%	0.8%	0.4%	3.0%	2.3%	10.6%	49.4%	3.1%	3.0%	16.8%	1.1%	0.6%	3.4%	2.9%	19.8%
$[\beta^+,\gamma^+]$	26.5%	34.7%	0.5%	4.6%	4.2%	0.0%	19.5%	0.2%	9.7%	28.6%	24.8%	1.0%	7.2%	3.6%	0.1%	15.9%	0.6%	18.2%
$[\beta^+,\gamma^-]$	22.7%	0.2%	38.3%	5.4%	0.0%	3.2%	0.1%	17.7%	12.5%	25.6%	0.4%	26.9%	8.0%	0.1%	2.9%	0.4%	14.9%	20.9%
β^-	29.4%	0.8%	1.0%	49.0%	2.6%	1.5%	3.9%	3.0%	8.9%	29.3%	1.4%	1.3%	38.1%	2.9%	1.4%	5.0%	3.0%	17.6%
$[\beta^-,\gamma^+]$	8.7%	4.5%	0.0%	19.7%	33.7%	0.1%	25.2%	0.1%	8.1%	11.8%	4.2%	0.2%	22.2%	22.1%	0.2%	22.9%	0.5%	15.9%
$[\beta^-,\gamma^-]$	8.7%	0.1%	6.2%	22.6%	0.1%	28.7%	0.1%	22.9%	10.5%	12.9%	0.2%	6.0%	25.1%	0.2%	18.8%	0.7%	16.2%	20.0%
γ^+	17.4%	10.2%	0.3%	12.0%	10.6%	0.1%	38.9%	0.4%	10.2%	20.5%	7.9%	0.7%	13.9%	8.7%	0.2%	27.3%	1.0%	19.7%
γ^-	16.8%	0.3%	13.0%	13.2%	0.1%	7.1%	0.4%	36.8%	12.3%	21.4%	1.2%	10.5%	14.2%	0.2%	5.8%	1.1%	23.5%	22.0%

The last analysis aims at identifying whether typical payoffs can be associated to hedge fund style. in this subsection reviews whether some types of option-like payoffs are specific to hedge fund categories. We report in Figure 4 the proportion of option-like payoffs displayed over time for each hedge fund category. Figure 4a shows the results for all types of option payoffs, while Figure 4b presents the results only when funds display a significant γ coefficient. For instance, the category "Event Driven" converges towards 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 (Mitchell and Pulvino 2001). One explanation for this classification is that in bad economic conditions, Event Driven funds will be more likely to fail and thus exhibit losses. Funds with strategies that resemble writing put options may appear attractive in a mean-variance framework, but they actually perform poorly when we consider higher order moments (DeRoon and Karehnke 2017). The reason is that such strategies bear significant tail risks because writing put options on the market index may severely impact the fund's performance when strong bearish trends affect the equity market (Agarwal and Naik 2004).

Exploiting these results, we note that our classification of option-like payoffs is in line with the findings of previous studies. We present these evidence by primary categories and attribute one type of option-like payoff to the highest proportion of funds found in Figure 4b that correspond to that option strategy.

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

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

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

Long/Short: Strangle, i.e., a directional bet with timing abilities.

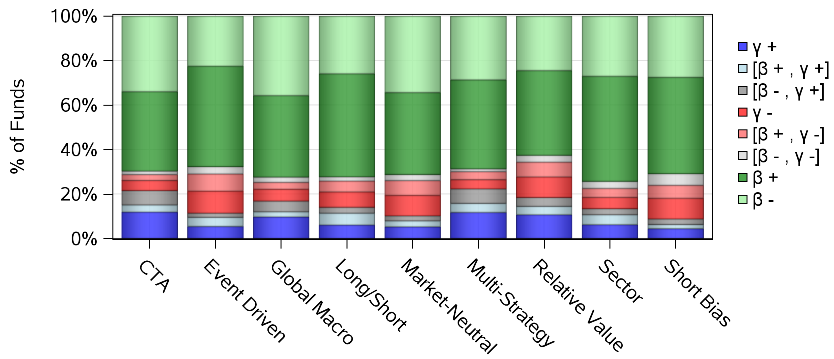
Market-Neutral: Short straddle, i.e., a neutral bet on the market with the objective of profiting from mispricing and not from market timing (Chen and Liang 2007).

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

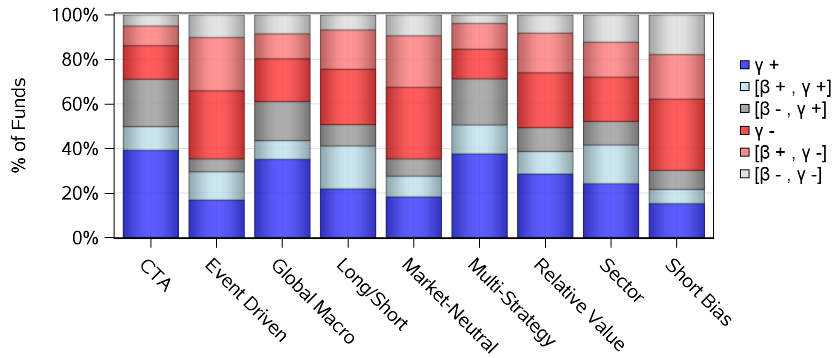
Figure 4: Time-Varying Option-Like Payoff

This figure illustrates the identification of option-like payoffs for the cross-sectional hedge funds sample. The classification of the funds follows the guidelines of Table 1. These guidelines are simply conducted by the linear (β) and non-linear (γ) terms from the regression presented in equation (4). The proportion of option-like payoffs is given across hedge fund categories. The sample period ranges from January 1996 to December 2016.

(a) All Funds



(b) Funds with significant γ Skills



Relative Value: Short straddle, 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 strangle, i.e., sell short overvalued securities and face substantial risk during good market conditions (Agarwal and Naik 2004).

3.2 Hedge Funds' Gammas and Adjusted Alphas

Similar to models that have the objective of providing measures with better precision for evaluating market timing (see, e.g., Jiang 2003), the aim of our model is to distinguish market timing from option-related spurious timing. We assume that accounting for the cost of options implied in the market timing model has a causal effect that enables better measurements of a manager's skills. For example when a fund manager presents market timing skills (γ^+) in equation (4), the model does not indicate whether this level of convexity is attainable through a passive strategy composed of options. The timing skill attributed to the manager should thus be valid (not artificial) when the manager trades securities different from the passive option strategy that delivers a similar timing coefficient and market exposure. Otherwise, the manager's strategy is a simple replication of the passive strategy – in which there is neither market timing nor security selection skills (Jagannathan and Korajczyk 1986) – and the manager should be accredited with zero alpha (security selection) and spurious timing. Our model provides a solution to this problem. Specifically, our framework establishes individual benchmarks for fund managers who trade derivatives or option-like stocks.

We present in the next two subsections, the characteristics of the selected options from the passive replication exercise and quantify its impact in terms of alpha adjustments.

3.2.1 Selected Option Characteristics

Table 5 displays descriptive statistics of the selected options to replicate a fund's β and γ estimates from equation (4). For example, a fund with positive market timing skills (positive linear and quadratic terms) could be replicated by investing, on average, 49.14% of the strategy's capital in a call option with a moneyness of 0.87 while investing a small amount (only 1.27%) in a put option with a moneyness of 0.74, both options having a equivalent maturity of 60 days. We note that the classifications $[\beta^+, \gamma^+]$ and $[\beta^-, \gamma^-]$ share the same type of moneyness (OTM put and ITM call) and maturity (60 days) in the option selection process. The difference between these categories comes solely from being long or short the straddle strategy. This finding is similar for the classifications $[\beta^+, \gamma^-]$ and $[\beta^-, \gamma^+]$, which share equivalent moneyness (ITM put and OTM call) and maturity ($\sim$ 85 days). For straddle strategies, the selection of ATM options is consistent with the idea that the γ of a straddle strategy is the highest for ATM options. Furthermore, our model forms straddles by selecting a maturity of approximately 5 months ($\sim$ 150 days) and that regardless of whether the strategies are long or short in the straddle. Finally, we also note that the selected options are highly liquid, as shown by the large open interest values found in the last columns of the Table.

What does the option selection process in our model tell us about the traditional methodological choices in option-based replication strategies? According to the conjecture of Merton (1981), market timers were originally identified as having a similar payoff as a long straddle strategy. Naturally, the choice of pre-defining options to be ATM is consistent with the idea of capturing the sensitivity to market volatility rather than the direction of the market return (Coval and Shumway 2001). The traditional option-based risk factors from Fung and Hsieh (2001) and Agarwal and Naik (2004) also select ATM options to explain the performance of market-neutral funds. However, we differ from these studies, as our model selects options with an average maturity of 5 months but large standard deviations, whereas traditional option factors use a fixed maturity of one or three months.[15] Turning to strangle strategies for which the maturity and the moneyness are endogenous to our model, we see that for the intention of replicating funds with directional and non-directional bets is produced by investing in a combination of ITM and OTM options where most of the weight is attributed to the ITM option. OTM options thus play a marginal role in our model, whereas they compose half of the set of option risk factors in Agarwal and Naik (2004). We illustrate in Figure 6 the empirical distribution of the characteristics of options composing the replication strategies.

[15]This flexibility in the selection of options is one advantage of our model. In fact, this type of information could be interesting regarding the development of a new set of option-based risk factors that better capture nonlinearities in hedge funds' returns. However, this is outside the scope of the present research. Rather, we are interested in pointing out the endogenous choices of our model and assessing whether they converge towards those of previous studies.

Table 5: Option Replication Strategies

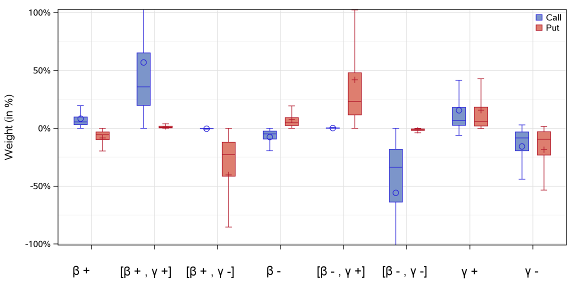
This table summarizes the average characteristics of the options that replicate all possible patterns of the TM regression. We reports the average amount of capital (weight) invested in the call and put options of the replicating strategy as well as the maturity, moneyness and open interest of these these options. Standard deviations of the average values are reported in parentheses.

Fund	# Obs	Weight		Moneyness		Maturity		Open Interest	
Classification		Call	Put	Call	Put	Call	Put	Call	Put
β^+	262,191	8.15%	-8.15%	1.01	1.01	149	149	11559	9343
		(15.29%)	(15.29%)	(0.02)	(0.02)	(170)	(170)	(18287)	(13244)
$[\beta^+, \gamma^+]$	26,646	49.14%	1.27%	0.87	0.74	60	60	4031	15244
		(68.54%)	(2.14%)	(0.05)	(0.14)	(47)	(47)	(10729)	(26440)
$[\beta^+, \gamma^-]$	30,354	-0.25%	-37.64%	1.17	1.12	83	83	10518	3582
		(0.42%)	(83.49%)	(0.09)	(0.07)	(76)	(76)	(16100)	(11170)
β^-	169,192	-8.94%	8.94%	1.01	1.01	166	166	11407	9659
		(17.10%)	(17.10%)	(0.02)	(0.02)	(176)	(176)	(17089)	(14829)
$[\beta^-, \gamma^+]$	23,245	0.31%	47.67%	1.16	1.12	87	87	9625	2693
		(0.46%)	(85.90%)	(0.09)	(0.07)	(78)	(78)	(14248)	(7977)
$[\beta^-, \gamma^-]$	13,203	-60.20%	-1.42%	0.87	0.74	62	62	2977	10395
		(107.38%)	(2.34%)	(0.05)	(0.11)	(47)	(47)	(9637)	(20416)
γ^+	49,764	14.15%	14.86%	1.01	1.01	144	144	11712	10183
		(32.29%)	(38.31%)	(0.02)	(0.02)	(153)	(153)	(16444)	(13981)
γ^-	41,902	-14.82%	-17.66%	1.01	1.01	165	165	11287	10294
		(30.58%)	(39.49%)	(0.02)	(0.02)	(167)	(167)	(16948)	(16467)

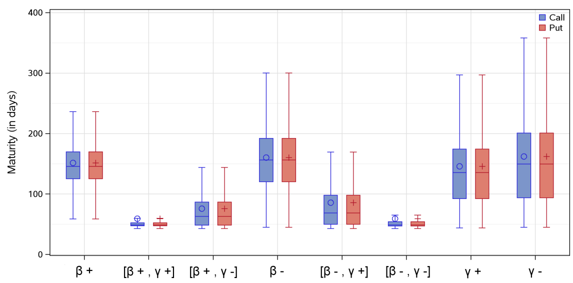
Figure 5

The figures illustrate the distribution of the characteristics from the selected call and put options of the replication strategies, in blue and red, respectively. We display in (a) the weight, (b) the maturity (in days), (c) the moneyness and (d) the open interest attributed to the options in the strategy. The boxes show the 5-th percentile and 95-th 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.

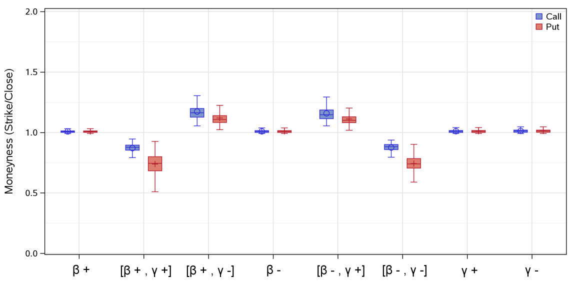
(a) Weight



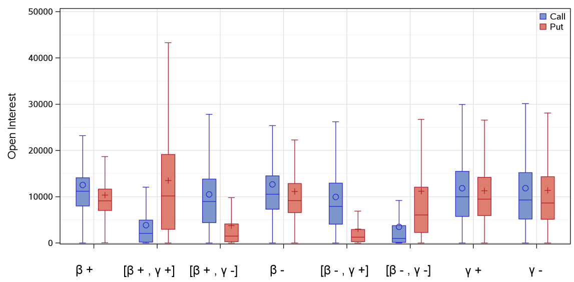
(b) Maturity



(c) Moneyness



(d) Open Interest



3.2.2 Adjusted Performance

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 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 be regarded as the total performance ($Perf$) of the fund (see also, Bollen and Busse 2004). However, if we believe that the quadratic term (γRm_t^2) could 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 our replication framework satisfies the condition of passively replicating the linear and quadratic terms 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 option-based benchmark.

We report in Table 6 the distribution of the monthly raw and adjusted-alpha estimates from the extended TM model with respect to the type of strategy the model tries to replicate. The first column displays the raw alphas, while the second column displays the distribution of the adjusted alphas. The third and the fourth column show the results for the total performance and the total adjusted-performance of the fund, respectively. The figures are aggregates of monthly values from rolling-window regressions. Results show that a fund with both a positive direction and timing ability on the market $[\beta^+, \gamma^+]$ delivers, on average, a negative raw alpha ($\sim$ -0.06% per month). Conversely, a fund with a positive bet but negative timing ability on the market $[\beta^+, \gamma^-]$ delivers a positive raw alpha ($\sim$ 1.09% per month). This strategy is similar to a strangle strategy strongly invested in the short ITM put position and with small weight in the short OTM call position. DeRoon and Karehnke (2017) demonstrate that writing put options may appear successful in a mean-variance framework but performs poorly when higher-order moments are introduced into the performance evaluation. In fact, Jurek and Stafford (2015) define writing put options as "dumb" alpha strategies. The results in the adjusted-α column substantially change the overall picture; the "dumb" alpha from writing put options shrinks to an average of -0.06% per month, while the alpha of a market timer is now raised to an average of 3.81% per month with a variability of xxx. The large volatility on alpha estimate suggests that funds with positive direction and timing ability on the market $[\beta^+, \gamma^+]$ have on average a lower hurdle compared to passive option-based strategies but that this hurdle is not systematic. This is because the adjustment depends not only on the options' availability on the market at time t but mostly the degree of convexity of the fund. Again, such outcomes make us confident that the flexibility of the model in the option selection process is key to distinguish spurious option timing. Similar interpretations can be inferred for other classifications with a significant timing coefficient (γ). Overall, the aggregate results obtained for all funds preserve an equivalent level of average fund alpha even after adjustment while making the estimate more volatile in the cross-section of hedge funds.

The next subsection questions whether the alpha adjustment mitigates the artificial negative correlation embedded in market timing or is simply another systematic bias but from opposite sign.

3.3 Artificial Negative Correlation in Market Timing Models

The presence of an artificial negative correlation between the intercept and quadratic term of market timing models has been documented in previous literature such as in the work of Jagannathan and Korajczyk (1986), among others. The alpha for option-like strategies such as hedge funds, measured by the intercept of a regression model, may thus be inflated by a positive convexity. Indeed, the alpha of exotic investments with option-like (nonlinear) payoffs from a typical linear regression is different from the traditional alpha of vanilla strategies (e.g., passive equity and bond strategies). The effect of skills for these exotic investments should thus be contingently adjusted for the non-linearities in their returns. A quadratic model, such as the TM model, by construction shifts upward (downward) the alpha of a strategy that has a negative (positive) OLS coefficient on the quadratic term because the average squared market return is positive (negative) (DeRoon and Karehnke 2017). This is in line with the empirical studies of Coggin, Fabozzi, and Rahman (1993) and Jiang (2003), which also report evidence of an artificial negative correlation between the intercept and the quadratic coefficients.

To better understand this bias, we word under the controlled environment presented in Section 1.4 with the hypothetical funds of Hasanhodzic and Lo (2007) and Chen and Liang (2007) for which we know that selection skill is absent and therefore, independent of the market timing skill. We demonstrate that (i) there is, indeed, an artificial negative correlation between the intercept and the quadratic term of a market timing model where there should be none, by construction, and (ii) that

Table 6: Alpha and Adjusted-Alphas

This table summarizes the average alpha and adjusted-alpha 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.

Classification	# Obs	α	Adjusted-α	$Perf$	Adjusted-$Perf$
β^+	262,191	0.50%	0.50%	0.55%	0.56%
		(0.97%)	(1.18%)	(1.72%)	(1.88%)
$[\beta^+, \gamma^+]$	26,646	-0.06%	3.81%	1.00%	4.87%
		(0.85%)	(6.94%)	(4.09%)	(9.80%)
$[\beta^+, \gamma^-]$	30,354	1.09%	-0.06%	0.30%	-0.84%
		(1.11%)	(1.97%)	(1.73%)	(2.94%)
β^-	169,192	0.56%	0.16%	0.50%	0.11%
		(1.00%)	(1.31%)	(1.61%)	(1.86%)
$[\beta^-, \gamma^+]$	23,245	-0.22%	0.63%	0.65%	1.49%
		(0.96%)	(2.40%)	(1.99%)	(3.67%)
$[\beta^-, \gamma^-]$	13,203	1.28%	-3.49%	0.22%	-4.55%
		(1.29%)	(5.37%)	(3.36%)	(7.75%)
γ^+	49,764	-0.20%	3.03%	1.59%	4.83%
		(0.95%)	(8.69%)	(6.45%)	(12.80%)
γ^-	41,902	1.18%	-1.85%	-0.45%	-3.49%
		(1.34%)	(4.82%)	(4.40%)	(8.11%)
All funds	616,497	0.50%	0.49%	0.56%	0.55%
		(1.08%)	(3.69%)	(2.84%)	(5.54%)

the alpha correction implied in our framework adjusts perfectly for this bias.

To show this, we present the correlation between the time-varying coefficients of the TM model obtained through rolling-window regressions (min. 36 months and max. 60 months) for a sample period ranging from January 1996 to December 2016 (252 monthly observations). Each strategy has 216 coefficient estimates for the α and γ from the TM model. Our replication framework also provides an equivalent number of estimates for the alpha (α_{τ}^{κ}) of the option-based strategies. The adjusted-α is equal to the alpha (α) from the TM model minus the alpha (α_{τ}^{κ}) from the option-based replication strategy. Table 7 presents the results of the controlled environment and clearly shows that the artificial negative correlation embedded in market timing models is significant (at a 99% confidence level) with an average correlation between γ and α close to -78%. Conversely, the correlation between γ and α_{τ}^{κ} is low and insignificant for all hypothetical strategies. We remain confident that the alpha correction is not another artifact that cures the correlation bias by simply adding another mechanical effect but with the opposite sign. Nevertheless, due to the magnitude of the artificial negative correlation, the adjusted-α also present a significant negative correlation but for which the average value drops to -18%.

Next, we turn our analysis to the empirical evidence in our hedge fund sample. Table 8 reports that average correlation between the γ and α is, as expected, strongly negative (on average -42.02%). The correlation between γ and adjusted-α increases to 40.51%. This suggests that for some fund classifications, α_{τ}^{κ} is strongly negative. In an empirical and uncontrolled environment as our hedge fund sample, distinguishing between uncorrelated timing and selectivity information is difficult, or almost impossible (Grinblatt and Titman 1989; Jiang 2003). Therefore, we must rely on the fact that the alpha adjustment remains unbiased in the controlled environment and should behave identically when applied to our sample. The most appealing results are for fund classifications that exhibit opposite signs for the directional (β) and non-directional (γ) bets. Funds in the classifications $[\beta^{+}, \gamma^{-}]$ and $[\beta^{-}, \gamma^{+}]$ demonstrate low levels of correlation, 14.39% and 18.48%, respectively. Interestingly, the correlation during the NBER expansion periods is almost null (-1.43% and -4.98%) but stronger in periods of recession (40.00% and 45.71%). One potential explanation for these results would be that funds classified as $[\beta^{+}, \gamma^{-}]$ have a payoff that resembles short put option strategies; in good economic conditions, such strategies pocket the "option" premium but suffer during sudden market crashes because of bad market timing. So, the alpha has a positive relationship with bad market timing in recession periods. The rationale is similar for funds with a long put payoff $[\beta^{-}, \gamma^{+}]$.

Table 7: Negative Correlation Bias in a Controlled Environment

This table presents the artificial correlation bias embedded in the TM market timing model. Results are presented for six hypothetical market timing managers for whom we list their strategy and the option-like payoffs they exhibit. The last three columns report the correlation between the γ and the alpha (α) from the market timing model, the correction of alpha (α^{κ}_{τ}) from the option-based replication strategy and the final adjusted-α of the manager. The results are obtained through rolling-window regressions and impose a minimum of 36 up to a maximum of 60 available months.

		Correlation with γ		
Strategy	Fund Payoff	α	α^{κ}_{τ}	Adjusted-α
max(Rm,Rf)	Long Call	-76.25%***	7.55%	-21.45%***
min(Rm,Rf)	Short Call	-76.25%***	0.91%	-14.81%**
max(-Rm,-Rf)	Long Put	-74.01%***	7.38%	-18.89%***
min(-Rm,-Rf)	Short Put	-74.01%***	1.75%	-14.34%**
max(-Rm,Rm)	Long Straddle	-84.14%***	8.58%	-21.19%***
min(-Rm,Rm)	Short Straddle	-84.14%***	5.50%	-18.37%***

The most puzzling results are for fund classifications that exhibit similar signs in the directional (β) and non-directional (γ) bets. Funds in the classifications $[\beta^+, \gamma^+]$ and $[\beta^-, \gamma^-]$ demonstrate high levels of correlation between the coefficients, 63.05% and 74.19%, respectively. According to Kacperczyk, Van Nieuwerburgh, and Veldkamp (2014) during recession periods these funds would stop picking securities to the benefit of timing the market, we should thus expect lower levels of correlation between the coefficients. However, this intuition is not valid as the levels of correlation increase to 74.58% and 79.03%, respectively. One potential explanation is that funds with both a directional and a non-directional bet on the market share similar information in their selectivity and timing skills.

Table 8: Negative Correlation Bias in an Uncontrolled Environment

This table reports the artificial correlation bias embedded in the TM market timing model. Results are presented for hedge fund managers for whom we list their fund classification in the first column. The last three columns report the correlation between the γ and the alpha (α) from the market timing model and the final adjusted-α of the manager. We distinguish the results for periods of expansion and recession as defined by the NBER. The results are obtained through rolling-window regressions and impose a minimum of 36 up to a maximum of 60 available months.

Fund	Correlation with γ		in expansion		in recession	
Classification	α	Adjusted-α	α	Adjusted-α	α	Adjusted-α
β^+	-25.94%	-23.41%	-25.94%	-25.61%	-30.57%	-16.45%
$[\beta^+, \gamma^+]$	-26.53%	63.05%	-33.02%	51.96%	-33.13%	74.58%
$[\beta^+, \gamma^-]$	-47.96%	14.39%	-49.92%	-1.43%	-37.39%	40.00%
β^-	-30.04%	-18.92%	-29.28%	-19.03%	-35.49%	-22.48%
$[\beta^-, \gamma^+]$	-45.40%	18.48%	-46.73%	-4.98%	-47.99%	45.71%
$[\beta^-, \gamma^-]$	-49.95%	74.19%	-56.95%	68.30%	-38.43%	79.03%
γ^+	-30.20%	52.18%	-26.89%	63.64%	-50.62%	56.25%
γ^-	-44.33%	53.78%	-42.91%	66.83%	-53.45%	54.88%
All funds	-42.02%	40.51%	-40.48%	33.13%	-53.64%	61.00%

Finally, we present the implications of adjusting the alpha on the negative correlation bias between the security and timing skill coefficients. To show this, we use of a double conditional sort on the α and the adjusted-α while controlling for the level of γ skills. We predict that if the correlation between γ and adjusted-α were artificially constructed, we should not be able to perceive any symmetrical effect between the groups of hedge funds and subsequent (t+1) fund returns. We perform this test by forming portfolios of hedge funds and assume for simplicity that there are no transaction costs and lock-up periods for grouping hedge funds. Table 1 reports the results for the spread portfolios constructed by the joint sort of funds in quintile portfolios based on their γ skill and by their selectivity skill. The raw selectivity skill (α) is reported in Panel A, whereas the adjusted selectivity skill (Adjusted-α) is in Panel B. As expected, in Panel A, the abnormal returns of these spread portfolios over the FF 3-factor model are not symmetrical, that is, the spread portfolio for funds with high γ skill is close to 0 (t-stat of -0.176). Conversely, adjusting for the negative correlation bias leads to a symmetrical effect in predicting subsequent hedge fund returns; the same portfolio now delivers a monthly return of 0.651% (t-stat of 3.423). And the effect is valid up to nine months after portfolio formation; however, we do not report these results for brevity.

4 Skill Index

In a similar vein as Kacperczyk, Van Nieuwerburgh, and Veldkamp (2014), we construct a hypothetical *Skill Index* at time t+1 using the adjusted measure for the selectivity skill and timing skill at time t. The index is constructed by aggregating the standardized values (z-score) of the selectivity skill and timing skill and weighting each component by the recession probability index from Chauvet and Piger (2008), denoted w.

The equation is as follows:

$$\text{Skill Index}_{t+1}^{i} = w_t \times \text{Timing}_t^{i} + (1 - w_t) \times \text{Selection}_t^{i} \tag{20}$$

The intuition behind the linear methodology is simple; a manager is more likely to time the market in stressed economic conditions, while in prosperous conditions, he concentrates on the selection of securities. In our framework, the timing skill is defined by the slope on the squared market return from the TM model (γ), and the selection skill is the adjusted-α ($\pi_{\tau,k} = \alpha - \alpha_{\tau,k}$).

Panel A of Table 10 demonstrates that a skill index applied to the raw selectivity measure from the TM model does not allow to identify persistent skilled funds. Indeed, long/short strategy formed on the decile portfolios sorted on the skill show average returns (E[R]) close to zero. We

Table 9: Conditional Sort on the Adjusted-Alpha

For each month, we sort hedge funds into quintile portfolios according to their selectivity skills, i.e., α or adjusted-α. Groups are formed using a conditional sort that first splits hedge funds according to their level of gamma skill and then by their level of selectivity skill. In each level of gamma skill, the spread between funds with the highest (Q5) and the lowest (Q1) selectivity skill are reported in the column (Q5-Q1). The reported values are the alpha (in %) from the FF 3-factor model, and t-stats are in parentheses.

γ	Panel A: α						Panel B: Adjusted-α					
$\downarrow$	1	2	3	4	5	Q5-Q1	1	2	3	4	5	Q5-Q1
1	-0.289	0.032	0.148	0.094	0.305	0.593	-0.392	0.033	0.089	0.112	0.454	0.846
	(-1.620)	(0.270)	(1.273)	(0.741)	(1.366)	(2.827)	(-1.882)	(0.259)	(0.793)	(0.896)	(2.584)	(4.943)
2	-0.085	0.051	0.159	0.162	0.289	0.374	-0.298	0.064	0.103	0.256	0.445	0.743
	(-0.680)	(0.712)	(2.250)	(2.244)	(2.649)	(2.695)	(-2.228)	(0.813)	(1.525)	(3.375)	(4.054)	(4.737)
3	0.078	0.126	0.221	0.268	0.436	0.358	0.020	0.122	0.247	0.235	0.504	0.484
	(0.852)	(1.821)	(3.276)	(3.891)	(4.366)	(3.307)	(0.198)	(1.726)	(3.787)	(3.650)	(4.484)	(3.667)
4	0.103	0.206	0.243	0.286	0.447	0.345	0.072	0.201	0.250	0.308	0.453	0.381
	(0.877)	(2.145)	(2.495)	(3.106)	(3.596)	(2.718)	(0.561)	(2.001)	(2.675)	(3.400)	(4.007)	(3.070)
5	0.650	0.460	0.437	0.415	0.610	-0.040	0.323	0.380	0.402	0.487	0.974	0.651
	(2.395)	(2.493)	(2.744)	(2.747)	(3.118)	(-0.176)	(1.555)	(2.110)	(2.474)	(2.774)	(4.197)	(3.423)

found similar findings when spread returns are regressed again the Fung and Hsieh (2001, FH) and Agarwal and Naik (2004, AN) models; the intercepts α-FH and α-AN are not significantly different from 0. Panel B of Table 10 shows that sorting hedge funds on the Adjusted-Skill Index predict future returns. The long/short strategy presents a postivie gamma at a 95% confidence level. This suggests that relationship between the Adjusted-Skill Index and subsequent hedge fund returns is monotonic across the decile portfolios. In unreported results, we confirm that this linear relationship holds up to 12 months after portfolio formation.

Table 10: Option Replication Strategies

For each month, we sort hedge funds into decile portfolios according to the level of their *Skill Index*, i.e., a linear combination of γ and α or adjusted-α. In each symmetric level of Skill, the spread between portfolios of funds is reported in the columns named Differences. The reported values are the average fund's one month ahead returns (from t+1 until t+2). The corresponding t-stats of the expected returns are displayed in parentheses. The notations E[R] refers to average return whereas α-FH and α-AN refers to the intercept coefficient from the factor models of Fung and Hsieh (2001) and Agarwal and Naik (2004), respectively. Returns are in percent. The sample period ranges from February 1996 to December 2015.

	Decile Portfolios (Equal-Weighted)										Differences				
	1	2	3	4	5	6	7	8	9	10	10-1	9-2	8-3	7-4	6-5
	Panel A: Skill Index														
E[R]	0.43	0.39	0.36	0.33	0.37	0.39	0.41	0.43	0.47	0.72	0.29	0.08	0.07	0.08	0.02
t-stat	(1.518)	(2.084)	(2.221)	(2.307)	(2.702)	(2.897)	(2.906)	(2.852)	(2.657)	(2.869)	(1.294)	(0.779)	(0.905)	(1.345)	(0.417)
α-FH	0.14	0.18	0.17	0.18	0.19	0.21	0.22	0.23	0.21	0.44	0.31	0.03	0.07	0.04	0.02
t-stat	(0.718)	(1.592)	(1.726)	(2.150)	(2.452)	(2.762)	(2.912)	(2.492)	(1.902)	(2.413)	(1.293)	(0.269)	(0.858)	(0.711)	(0.416)
α-AN	0.16	0.22	0.18	0.17	0.19	0.23	0.27	0.27	0.31	0.58	0.42	0.09	0.09	0.10	0.04
t-stat	(0.660)	(1.647)	(1.771)	(1.907)	(2.160)	(2.839)	(2.761)	(2.815)	(2.585)	(2.985)	(1.685)	(0.749)	(1.099)	(1.592)	(0.788)
	Panel B: Adjusted-Skill Index														
E[R]	0.03	0.26	0.26	0.32	0.38	0.44	0.44	0.47	0.64	1.04	1.01	0.38	0.21	0.11	0.06
t-stat	(0.104)	(1.238)	(1.506)	(2.277)	(2.819)	(3.433)	(3.182)	(3.324)	(4.001)	(4.801)	(3.941)	(3.046)	(2.771)	(2.185)	(1.675)
α-FH	-0.44	-0.02	0.02	0.15	0.21	0.30	0.27	0.32	0.46	0.89	1.34	0.48	0.30	0.12	0.08
t-stat	(-2.185)	(-0.135)	(0.228)	(1.891)	(2.723)	(4.028)	(3.359)	(3.459)	(4.097)	(5.182)	(5.543)	(3.857)	(3.987)	(2.192)	(2.090)
α-AN	-0.34	-0.04	0.03	0.17	0.22	0.31	0.31	0.37	0.57	0.95	1.29	0.61	0.34	0.14	0.10
t-stat	(-1.744)	(-0.308)	(0.307)	(1.938)	(2.503)	(3.718)	(3.127)	(3.340)	(4.196)	(4.672)	(5.607)	(5.242)	(4.647)	(2.385)	(2.197)

5 Robustness

5.1 Model Specification

5.1.1 In-sample Bootstrap Test

We posit the hypothesis that estimating an ad hoc model specification of active investors should deliver (in-sample) an aggregate distribution of skills similar to a zero-alpha distribution. In other words, if the model is accurate enough (in-sample) we should see an aggregate alpha close to zero: for every winning investor, there should be losers (Fama and French 2010).

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 conducted based on the normalization of the coefficient through the t-statistics ($t(\alpha)$) of the alpha and bootstrap methods. We next explain 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. In our framework, we are rather interested to check whether the distribution of skill for well and poorly performing funds remains the same before and after our alpha adjustment.[16] 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 the 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 instrumental variables that control for public information.

[16] 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).

We describe the bootstrap procedure in the four following steps.

The first step consists in estimating the actual alphas of the i^{th} hedge fund using a multi-factor model. In our application, we use the TM model augmented with conditional lagged instruments described in Section 1.1:

$$R_t = \alpha + \beta_c Rm_t + \gamma_c Rm_t^2 + \sum_{l=1}^{L} \delta_l (z_{l,t-1} Rm_t) + \sum_{l=1}^{L} \Delta_l (z_{l,t-1}^{*} Rm_t) + e_t \tag{21}$$

where R_t denotes the i^{th} hedge fund's return in excess of the risk-free rate (the one-month T-bill from Ken French's website) at time t. $z_{l,t-1}$, and $z_{l,t-1}^{*}$ denote the conditional lagged instruments measured on monthly and aggregate daily observations, respectively. We still consider the excess return of the S&P 500 as a proxy for the excess market return (Rm_t). We also assume that $e_t \sim N(0, \sigma^2)$.

In the second step, we subtract the estimated α of the i^{th} fund from its return (R_t) to construct a time series of zero-alpha returns, i.e., ($R_t - \alpha$). 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[17] 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

[17]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.

bootstrapped) and estimates the alpha and t-statistic for the i^{th} fund in a world in which its true alpha is zero:

$$(R_t - \alpha_t)^b = \hat{\alpha}_0^b + \hat{\beta}^b Rm_t + \hat{\gamma}^b Rm_t^2 + \sum_{l=1}^{L} \hat{\delta}_l^b z_{l,t-1} Rm_t + \sum_{l=1}^{L} \omega_l^b (z_{l,t-1}^* Rm_t) + e_t^b \qquad (22)$$

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 ($\hat{\alpha}_b^0$). 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. 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 (21) with ($R_t^i - \alpha_i^{(\tau,\kappa)}$).

Overall, Figure 6 demonstrates that the in-sample α adjustment from our option-based framework delivers an aggregate picture of the distribution t-(α) similar to a distribution where α is by design equal to zero. This supports the hypothesis that the combination of the extended TM model with instrumental variables and our alpha adjustment provides a good model specification to explain the cross-section of hedge fund returns.

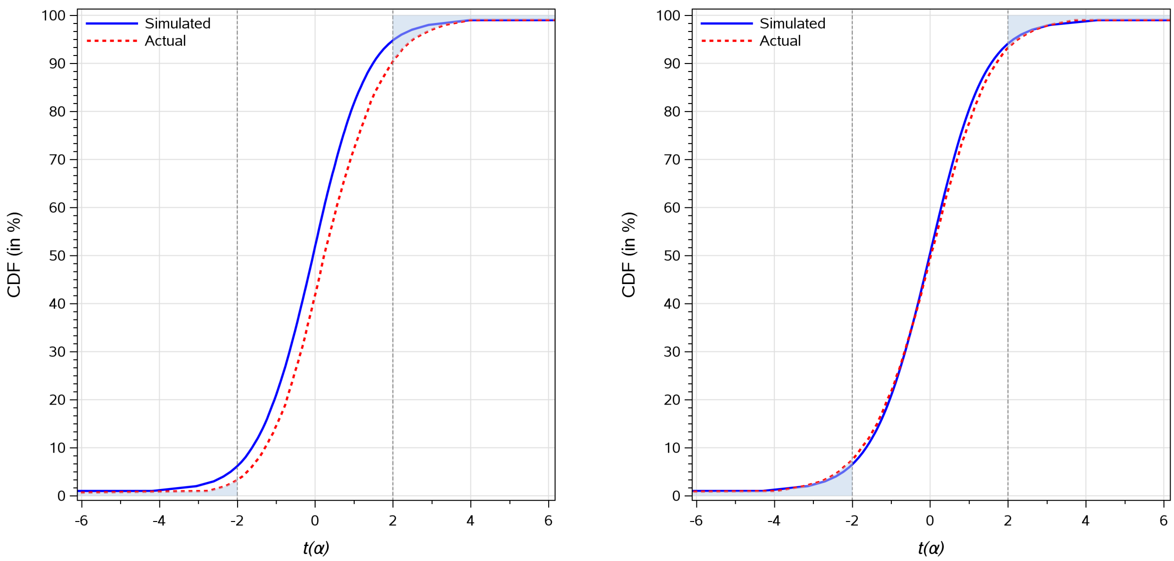
5.1.2 Exclusion Restriction Variables

To verify that our findings are not driven by model misspecifications, we re-estimate our results using two "placebo" variables which control for spurious significant loadings on the quadratic term in equation (4). Following the work of Jagannathan and Korajczyk (1986), Chen and Liang (2007) complement the specification of the regression model by adding one of these two nonlinear variables of the benchmark, i.e., ln($|Rm|$) and 1/Rm. Performing equivalent analysis as in Section 1.1 with these additional variables verifies whether nonlinear coefficients on the benchmark load up significantly in the regression, by design. A significant estimate serves as the exclusion of the model specification. We report in Table 11 the proportion of rolling regressions for which one of these term coefficients is significant. The first column present the significance level for the coefficient estimate of the placebo variable; the second column reports the proportion of significant estimates in the OLS-regression when the variable 1/Rm is added to the model while the third column report the average adjusted R-

Figure 6: 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 figure 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 the factors of the TM model and conditional lagged instruments from Chen and Liang (2007).

(a) Raw α **(b)** Adjusted-α



squared for the regressions with a significant estimates; Columns four and five display the equivalent results when the variable $\ln(|Rm|)$ is added to the model. Our results indicates that the proportion of regressions with a significant estimate on the placebo variable are proportional to their specified significance levels, i.e. around 10%, 5%, 1% for a confidence level of 90%, 95%, 99%, respectively. These findings confirm that our results should not be driven by model misspecification. In unreported tests, we perform again all analysis present in the paper by discarding regressions with a significant coefficient on a placebo variable. This selection process does not affect the results presented in the previous sections.

Table 11: Model Misspecification

This table summarizes the proportion of rolling regressions with a total amount equal to 616,497 in our sample for which a coefficient on the nonlinear placebo variable is found significant. The placebo variable is either: l/Rm or $\ln(|Rm|)$. We also report the average adjusted R-squared for regressions with a significant estimate.

Significance level	1/Rm	Adj-R^2	$\ln(\|Rm\|)$	Adj-R^2
10%	9.80%	3.70%	10.61%	3.89%
5%	5.31%	2.10%	5.60%	2.16%
1%	1.36%	0.59%	1.36%	0.54%

5.2 Henriksson and Merton Model

Ferson and Schadt (1996, p. 431) identify for dynamic models that: "*the investment horizon of the investor becomes a complex issue [...] and the optimal investment horizon is an endogenous variable.*" In this part, we briefly present evidence that the nonlinear variable from the market timing model of Henriksson and Merton (1981, HM) is pertinent for adjusting the alpha of a manager only when her investment horizon is short-term (up to 3 months). We proxy the investment horizon by the maturity of the selected options that replicate the manager's strategy. The reason to this choice is simple; as the investment horizon of the manager gets closer to one period, the Treynor and Mazuy (1966, TM) model degenerates into the HM model. In their model, Henriksson and Merton substitutes the squared market return (Rm^2) by the payoff to a one-period call option on the market portfolio (max(0,Rm)). This alternative specification provides a kinked rather than function which gradually becomes nonlinear to capture the market timing skill of fund managers. The model is thus well suited for replicating managers' performance with short investment horizons because the gamma for options with low maturity tends to converge to $+\infty$ and it is precisely what the kink of the function intends to capture.

To demonstrate that the HM model is only well suited for short investment horizons, we use the joint sorting test on γ and the adjusted-α which allows to distinguished good from bad performing funds for all level of gamma skills. In this test, we implement a simple selection process to estimate the adjusted-α of managers: funds identified with low investment horizons under the TM model and for which the HM model show higher R^2 are corrected with the adjusted-α from the HM model otherwise the correction is provided from the TM model. The first column of Table 12 reports the results when no investment horizons are specified and simply refers to the adjusted-α from the HM model only. Each row of the Table reports the spread return between funds ranked in high quintile (Q5) and low quintile (Q1) on their adjusted-α for a given level of γ. Clearly results show that the HM model fails at distinguishing good from bad performing funds with a high level of γ (Q5) and mixed investment horizons because the spread return (Q5-Q1) is close to zero (0.053% with a t-stat of 0.212). Columns (2) to (4) demonstrates that the spread returns (Q5-Q1) between high versus low adjusted-α funds increase significantly as the investment horizon shrinks from 180 to 120, and 60 days, respectively.

According to Ferson and Schadt (1996) the investment horizon of an investor is an important but difficult issue that deserves particular attention for performance evaluations. We thus motivate the initial choice of the TM model not only by its strong relationship with the Taylor expansion series that serves as a basis for the option-based replication framework but also by the important flexibility it gives for replicating a complex variety of investment horizons compared to the HM model.

Table 12: Adjusted-alpha and Managers' Investment Horizons

For each month, we sort hedge funds into quintile portfolios according to their selectivity skills, i.e., α or adjusted-α. Groups are formed using a conditional sort that first splits hedge funds according to their level of gamma skill and then by their level of selectivity skill. In each level of gamma skill, the spread between funds with the highest (Q5) and the lowest (Q1) selectivity skill are reported in each column (Q5-Q1). The reported values are the alpha (in %) from the FF 3-factor model, and t-stats are in parentheses. We provide four model specification: (1) refers to the alpha-adjusted from the HM model only, while for the next columns the model selection combine the adjusted-α from the HM and the models. More precisely, funds identified with low investment horizons under the TM model and for which the HM model show higher R^2 are corrected with the adjusted-α from the HM model otherwise the correction is provided from the TM model. Columns (2) to (4) specify that the HM model used when investment horizons are lower than 180, 120, and 60 days, respectively.

	Adjusted-α : Q5-Q1			
	(1)	(2)	(3)	(4)
$\downarrow \gamma$	None	180 days	120 days	60 days
1	1.005	0.644	0.655	0.725
	(4.485)	(3.296)	(3.337)	(3.878)
2	0.600	0.727	0.728	0.677
	(4.278)	(4.658)	(4.639)	(4.365)
3	0.465	0.365	0.370	0.430
	(3.371)	(3.152)	(3.206)	(3.633)
4	0.527	0.303	0.302	0.399
	(3.535)	(1.903)	(1.904)	(2.646)
5	0.053	0.395	0.423	0.513
	(0.212)	(1.979)	(2.124)	(2.619)

6 Conclusion

This paper establishes a time-varying benchmark methodology 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 from the Treynor and Mazuy (1966, TM) model, such that the combination of the intercept and the quadratic term ($\alpha_{TM} + \gamma Rm^2$) captures these skills. However, when assuming that the quadratic term (γRm^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 extend the replication model of Hübner (2016) to satisfy the condition of passively replicating the linear and quadratic terms of the market timing model in a time-varying framework. 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 option-based benchmark with equivalent convexity.

After adjusting the alpha of the managers by that of the replication strategy, we simply assess the systematic sources of fund returns through traditional multi-factor models. Overall, the alpha adjustment in our model delivers an interesting picture of the cross-sectional skills in our hedge fund sample (a merged sample of HFR and Morningstar): the construction of an Adjusted-Skill Index correlates with future returns and that up to twelve months ahead. This monotonic relationship is not present when using the traditional specification of the TM model.

This research contributes to the literature on the gamma trading in hedge funds' trades because it first sets individual benchmarks 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 factor models. Third, the approach allows 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 the whole cross-section of our hedge funds sample into three main categories: directional with market timing skills (e.g., long-short and short bias hedge funds), non-directional with market timing (e.g., multi-strategy, global macro, CTAs), and non-directional with convergence bets (event driven, relative value, market-neutral). We find positive adjustments for market timers with directional bets and positive non-directional bets (long call, long put, and long straddle payoffs) but negative adjustments for negative timers with convergence bets (short call, short put, and short straddle payoffs). We note however that the alpha adjustment is strongly dependent on the vertex of the quadratic payoff – i.e., the ratio $-\beta/2\gamma$. The flexibility of our model leaves an alpha adjustment that is free from the bias arising from the artificial negative correlation in market timing models.

We hope this study can improve our understanding of the non-linearities 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.

References

Agarwal, V., Arisoy, Y. E., and Naik, N. Y. (2017) Volatility of Aggregate Volatility and Hedge Fund Returns, *Journal of Financial Economics* **125**, 491–510.

Agarwal, V., Bakshi, G., and Huij, J. (2009) Do Higher-Moment Equity Risks Explain Hedge Fund Returns?, *Robert H. Smith School Research Paper No. RHS 06-153*.

Agarwal, V., Mullally, K. A., and Naik, N. Y. (2015) *The Economics and Finance of Hedge Funds : A Review of the Academic Literature*. Foundation, 1–107.

Agarwal, V. and Naik, N. Y. (2004) Risks and Portfolio Decisions Involving Hedge Funds, *Review of Financial Studies* **17**, 63–98.

Aragon, G. O. (2007) Share Restrictions and Asset Pricing: Evidence from the Hedge Fund Industry, *Journal of Financial Economics* **83**, 33–58.

Asness, C., Krail, R., and Liew, J. (2001) Do hedge funds hedge?, *Journal of Portfolio Management* **28**, 6–19.

Avramov, D., Kosowski, R., Naik, N. Y., and Teo, M. (2011) Hedge funds, Managerial Skill, and Macroeconomic Variables, *Journal of Financial Economics* **99**, 672–692.

Bali, T. G., Brown, S. J., and Caglayan, M. O. (2014) Macroeconomic risk and hedge fund returns, *Journal of Financial Economics* **114**, 1–19.

Becker, C., Ferson, W., Myers, D. H., and Schill, M. J. (1999) Conditional Market Timing with Benchmark Investors, *Journal of Financial Economics* **52**, 119–148.

Bollen, N. and Busse, J. A. (2004) Short-Term Persistence in Mutual Fund Performance, *Review of Financial Studies* **18**, 569–597.

Bollen, N. and Whaley, R. E. (2009) Hedge Fund Risk Dynamics: Implications for Performance Appraisal, *The Journal of Finance* **64**, 985–1035.

Bollen, N. and Busse, J. (2001) Does the Market Timing Ability of Mutual Fund Managers Persist?, *The Journal of Finance* **56**, 1075–1094.

Cao, C., Chen, Y., Liang, B., and Lo, A. W. (2013) Can Hedge Funds Time Market Liquidity?, *Journal of Financial Economics* **109**, 493–516.

Chauvet, M. and Piger, J. (2008) A comparison of the real-time performance of business cycle dating methods, *Journal of Business and Economic Statistics* **26**, 42–49.

Chen, Y., Cliff, M., and Zhao, H. (2017) Hedge Funds : The Good, the Bad ,and the Lucky, *The Journal of Financial and Quantitative Analysis* **52**, 1081–1109.

Chen, Y. and Liang, B. (2007) Do Market Timing Hedge Funds Time the Market ?, *The Journal of Financial and Quantitative Analysis* **42**, 827–856.

Coggin, D. T., Fabozzi, F. J., and Rahman, S. (1993) The Investment Performance of U.S. Equity Pension Fund Managers: An Empirical Investigation, *The Journal of Finance* **48**, 1039–1055.

Comer, G., Larrymore, N., and Rodriguez, J. (2009) Controlling for Fixed-Income Exposure in Portfolio Evaluation: Evidence from Hybrid Mutual Funds, *Review of Financial Studies* **22**, 481–507.

Coval, J. D. and Shumway, T. (2001) Expected option returns, *Journal of Finance* **56**, 983–1009.

DeRoon, F. and Karehnke, P. (2017) Spanning Tests for Assets with Option-Like Payoffs: The Case of Hedge Funds, *Working Paper*, Tilburg University.

Fama, E. F. (1972) Components of Investment Performance, *The Journal of Finance* **27**, 551–567.

Fama, E. F. and French, K. R. (2007) Migration, *CRSP Working Paper No. 614*.

Fama, E. F. and French, K. R. (2010) Luck versus Skill in the Cross-Section of Mutual Fund Returns, *Journal of Finance* **65**, 1915–1947.

Ferruz, L., Muñoz, F., and Vargas, M. (2010) Correcting the Merton and Henriksson timing model, *Applied Economics Letters* **17**, 1183–1187.

Ferson, W. E. and Schadt, R. W. (1996) Measuring Fund Strategy and Performance in Changing Economic Conditions, *The Journal of Finance* **51**, 425.

Ferson, W. E. and Siegel, A. F. (2001) The Efficient Use of Conditioning in Portfolios Information, *The Journal of Finance* **56**, 967–982.

Fung, W. and Hsieh, D. A. (2001) The Risk in Hedge Fund Strategies : Theory and Evidence from Trend Followers, *Review of Financial Studies* **14**, 313–341.

Fung, W. and Hsieh, D. A. (2004) Hedge Fund Benchmarks : A Risk-Based Approach, *Financial Analysts Journal* **60**, 65–80.

Gatev, E., Goetzmann, W. N., and Rouwenhorst, K. G. (2006) Pairs trading: Performance of a relative-value arbitrage rule, *Review of Financial Studies* **19**, 797–827.

Getmansky, M., Lo, A., and Makarov, I. (2004) An Econometric Model of Serial Correlation and Illiquidity in Hedge Fund Returns, *Journal of Financial Economics* **74**, 529–609.

Goetzmann, W. N., Ingersoll, J., and Ivković, Z. (2000) Monthly Measurement of Daily Timers, *The Journal of Financial and Quantitative Analysis* **35**, 257–290.

Graham, J. R. and Harvey, C. R. (1996) Market Timing Ability and Volatility Implied in Investment Newsletters' Asset Allocation Recommendations, *Journal of Financial Economics* **42**, 397–421.

Grinblatt, M. and Titman, S. (1989) Mutual Fund Performance : An Analysis of Quarterly Portfolio, *The Journal of Business* **62**, 393–416.

Harvey, C. R. and Liu, Y. (2016) Lucky Factors, *Working Paper*, Duke University.

Hasanhodzic, J. and Lo, A. W. (2007) Can Hedge-Fund Returns Be Replicated? The Linear Case, *Journal of Investment Management* **5**, 5–45.

Henriksson, R. D. and Merton, R. C. (1981) On Market Timing and Investment Performance . II . Statistical Procedures for Evaluating Forecasting Skills, *The Journal of Business* **54**, 513–533.

Huang, J.-Z., Liechty, J., and Rossi, M. (2012) Return Smoothing and its Implications for Performance Analysis of Hedge Funds, *Working Paper*, University of Notre Dame.

Hübner, G. (2016) Option Replication and the Performance of a Market Timer, *Studies in Economics and Finance* **33**, 2–25.

Hübner, G., Lambert, M., and Papageorgiou, N. (2015) Higher - moment Risk Exposures in Hedge Funds, *European Financial Management* **21**, 236–264.

Ingersoll, J., Spiegel, M., Goetzmann, W., and Welch, I. (2007) Portfolio Performance Manipulation and Manipulation-proof Performance Measures, *The Review of Financial Studies* **20**, 1503–1546.

Jagannathan, R. and Korajczyk, R. (1986) Assessing the Market Timing Performance of Managed Portfolios, *The Journal of Business* **59**, 217–235.

Jiang, G. J., Yao, T., and Yu, T. (2007) Do Mutual Funds Time the Market ? Evidence from Portfolio Holdings, *Journal of Financial Economics* **86**, 724–758.

Jiang, W. (2003) A nonparametric test of market timing, *Journal of Empirical Finance* **10**, 399–425.

Joenväärä, J., Kosowski, R., and Tolonen, P. (2016) Hedge Fund Performance: What Do We Know?, *Working Paper*.

Jurek, J. W. and Stafford, E. (2015) The Cost of Capital for Alternative Investments, *Journal of Finance* **70**, 2185–2226.

Kacperczyk, M., Van Nieuwerburgh, S., and Veldkamp, L. (2014) Time-Varying Fund Manager Skill, *The Journal of Finance* **69**, 1455–1484.

Kosowski, R., Naik, N. Y., and Teo, M. (2007) Do Hedge Funds Deliver Alpha? A Bayesian and Bootstrap Analysis, *Journal of Financial Economics* **84**, 229–264.

Kosowski, R., Timmermann, A., and Wermers, R. (2006) Can Mutual Fund " Stars " Really Pick Stocks ? New Evidence from a Bootstrap Analysis, *Journal of Finance* **61**, 2551–2595.

Kryzanowski, L., Lalancette, S., and To, M. C. (1997) Performance Attribution using an APT with Prespecified Macrofactors and Time-Varying Risk Premia and Betas, *The Journal of Financial and Quantitative Analysis* **32**, 205–224.

Merton, R. C. (1981) On Market Timing and Investment Performance. I. An Equilibrium Theory of Value for Market Forecasts, *The Journal of Business* **54**, 363.

Mitchell, M. and Pulvino, T. (2001) Characteristics of Risk and Return in Risk Arbitrage, *The Journal of Finance* **56**, 2135–2175.

Patton, A. J. and Ramadorai, T. (2013) On the High-Frequency Dynamics of Hedge Fund Risk Exposures, *The Journal of Finance* **68**, 597–635.

Pfleiderer, P. and Bhattacharya, S. (1983) A Note on Performance Evaluation, *Technical Report 714 Stanford, Calif: Stanford University, Graduate School of Business.*

Titman, S. and Tiu, C. (2011) Do the Best Hedge Funds Hedge ?, *Review of Financial Studies* **24**, 123–168.

Treynor, J. and Mazuy, K. (1966) Can Mutual Funds Outguess the Market, *Harvard Business Review* **44**, 131–136.

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, Currrent, 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