Incentives and Endogenous Risk Taking: Implications for Reduced-Form Estimates of Risk-Adjusted Performance in Hedge Funds

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ABSTRACT

This paper studies portfolio choice and proposes a comprehensive structural approach to better measure and predict the performance of levered …nancial institutions with complex non-linear contracts. The empirical application of the structural model allows us to use previously unexploited information about risk preference to draw inference about genuine risk-adjusted performance of investment funds with option-like contractual features. Intuitively, we are able to better distinguish the e¤ect of risk taking and skill on past fund performance, thus providing superior forecasts of hedge fund performance. In the structural model, we carefully motivate our assumptions about the manager's objective and trading technology, and derive the optimal investment strategy and the implied dynamics of assets under management. We extend the work of Koijen (2010) on mutual funds by explicitly modelling hedge fund speci…c contractual features such as (i) incentive options, (ii) equity investor's redemption options and (iii) primer broker contracts that together create option-like payo¤s and a¤ect hedge fund's risk taking. The optimal investment strategy derived from the model reveals that call feature of the contracts motivates manager to use more leverage while the capital related options and concern on future value of incentive options induce the manager to reduce leverage when her fund performs poorly. We show that traditional reduced-form measures of risk-adjusted performance are biased estimate of true skill. In the empirical study, we use a large dataset containing fund speci…c information on fees and distance to watermark to document the di¤erence between true skill and reduced-form alpha.

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THIS PAPER STUDIES THE IMPLICATIONS that non-linear investment and funding contracts have on traditional reduced-form tests of performance attribution for hedge funds. We solve the structural optimal portfolio choice problem of a hedge fund investor who is subject to (i) performance fee-based incentives (a call option), (ii) funding redemption options by the prime broker (a put option), and (iii) equity investor's redemption options, which together create a non-linear payo¤ structure that a¤ect endogenous hedge fund's risk taking. The resulting optimal portfolio choice is state dependent due to the time-varying endogenous incentives perceived by the manager, depending on the distance of the assets under management from the high-watermark. This implies that optimal leverage and reduced-form fund alphas ‡uctuate over time. This is important since it implies that traditional performance regressions with constant coe¢ cients are misspeci…ed. The call option like performance-fee incentive motivates the manager to use more leverage, while the put option-like capital out‡ow feature and concern on future value of incentive options induce the manager to reduce leverage, when her fund performs poorly. We use the results of the model to estimate, using a large panel dataset of hedge fund returns, the di¤erence between reduced-form and structural alpha. The empirical method allows us to use previously unexploited information about endogenous risk preference to draw inference about genuine risk-adjusted performance. We …nd that a structural approach that corrects for endogenous portfolio choice incentives provides superior forecasts of future hedge fund performance.

Although we use hedge funds in our empirical application, our results have much broader economic implications. Separating the e¤ect of risk aversion and skill on investment performance is a fundamental problem that not only a¤ects investors in alternative investment funds, but also investors (and regulators of) levered …nancial institutions such as banks which employ incentive contracts. A Financial Times article in 2009 quotes a Bank of England o¢ cial as saying that "The superior performance of the …nancial services sector in the years leading up to the credit crisis was almost entirely due to luck rather than skill – and banks increasingly gambled on luck in an e¤ort to keep up with their peers. [...]Good luck and good management need to be better distinguished".[1] This quote illustrates not only the risk management challenges that policy makers face but also the performance attribution problem that investors face when evaluating a hedge fund. Using traditional tools it is di¢ cult to distinguish performance that is due to true investment skill from that attributable to excessive risk taking.

Most studies of hedge fund performance are based on net returns and reduced form regressions

[1] 'Bank pro…ts were due to 'luck, not skill', By Norma Cohen (July 1, 2009)

(Agarwal and Naik, 2004, Fung and Hsieh, 1997 and 2004, Kosowski, Teo and Naik, 2007, Buraschi, Kosowski and Trojani, 2010). Several caveats apply to reduced form regressions. First, the regression based approach ignores the fact that fund performance is the outcome of a portfolio management problem. In the problem, a manager uses managerial ability to determine her investment opportunity set while manager's risk preferences influence her portfolio choice. Therefore, there are two dimensions of heterogeneity, managerial ability and risk preference, which investors should take into account when assess fund performance. By assessing only alpha, investors cannot ascertain whether manager's performance stems from the manager's genuine skills or is just the result of luck and excessive risk taking. Second, the reduced form alphas are based on relatively short samples of data and are therefore imprecisely estimated. We build on and extend the pioneering work of Koijen (2010), who applies a structural approach to estimate skill and risk preferences of mutual funds. Koijen (2010) suggests a novel approach to recover cross-sectional information of mutual fund manager's managerial ability and risk preferences by using the Euler condition of mutual fund managers. He shows that the restrictions derived from structural portfolio management models can be used to recover both attributes from mutual data. However, the application of Koijen's (2010) approach to hedge funds is not straighforward since incentive contracts that govern hedge funds are significantly more complex than those of mutual funds.

While both mutual funds and hedge funds are delegated managers, they differ in most other institutional dimensions: legal framework, capital structure, investment mandate and business model. First, hedge funds' limited partnership structure allows for both asset segregation and liquidity lock-ups imposed on investors, which give the possibility to obtain prime brokerage contracts.[2] The private nature of their legal structure grants them the contractual flexibility in setting longer lock-ups to investors, whose legal rights are those of a (limited) partner, as opposed to a client. Second, investment advisors that manage hedge funds typically receive an asset management fee and a performance fee. The performance fee is typically subject to a high water mark, which means that the manager receives performance fees only on increases in the net asset value (NAV) of the fund in excess of the highest net asset value it has previously achieved. The high-water mark provisions can be viewed as a call option issued by the investors to the fund manager (Goetzmann, Ingersoll and Ross (2003)).

[2] The prime broker plays an essential role in the capital structure of a hedge fund. By contrast, most mutual funds, as Almazan, Brown, Carlson, and Chapman (2004) document, are restricted (by government regulations or investor contracts) with respect to using leverage, holding private assets, trading OTC contracts or derivatives, and short-selling; see also Koski and Pontiff (1999), Deli and Varma (2002) and Agarwal, Boyson and Naik (2009).

However, the funding role played by the prime-broker also makes the capital structure of hedge funds potentially fragile: As the 2007-2008 experience shows, when counterparty risk becomes acute during systemic events, prime brokers tend to increase hedge funds' collateral requirements and mandate haircuts in response to higher perceived counterparty risk, thus inducing forced deleverage of risky positions. Dai and Sundaresan (2010) note that a hedge fund's contractual relationships with its equity investors and prime broker can be considered as short option positions given to its prime brokers and investors. Therefore, the option-like features embedded in a hedge fund's balance sheet both on the liability and assets side makes it challenging to model the equilibrium hedge fund risk-return profile. Any structural model of hedge fund behavior must account for these features as they affect the objective function of the fund manager.

Our first contribution in this paper is to explicitly model hedge fund specific contractual features such as (i) incentive options, (ii) equity investor's redemption options and (iii) prime broker contracts, which jointly create option-like payoffs and affect hedge fund's risk taking. The solution to the investment problem provides an optimal dynamic investment strategy, which affects monthly hedge fund returns and risk taking. We derive the model-implied endogenous optimal leverage of a hedge fund by taking into account both capital structure fragility and performance-based fees depending on the distance of the NAV from the high watermark. Our second contribution is to apply the model to a large sample of hedge funds. We impose the structural restrictions implied by economic theory to estimate the deep parameters of the model. These restrictions allows us to separately identify true skill from endogenous risk appetite. We document differences between in-sample reduced form regression estimates of performance and the estimates based on the structural model. We link structural parameter estimates to fund characteristics such as investment style, management fees and performance fees. Our third contribution is to document the economic size of the bias induced by simple reduced form models. Moreover, out-of-sample the structural risk-adjusted estimates of skill are shown to provide superior forecasts of future fund risk-adjusted performance than traditional reduced form alpha. Funds with low risk aversion estimates generate the largest cumulative dollar growth over time. However, this growth comes at the expense of more pronounced volatility of cumulative wealth. At the same time, funds sorted based on structural estimates of skill outperform funds ranked based on reduced form α in terms of out-of-sample Sharpe Ratio and Information Ratio.

Our work is related to several streams of the literature. First, we build on the work of Carpenter (2000) who examiners the dynamic investment problem of a risk averse manager compensated with a

call option on the assets he controls. She shows that under the manager's optimal policy, as the asset value goes to zero, volatility goes to infinity. However, the option compensation does not strictly lead to greater risk seeking: sometimes, the manager's optimal volatility is less with the option than it would be if he were trading his own account. While the importance of convex incentives for the optimal risk-taking behavior of a hedge fund manager has been long noted, its implications are not trivial. Initially, one might think that the option-like character of hedge funds' performance fee contracts could induce the manager to assume extremely risky positions in the hope of huge payoffs, especially as the manager does not share directly in any loss of the fund's assets. However, this does not necessarily hold in the case of performance fee incentives with highwatermarks features. Panageas and Westerfield (2009) extend the work of Carpenter (2000) to account for watermarks restrictions and show, for instance, that while risk-taking may be increasing in convexity of incentives in the context of a static two period model, in an intertemporal model it may no longer hold. Since any loss of fund assets reduces the value of the anticipated sequence of future call options, a higher risk taking today increases the risk to lose future options. This is due to the fact that the current high-water mark remains as the effective strike price: all later call options must have strike prices higher than the current high-water mark. They show that even risk-neutral managers do not take unbounded risk, despite convex payoffs, when horizon of contract is in(de)finite, thus reversing some of the results obtained in static two period models. Hodder and Jackwerth (2007) investigate incentive effects of a typical hedge-fund contract as a function of the incentive horizon. In our paper, we build on previous contributions and further develop the analysis on optimal risk taking behavior by considering not only the payoff convexity related to the performance fee structure, but also the capital structure fragility induced by the possibility of investors to withdraw capital and prime-brokers to force deleveraging. We show that the interaction of capital structure fragility and watermark restrictions gives rise to important non-linearities in the endogenous risk-taking behavior.

A second stream of the literature, study the role of incentive arrangement and discretion in hedge fund performance (Agarwal, Daniel and Naik, 2009). They conclude that the level of managerial incentives affects hedge fund returns. In particular, funds with better managerial incentives (such as higher option deltas, greater managerial ownership and the presence of high-water mark provision) deliver better performance. They compute measures of risk-adjusted performance using reduced-form regressions. In our paper, we document how convex incentives affect endogenous risk taking behavior thus inducing a bias in reduced-form regressions. Based on a large hedge fund data base that contains fund specific information on fees and high watermarks, we use the restrictions from the

structural model to obtain unbiased estimated of risk adjusted performance. We document how the bias varies across di¤erent fund strategies and …nd that selecting funds based on structural measures of skill leads to superior out-of-sample performance.

Third, several studies shed light on the fragility of the capital structure of levered …nancial institutions, such as hedge funds (Dai and Sundaresan (2010), Liu and Mello (2009) and Brunnermeier and Pedersen (2009)). We built on their insights and incorporate the capital structure of a hedge fund into our structural model. Guasoni and Obloj (2010) examine the risk shifting implications of performance fees depending on a manager's risk aversion.

These results are useful to hedge fund investors. Knowledge of both true alpha and of endogenous risk-appetite can provide investors with a framework to better assess hedge fund performance and the e¤ects of the underlying contractual relationship. In particular, this knowledge can assist investors in designing optimal contracts that can limit manager's excessive risk taking behavior while providing them the ‡exibility to deploy their managerial abilities. At the same time, the results are also useful to fund managers, since it allows them to evaluate the implications of the fragility of their capital structure and design contractual arrangements with their prime brokers.

The paper is structured as follows. In Section I we develop a structural model of the hedge fund manager's objective function. Section II describes the data that we use in this study. Section III presents the estimation methodology. Section IV presents empirical results for the application of the structural model to hedge fund returns. Section V concludes.

Structural Model and Manager's Investment Problem

In this section we describe our structural model by …rst de…ning the investment opportunity set of a hedge fund manager. Then we provide the optimal investment solution of the manager's portfolio problem. According to the optimal portfolio solution we derive the restriction on α, β and σ_ε. Finally we study the model implications for reduced form risk-adjusted performance and compare them to the structural estimates of true managerial ability.

Trading technology

We assume that the hedge fund manager can trade in a money market account with a constant interest rate r:

$$dS_t^0 = S_t^0 r dt. \tag{1}$$

She can also invest in a benchmark portfolios which follow

$$dS_{i,t}^B = S_{i,t}^B(r + \sigma_{i,B}\lambda_{i,B})dt + S_{i,t}^B\sigma_{i,B}dZ_t^B. \tag{2}$$

Hedge fund managers di¤er in terms of their alpha generating technology, which is assumed to be fund speci…c. The pure alpha investment technology can be summarized by a process S_t^A which follows

$$dS_t^A = S_t^A(r + \alpha^*)dt + S_t^A\sigma_A dZ_t^A, \tag{3}$$

where $\alpha^* = \sigma_A\lambda_A$. Where λ_A is a proxy of true managerial skill. The larger λ_A, the larger the true managerial skill.

Asset value process

The hedge fund manager decides the proportion of her fund wealth, θ_t, to invest in the risky assets S_t^A and $S_{i,t}^B$. Thus, the fund asset value evolves as:

$$dA_t = A_t(r + \theta_t'\mu)dt + A_t\theta_t'\Sigma dZ_t \tag{4}$$

where $\mu \equiv (\alpha^*, \sigma_{i,B}\lambda_{i,B})', \Sigma \equiv diag(\sigma_A, \sigma_{i,B})'$.

Manager's Investment Problem

The manager's investment problem to decide on an optimal trading strategy, θ, to maximize the following objective function

$$\max_\theta E[U(\alpha(A_T - HWM)^+ + mA_T - c(K - A_T)^+)] \tag{5}$$

subject to the budget constraint (4) and the restrictions

$$0 \leq A_t, \qquad \forall t \in [0, T] \tag{6}$$

and

$$K \leq HWM, \tag{7}$$

where α denotes performance fee, m denotes management fee and c denotes concern level regarding to short put option positions.

In this problem we assume that a hedge fund manager derives her utility from three components. The first two components, the management and performance fee, are common in most hedge fund compensation contracts. The first component is a claim on a fraction α of a call option-like payoff with the fund's high-water mark as its strike price. The level of high-water mark is the running maximum process of fund's historical net asset value and is known at the beginning of every evaluation periods. The second component is a linear claim on fund value at the end of the evaluation period. It claims a fraction m from the value as a management fee. The last component is intended to capture the nature of the relationship of the hedge fund with its prime broker. Typically, a hedge fund's contract with its prime broker gives the prime broker the right to reduce the supply of funding or to increase margin calls in adverse economic states or when the counterparty risk of the hedge fund is considered dangerously high. According to Dai and Sundaresan (2010), the relationship between a hedge fund and its prime broker can be thought as a short put option position. We capture the deadweight costs induced by the forced deleveraging imposed by the prime broker with the parameter c. A similar situation is also induced by the contractual arrangement of the hedge fund with its investors, which gives investors the option to redeem their shares upon their requests.

It should be noticed that the short put option of the prime broker interacts with the incentive contract of a fund manager. In fact, the call option feature is a perpetual call option rather than a series of individual call options on fund value. The performance of the fund in the current period affects the value of the call option in the next period. For instance, if the fund performs well and the current fund value is in the money, the fund manager knows that he will start the next period with an at the money call option with its strike price equals to the current fund value. However, if he performs poorly and the current call option is out of the money, he will not only receive no performance fee for this period but also reduce value of her call options in later periods. This is the continuation value of the call option referred to in Panageas and Westerfield (2010). Therefore the presence of funding option, redemption option and continuation value of perpetual call option justify the existence of put option in our model.

A. Model's solution

If markets are complete, one can use the martingale approach developed in Cox and Huang (1989) to solve the optimal investment problem. This allows to solve an easier static problem, instead of solving the dynamic investment problem presented in previous section. Let φ_t be the state price process, which follows the process:

$$\frac{d\varphi_t}{\varphi_t} = -rdt - \lambda' dW_t, \tag{8}$$

where $\lambda \equiv \sigma^{-1}\mu$. When markets are complete, there exists a unique state price process φ_t such that the solution of the optimal investment problem is such that:

$$\max_{A_T} E[U(\alpha(A_T - HWM)^+ + mA_T - c(K - A_T)^+)], \tag{9}$$

subject to

$$E[\varphi_T A_T] \leq A_0 \tag{10}$$

and $0 \leq A_T$. The utility function is de...ned by

$$U(A_T, HWM, K, \alpha, m, c) = \begin{cases} U(\alpha(A_T - HWM) + mA_T) & \text{for } A_T > HWM \\ U(mA_T) & \text{for } K < A_T \leq HWM \\ U(mA_T - c(K - A_T)) & \text{for } b < A_T \leq K \\ -\infty & \text{for } A_T \leq b \end{cases}, \tag{11}$$

where b is the fund value at which the hedge fund manager begins to receive negative utility. This is illustrated in Figure 1 and utility function is CRRA of the form: $U(W) = \frac{W^{1-\gamma}}{1-\gamma}$.

[Insert Figure 1 here]

We now solve for the Lagrangian corresponding to (9) subject to (10) and the utility function described in (11). The Lagrangian reads:

$$\max_{A_T} \frac{(\alpha(A_T - HWM)1_{\{A_T > HWM\}} + mA_T - c(K - A_T)1_{\{K > A_T\}})^{1-\gamma}}{1-\gamma} - \zeta\varphi_T A_T. \tag{12}$$

The Lagrangian implies the following optimal terminal fund value:

$$\begin{aligned} A_T^* &= \frac{\left(\frac{\zeta^* \varphi_T}{\alpha+m}\right)^{-1/\gamma} + \alpha HWM}{\alpha+m} 1_{\{A_T > HWM\}} + \frac{(\zeta^* \varphi_T)^{-1/\gamma}}{m^{1-1/\gamma}} 1_{\{K < A_T \le HWM\}} \\ &+ \frac{\left(\frac{\zeta^* \varphi_T}{m+c}\right)^{-1/\gamma} + cK}{m+c} 1_{\{b < A_T < K\}} + b 1_{\{A_T \le b\}} \end{aligned} \tag{13}$$

where ζ^* solves $E[\varphi_T A_T^*] = A_0$ and $1_F = 1$ when F occurs and $1_F = 0$ otherwise.

We can simplify the derivation of expectation of $\varphi_T A_T^*$ by mapping set of terminal fund value to state price density. This is similar to the solution method used in Carpenter (2000). Therefore equation (13) is equivalent to :

$$\begin{aligned} A_T^* &= \frac{\left(\frac{\zeta^* \varphi_T}{\alpha+m}\right)^{-1/\gamma} + \alpha HWM}{\alpha+m} 1_{\{\varphi_T < z_{HWM}\}} + \frac{(\zeta^* \varphi_T)^{-1/\gamma}}{m^{1-1/\gamma}} 1_{\{z_K > \varphi_T > z_{HWM}\}} \\ &+ \frac{\left(\frac{\zeta^* \varphi_T}{m+c}\right)^{-1/\gamma} + cK}{m+c} 1_{\{z_b > \varphi_T > z_K\}} + b 1_{\{\varphi_T > z_b\}} \end{aligned} \tag{14}$$

where z_i solves $U'(A_T, HWM, K, \alpha, m, c) = \zeta^* z_i$. This is the …rst order condition of the Lagrangian.

Notice that there is an inverse relation between state price space and fund value space. This is quite intuitive since state price is closely related to marginal utility which is a decreasing function of the level of consumption. According to the martingale property, the optimal fund value is the process:

$$A_t^* = E_t\left(\frac{\varphi_T}{\varphi_t} A_T^*\right) \tag{15}$$

This can be analytically derived, therefore the optimal fund value is the process:

$$\begin{aligned} A_t^* &= \frac{\zeta^{-1/\gamma}}{(\alpha+m)^{1-1/\gamma}} I_{1,t} + \frac{\alpha HWM}{(\alpha+m)} I_{2,t} + \frac{\zeta^{-1/\gamma}}{(m)^{1-1/\gamma}} I_{5,t} \\ &+ \frac{\zeta^{-1/\gamma}}{(m+c)^{1-1/\gamma}} I_{3,t} + \frac{cK}{(m+c)} I_{4,t} + b I_{6,t} \end{aligned} \tag{16}$$

where $I_{1,t} \equiv D_t N(d_{2,t}^{z_{HWM}}) \varphi_t^{-1/\gamma}$, $I_{2,t} \equiv E_t N(d_{1,t}^{z_{HWM}})$, $I_{3,t} \equiv D_t \varphi_t^{-1/\gamma}(N(d_{2,t}^{z_b}) - N(d_{2,t}^{z_K}))$, $I_{4,t} \equiv E_t(N(d_{1,t}^{z_b}) - N(d_{1,t}^{z_K}))$, $I_{5,t} \equiv D_t \varphi_t^{-1/\gamma}(N(d_{2,t}^{z_K}) - N(d_{2,t}^{z_{HWM}}))$, $I_{6,t} = N(-d_{3,t}^{z_b}) \varphi_t^{-1}$. Where $N(x)$

denotes the cdf function, with $d_{1,t}^{z_i} \equiv \frac{\ln(z_i/\varphi_t)+(r-0.5\lambda^2)(T-t)}{\lambda\sqrt{T-t}}$, $d_{2,t}^{z_i} \equiv d_{1,t}^{z_i} + \frac{\lambda\sqrt{T-t}}{\gamma}$, $d_{3,t}^{z_i} = \frac{z_i-\varphi_t+r(T-t)}{\lambda\sqrt{T-t}}$, $E_t \equiv \exp(-r(T-t))$ and $D_t \equiv \exp(\frac{1-\gamma}{\gamma}(r+0.5\lambda^2)(T-t)+0.5\left(\frac{1-\gamma}{\gamma}\right)^2\lambda^2(T-t))$.

According to the optimal fund value in equation (16), we can use Ito's lemma to derive the dynamic of $dA^*(t,\varphi_t)$ and then compare a coe¢ cient of its di¤usion term to equation (4) to obtain the following optimal allocation:

$$\theta_t^* = -\frac{\partial A^*(t,\varphi_t)}{\partial\varphi}\frac{\varphi_t}{A_t}(\Sigma\Sigma')^{-1}\mu \tag{17}$$

where

$$\begin{aligned}
\frac{\partial A^*(t,\varphi_t)}{\partial\varphi} &= -\frac{\zeta^{-1/\gamma}D_t}{\varphi_t^{\frac{1+\gamma}{\gamma}}(\alpha+m)^{1-1/\gamma}}\left(\frac{N(d_{2,t}^{z_{HWM}})}{\gamma}+\frac{N'(d_{2,t}^{z_{HWM}})}{\lambda\sqrt{T-t}}\right)-\frac{\alpha HWM}{\varphi_t(\alpha+m)}\frac{N'(d_{2,t}^{z_{HWM}})E_t}{\lambda\sqrt{T-t}} && (18)\\
&\quad -\frac{\zeta^{-1/\gamma}D_t}{\varphi_t^{\frac{1+\gamma}{\gamma}}(m)^{1-1/\gamma}}\left[\frac{N'(d_{2,t}^{z_K})-N'(d_{2,t}^{z_{HWM}})}{\lambda\sqrt{T-t}}+\frac{N(d_{2,t}^{z_K})-N(d_{2,t}^{z_{HWM}})}{\gamma}\right]\\
&\quad -\frac{\zeta^{-1/\gamma}D_t}{\varphi_t^{\frac{1+\gamma}{\gamma}}(m+c)^{1-1/\gamma}}\left[\frac{N'(d_{2,t}^{z_b})-N'(d_{2,t}^{z_K})}{\lambda\sqrt{T-t}}+\frac{N(d_{2,t}^{z_b})-N(d_{2,t}^{z_K})}{\gamma}\right]\\
&\quad -\frac{cKE_t}{\varphi_t(m+c)\lambda\sqrt{T-t}}(N'(d_{1,t}^{z_b})-N'(d_{1,t}^{z_K}))-b(\frac{N(-d_{3,t}^{z_b})}{\varphi_t}-\frac{N'(d_{3,t}^{z_b})}{\lambda\sqrt{T-t}}) && (19)
\end{aligned}$$

Although the optimal allocation described in equation (17) might look complicated, it can be rewritten as

$$\theta_t^* = \frac{(\Sigma\Sigma')^{-1}\mu}{\widetilde{\gamma}_t} \tag{20}$$

where $\widetilde{\gamma}_t$ is interpreted as e¤ective risk aversion and equivalent to $\widetilde{\gamma}_t(\gamma, A_t, \varphi_t, \lambda, HWM, K, \alpha, m, c) \equiv -\frac{\partial A^*(t,\varphi_t)}{\partial\varphi}\frac{\varphi_t}{A_t}$.

Equation (20) reveals that even if drift and di¤usion terms of the investment opportunity set are constant, the optimal allocation could be time varying and di¤erent from what is suggested by the constant level of risk aversion, γ. The equation also implies that the optimal allocation is not only driven by the characteristics of the investment opportunity set and the speci…c risk aversion of the hedge fund manager but also by the contractual parameters such as fee rates, the distance of fund value from HWM and the existence of short put option-like positions.

Figure 2 displays the results implied by (20). It shows that the optimal allocation to a risky asset varies with the current fund value level in relation to the high-water mark and strike price of put

option, K. The manager allocates her fund less than what would be implied by the Merton's (1969)[3] solution of a constant allocation to risky asset when fund value is slightly above the high-water mark level. This implies that the manager has an incentive to reduce leverage which in turn reduces her fund volatility when her call option is just in the money so that she can lock in her performance fee. However, the results suggest that the manager begins to increase her leverage again to Merton's allocation when her fund value is considerably higher than the high-water mark. The results in this region is similar to the analytical result of the problem studied in Carpenter (2000) as well as the numerical solution to the problem in Hodder and Jackwerth (2007).

However, our result implies di¤erent dynamics when fund value is less than the high-water mark. First, unlike the manager who is maximizing only the performance fee (Figure 3 , dashed line), the fund manager in our set up doesn't monotonically increase her allocation to the risky asset as fund value decreases but instead reduces her leverage as fund value deceases toward the put's strike.

The reduction of leverage when short put option positions exist is more aggressive than when the manager considers only performance and management fee. In the latter case, the manager reduces her leverage below what is implied by the Merton solution and keeps her allocation constant as fund value decreases (Figure 3 , solid line). [4] In contrast, the presence of short option positions causes the manager to continue reducing leverage as fund value decreases and eventually put all her funds into risk free asset. Based on the above, we can interpret the contractual relationship between a hedge fund, its prime broker and fund investors as well as the continuation value implied by the incentive contract as resembling short option position to reduce leverage when the hedge fund manager underperforms.

[Insert Figure 2 and 3 here]

Model's Implied Restrictions and Bias in Reduced-Form Regression Alpha

Although the stochastic optimal control problem is nonlinear, it is possible to show that it admits a closed-form solution which is similar to the classical Merton (1969) optimal portfolio choice problem

[3] The Merton's (1969) constant allocation is $\frac{\mu}{\gamma\sigma^2}$

[4] This is similar to the numerical results shown in Hodder and Jackwerth (2007)

but with di¤erent structural parameters:

$$\theta_t^* = \frac{1}{\widetilde{\gamma}_t}(\Sigma\Sigma')^{-1}\Sigma\Lambda, \tag{21}$$

where $\theta \equiv (\theta^A, \theta^B)'$, $\Sigma \equiv diag(\sigma_A, \sigma_B)'$, $\Lambda \equiv (\lambda_B, \lambda_A)'$. Given this solution, we can derive restrictions that show the link between the parameters obtained from a standard reduced form regression and the structural parameters in the same way as in Koijen (2010). Consider the reduced form regression, where we regress fund performance on the benchmark excess return:

$$\frac{dA_t}{A_t} - rdt = \hat{\alpha}_r dt + \hat{\beta}_r(\frac{dS_t^B}{S_t^B} - rdt) + \hat{\sigma}_{\varepsilon,r} dZ_t^A. \tag{22}$$

If we substitute the return process of the benchmark, the standard reduced form regression becomes:

$$\frac{dA_t}{A_t} = (r + \hat{\alpha}_r + \hat{\beta}_r \sigma_B \lambda_B)dt + \hat{\beta}_r \sigma_B dZ_t^B + \hat{\sigma}_{\varepsilon,r} dZ_t^A. \tag{23}$$

According to the fund value process (4) and its optimal investment (21), the optimal fund value evolves according to:

$$\frac{dA_t^*}{A_t^*} = (r + \frac{\alpha^{*2}}{\widetilde{\gamma}_t \sigma_A^2} + \frac{1}{\widetilde{\gamma}_t}\lambda_B^2)dt \tag{24}$$

$$+\frac{\lambda_B}{\widetilde{\gamma}_t} dZ_t^B + \frac{\alpha^*}{\widetilde{\gamma}_t \sigma_A} dZ_t^A \tag{25}$$

By matching the drift and di¤usion terms, the cross restrictions implied by the structural model are :

$$\hat{\alpha_r} = \theta_{At}^* \alpha^* = \frac{\alpha^{*2}}{\widetilde{\gamma}_t \sigma_A^2}, \tag{26}$$

$$\hat{\beta}_r = \theta_{Bt}^* = \frac{\lambda_B}{\widetilde{\gamma}_t \sigma_B}, \tag{27}$$

$$\hat{\sigma}_{r,\varepsilon} = \theta_{At}^* \sigma_A = \frac{\alpha^*}{\widetilde{\gamma}_t \sigma_A}. \tag{28}$$

The restriction (26) provides a link between typical reduced-form alpha, $\hat{\alpha_r}$, and active managerial skill, α^*, which drives the alpha generating technology (3) of a hedge fund manager. This link implies that the reduced-form alpha obtained from a linear regression is not an unbiased measure of active managerial skill since it is also a¤ected by the e¤ective (endogenous) risk aversion, $\widetilde{\gamma}_t$, of the hedge fund manager. Therefore, evaluating fund performance only by reduced-form alpha could be

biased; the performance could be generated either by true skill, α^*, or risk-taking attribute, $\widetilde{\gamma}_t$. For instance, hedge fund investors might be mislead by investing in hedge funds with high reduced-form alpha, $\hat{\alpha_r}$. The high reduced-form alpha of the funds could be generated by excessive risk-taking when the managers aim to maximize their incentive options. This happens when fund value is around the high-water mark. We documented empirical evidence of this in Figure 4. The …gure shows that Fung and Hseih alphas exhibit higher level of dispersion when fund value is around high-water mark and low dispersion when fund value is relatively low; the cross-sectional range of Fung and Hsieh alphas in the interval [0,0.5] is 19.07 while in the interval [0.5,1] is 34.50.

[Insert Figure 4 here]

Figure 5 illustrates that typical reduced-form alpha, $\hat{\alpha_r}$, overestimates true active managerial skill, α^* when the call option is just out of the money. In contrast, the standard reduced-form alpha, $\hat{\alpha_r}$, underestimates true active managerial skill, α^*, in the region where the short option positions are exercised. This could happen if the manager is forced to reduce leverage due to common shocks despite having a pro…table trading strategy. This illustrates that the existence of nonlinear features in the hedge fund manager's investment problem causes reduced-form linear estimations to become ine¤ective. The issue is potentially economically signi…cant.

[Insert Figure 5 here]

The restriction also reveals that reduced-form alpha varies over time with e¤ective (endogenous) risk aversion, $\widetilde{\gamma}_t$. Therefore, the alpha inferred from typical regressions with constant coe¢ cients are misspeci…ed. In addition, the e¤ective risk aversion is state dependent and closely related to nonlinear contractual features; these in turn cause the use of traditional linear method to be problematic. As a result, the problem cannot be addressed simply with the use of sophisticated inference technique and it can only be addressed in the context of a structural approach.

I. Estimation Methodology

When estimating a manager's true alpha per unit of her investment technology's volatility, one notices that fund performance (25) is driven by $\frac{\alpha^*}{\sigma_A}$ rather than each of the two parameters separately. The $\frac{\alpha^*}{\sigma_A}$ ratio is in fact the Sharpe Ratio of the manager's investment technology, λ_A. Next, we estimate managerial skill using a structural approach and compare it to reduced-form values. First, we investigate the results in the context of a simulated economy, then we apply the methodology to an extensive hedge fund data set.

Structural Estimation

The structural estimation procedure is based on two-steps. First we estimate the set of parameters $\hat{\Theta}_B \equiv \{\hat{\sigma}_B, \hat{\lambda}_B\}$. Then, since the conditional fund's return generating process satisfies

$$\frac{dA_t^*}{A_t^*} = (r + \frac{\alpha^{*2}}{\widetilde{\gamma}_t \sigma_A^2} + \frac{1}{\widetilde{\gamma}_t}\hat{\lambda}_B^2)dt \tag{29}$$

$$+\frac{1}{\widetilde{\gamma}_t}\hat{\lambda}_B dZ_t^B + \frac{\alpha^*}{\widetilde{\gamma}_t \sigma_A} dZ_t^A, \tag{30}$$

we proceed to estimate the vector of parameters $\Theta_C \equiv \{\lambda_A, \widetilde{\gamma}_t\}$, where $\lambda_A \equiv \frac{\alpha^*}{\sigma_A}$. Assuming that asset prices are log-normal, we can estimate the structural parameters by maximizing log-likelihood, as $\arg\max_{\Theta_C} \sum_{t=h}^{T/h} \ell(r_t^A \mid r_t^B; \Theta_C, \hat{\Theta}_B)$. Under the assumption of log-normality, the joint dynamics of benchmark and asset returns can be written in discrete time as

$$r_t^B = (\bar{r} + \hat{\sigma}_B \hat{\lambda}_B - \frac{1}{2}\hat{\sigma}_B^2)h + \hat{\sigma}_B \Delta Z_t^B \tag{31}$$

$$r_t^A = (\bar{r} + \frac{\hat{\lambda}_B^2}{\widetilde{\gamma}_t} + \frac{\lambda_A^2}{\widetilde{\gamma}_t} - \frac{1}{2}\frac{\hat{\lambda}_B^2}{\widetilde{\gamma}_t^2} \tag{32}$$

$$-\frac{1}{2}\frac{\lambda_A^2}{\widetilde{\gamma}_t^2})h + \frac{\hat{\lambda}_B}{\widetilde{\gamma}_t} dZ_t^B + \frac{\lambda_A}{\widetilde{\gamma}_t}\Delta Z_t^A \tag{33}$$

where $\begin{pmatrix} \triangle Z_t^B \\ \triangle Z_t^A \end{pmatrix} \sim N(0, hI)$. Thus, the distribution of r_t^A satisfies :

$$r_t^A \mid r_t^B \sim N(\mu_t, \sigma_t^2) \tag{34}$$

where

$$\mu_t \equiv (\bar{r} + \frac{\hat{\lambda}_B^2}{\widetilde{\gamma}_t} + \frac{\lambda_A^2}{\widetilde{\gamma}_t} - \frac{1}{2}\frac{\hat{\lambda}_B^2}{\widetilde{\gamma}_t^2} \tag{35}$$

$$-\frac{1}{2}\frac{\lambda_A^2}{\widetilde{\gamma}_t^2})h + \frac{\hat{\lambda}_B}{\widetilde{\gamma}_t \hat{\sigma}_B}(r_t^B - (\bar{r} + \hat{\sigma}_B \hat{\lambda}_B - \frac{1}{2}\hat{\sigma}_B^2)h) \tag{36}$$

$$\sigma_t^2 = \frac{\lambda_A^2}{\widetilde{\gamma}_t^2} h \tag{37}$$

A. The Difference of Reduced-Form and Structural Alpha in a Calibrated Economy

To investigate both the precision of the estimation method and the economic signi…cance of the bias induced by reduced form estimates, we calibrate the economy and compute the model implied estimates. This also allows us to also analyze how optimal portfolio choices of a fund manager are a¤ected by the di¤erent non-linear incentive constraints depending on the distance to high-water-mark. First, the innovation terms $\triangle Z_t^A$ and $\triangle Z_t^B$ are simulated separately 2,500 times. Each simulation is then used to calculate 3-year simulated monthly returns. The simulated value of $\triangle Z_t^B$ is used to calculate r_t^B according to equation (31). We calibrate the parameters to the following values: $r = 0.05, \sigma_B = 0.2$ and $\lambda_B = 0.2$. Similarly, r_t^A is calculated according to equation (32) where the true skill per unit of volatility, $\frac{\alpha^*}{\sigma_A}$, is assumed to be $\lambda_A \in \{0.1, 0.3\}$ and the coe¢ cient of relative risk aversion is set to $\widetilde{\gamma}_t \in \{2, 5, 10\}$. Finally, the parameters Θ_C are recovered by means of maximum likelihood and then compared to the true parameters.

The distribution of the estimated parameters implied by the structural model are summarized in (34). Table 1 displays the resulting estimates of the structural parameters. The assumed true model's parameters are shown in the …rst two columns where the estimated values are shown in the last two columns. The numbers in parentheses provide the standard deviations of the estimates. The estimates are consistent with the hypothetical true parameters and the degree of precision shows that a good accuracy can be achieved in …nite samples. Moreover, true managerial skill and risk taking attributes that arise endogenously from the model can be separately identi…ed.

[Insert Table 1 here]

We also conduct another simulation exercise to analyze how the precision of di¤erent performance

measures are affected by the risk taking parameter. Similarly, we simulate benchmark returns r_t^B, and the hedge fund's proprietary trading technology returns r_t^A, 2,500 times with broad set of parameters. Then, we estimate the true skill parameter α^* and compare it to the values $\widehat{\alpha}_{OLS}$ and $\hat{\alpha_r}$ that would be obtained in a reduced-form and structural regression, respectively.[5]. Table 2 displays the resulting estimates of the different three measures with their standard deviations in parentheses. We find that the precision of typical reduced-form alpha, $\widehat{\alpha}_{OLS}$, are affected by the level of manager's risk aversion; the variation of the estimators is monotonically decreasing in the level of risk aversion. We find that the variation of structural standardized true managerial skill, $\hat{\alpha^*}$, is almost insensitive to the level of risk aversion. These results illustrate that traditional reduced-form alpha measures are not a reliable measure of true managerial skill since its precision is largely affected by risk taking behavior of the manager. Therefore, it is important to adopt a methodology that explicitly takes into account the endogenous effects generated by the non-linear incentive contracts.

[Insert Table 2 here]

To better see how the level of risk aversion affects the precision of the performance estimators we plot the estimation results in Figure 6, which summarizes the distribution of alphas obtained from different methodologies. Column (a) presents the distribution of structural true alpha, α^*.Column (b) presents the reduced form OLS alpha, $\widehat{\alpha}_{OLS}$ while column (c) presents alpha implied from structural restriction, $\hat{\alpha_r}$. We find that the variation of both traditional reduced-form alpha and restricted structural alpha are driven by the level of risk aversion. Especially in the first case, the variation of reduced-form alpha is sensitive to this parameter. Thus, a method that uses structural information to identify the risk aversion parameter improves the reliability of the estimator of true skill. This is important for a variety of reasons, among which the selection of hedge fund portfolios with superior out-of-sample performance

[Insert Figure 6 here]

II. Data

Our survivorship bias-free hedge fund return data is from the BarclayHedge database, which contains net-of-fee hedge fund returns from 1994 until December 2009. A key distinguishing feature of this

[5] See equation 26

database is its detailed cross-sectional information on hedge fund characteristics. Our initial fund universe contains more than 16000 live and dead hedge funds. We exclude funds of hedge funds. To ensure that we have a sufficient number of observations to precise estimate our model we exclude hedge funds with less than 36 monthly return observations.[6] To capture real world investment constraints we exclude small funds that large institutional investors would typically not invest in. For this purpose we impose a dynamic assets under management (AuM) filter as follows: we exclude all funds below the 5th AuM percentile that corresponds to an AuM value of $28 millions in 2008. This filter is applied each year so that at the beginning of the sample we exclude many smaller funds as well. The advantage of this dynamic AuM filter over a static AuM filter - of say $20 million - is that it allows for inflation and assets under management growth over time. These restrictions lead to a sample of 5025 funds.

We group the funds into 16 categories according to their investment objectives: CTA, Convertible Arbitrage, Distressed Securities, Emerging Markets, Equity Long Bias, Equity Long/Short, Equity Market Neutral, Equity Short Bias, Event Driven, Fixed Income, Fixed Income Arbitrage, Macro, Merger Arbitrage, Multi Strategies, Options, Statistical Arbitrage.

Table 3 displays summary statistics for the sample of funds including the medians as well as the first and third quantile of the first four moment of the funds' excess returns. The average excess return across all funds is 6.40 percent per year. Emerging Markets funds have the highest average return and while Equity Short Bias funds have the lowest average return and the highest volatility.

[Insert Table 3 here]

Table 4 reports reduced form regression results based on the Fung and Hsieh (2004) seven factor model including alphas, beta loadings and adjusted R^2 by investment style. The dependent variable in the regression is the equal-weighted average return of all funds in a given style. After adjusting for common hedge fund risk factors, emerging markets funds still exhibit the second highest risk-adjusted performance as the Fung-Hsieh alpha of 9.69 percent per year demonstrates.

[Insert Table 4 here]

[6] In unreported results we show that our results do not qualitatively change when we exclude funds with less than 24 monthly observations.

III. Empirical Results

In Sample Estimation

In this section we apply the structural model to hedge fund data and estimate model parameters using maximum likelihood. Figures 7 and 8 present scatter plots of the manager speci…c λ_A and $\tilde{\gamma}$ parameters, which are averaged over estimation period, for eight di¤erent hedge fund styles. For all styles we observe a positive relationship between managerial skill λ_A and risk aversion $\tilde{\gamma}$. We observe the biggest dispersion in risk aversion estimates for CTAs, Equity Long/Short funds and Fixed Income funds while Equity Short Bias and Equity Long Bias funds show the lowest dispersion. It is interesting to note that Fixed Income and CTA funds can vary their leverage considerably, either by using derivatives or by borrowing from prime-brokers, which may explain the cross-sectional di¤erences in risk taking and risk appetite estimates.

[Insert Figure 7 and 8 here]

Next we compare the structural estimates of true skill λ_A with the reduced-form regression $\widehat{\alpha}_{OLS}$ estimates for each investment style. Note that $\widehat{\alpha}_{OLS}$ and λ_A are not in the same units of measure, which implies that they cannot be compared directly with each other. This does not preclude us from using them separately to create an ordinal ranking of funds based on these measures. The main conclusion of Table 5 is that the ordinal ranking of funds di¤ers depending on whether one ranks funds based on reduced form or structural estimates. A bias in reduced-form estimates, due to the endogenous risk appetite, emerges in $\widehat{\alpha}_{OLS}$ and this may occur independent from the structural $\tilde{\gamma}$ estimate. As a result we would not expect the same funds to be held in portfolios over time that are sorted on skill that is based on reduced form instead of structural estimates.

Table 5 displays the (cross-sectional) median as well as the …rst and third quantile of the unconditional OLS $\widehat{\alpha}_{OLS}$, true managerial skill λ_A and level of risk aversion $\tilde{\gamma}$. On the one hand, if we rank funds by λ_A, Equity Short Bias funds have low skill estimates while Multi-strategy funds have the highest skill estimates. On the other hand, if we rank funds based on $\widehat{\alpha}_{OLS}$, Equity Market Neutral funds have the lowest $\widehat{\alpha}_{OLS}$ while Option Trader Funds have the highest $\widehat{\alpha}_{OLS}$ estimates. One possible interpretation is that some strategies have moderate reduced form alphas since they take moderate risk as a result of greater risk aversion. Merger arbitrage funds exhibit the highest average risk aversion coe¢ cients.

[Insert Table 5 here]

The results in the above table may be driven by a few funds with extreme parameter estimates. Therefore in Table 6 we compare the structural and reduced form estimates for equal-weighted hedge fund indices by style. The conclusions are similar to those drawn from averages of individual funds. Merger arbitrage and Multi-strategies funds appear to have the highest estimates of true skill as well as very high risk aversion parameters. The highest reduced-form alphas are obtained for emerging markets funds and CTAs. Overall, the differences in the ordinal rankings of skill based on structural and reduced form estimates of skill are significant.

[Insert Table 6 here]

In the previous tables we examined results for the average fund. One important question that our analysis is attempting to answer is how our inference regarding top managerial skill changes when we consider structural instead of reduced form estimates of skill. Next we consider average skill estimates for the top decile of funds. Table 7 reports average in-sample estimates for different portfolios which are sorted into deciles based on the data available at the end of the sample.

Portfolio TA (Top Alpha) consists of the top decile of funds sorted by reduced form (OLS) alpha. Portfolio TS consists of the top decile portfolio of funds sorted by the structural true skill (λ_A) proxy. Portfolio's TDS1 to TDS4 are the result of a further double sort in which funds in portfolio TS (Top Skill) are sorted into quartiles according to the risk aversion parameter $\widetilde{\gamma}$. It is interesting to observe that the rankings based on structural and reduced form skill estimates differ quite substantially. The TA portfolio has a higher reduced-form alpha but also a lower risk aversion and true skill level than the TS portfolio. Across the TDS1 to TDS4 portfolios, reduced-form alpha is monotonically decreasing with risk aversion as we would expect. One interpretation that would be consistent with these results is that some funds generate high risk adjusted OLS alpha performance by taking large risks. Since the decision to take risks is endogenous to current distance of the fund NAV from its high water mark, a structural estimation can correct for the bias.

[Insert Table 7 here]

To test this hypothesis we examine the beta loadings of these funds with respect to the Fung and Hsieh alpha in Tables 8 . The panel for all investment styles confirms our conjecture and shows

that equity market betas are monotonically increasing as endogenous risk appetite increases, that is risk aversion decreases from TDS1 to TDS4. The same pattern obtains for beta exposures to the size, term and default spread betas.

[Insert Table 8 here]

Out of Sample Estimation

One of the most important potential implications of a better estimate of true skill and risk appetite is that it can improve the out-of-sample performance of portfolios that are based on risk adjusted performance measures. Avoiding funds that generate large risk-adjusted performance in the past due to excessive risk taking as opposed to skill, can be expected to lead to superior risk adjusted returns.

To assess the economic value of selecting funds based on structural skill estimates, we examine performance persistence by selecting funds into top decile performance portfolios based on reduced form and structural skill estimates. Table 9 reports summary statistics for out of sample portfolio analytics for portfolios based on holding the top OLS alpha as well as structural skill estimate funds. Portfolios are rebalanced annually and the …rst portfolio is formed in January 1997 and the last observation is December 2009. The TS portfolio outperform the TA portfolio in terms of risk-adjusted performance as captured by the Sharpe Ratio and the t-statistic of alpha, which is a transformation of the Information Ratio. It does not outperform in terms of alpha which suggests that the alpha of the TA portfolio may be more volatile. Moreover, the double sorted portfolio TDS4 with the lowest risk aversion outperforms the TA portfolio both in terms of total annual return, alpha and in terms of t-statistic of alpha. As the beta loadings show, the lower risk aversion manifests itself in portfolio TDS4 higher beta loadings.

[Insert Table 9 here]

To shed further light on the out-of-sample performance we plot the cumulative dollar growth of one dollar invested in January 1997 in the TS, TA and TDS1-TDS4 portfolios in Figure 9. As we would expect from Table 9, the highest cumulative dollar growth is achieved by portfolio TDS4 which contains the funds with lowest risk aversion among the top decile funds with the highest skill. 10,000 dollars invested in the TDS4 portfolio in 1997 grow to around 4 dollars by January 2010. The high cumulative growth comes at the expense of pronounced volatility. However, Table 9 allows us

to attribute the volatility to beta risk loadings on the benchmark factors which are much higher for the TDS4 than the TDS1 portfolio.

The TDS4 portfolio experiences a 25 percent drawdown in 2008-2009 as cumulative wealth drops from 40,000 to 30,000 dollars. However, despite this drawdown it signi…cantly beats the TA portfolio that selects funds with the highest reduced form α each year. 10,000 dollars invested in the TA portfolio grow to less than 30,000 dollars by January 2010.

Moreover all TS portfolios avoid the signi…cant drawdown that the TA portfolio experiences during the 2001-2004 period. The …gure clearly indicates that investors with di¤erent risk return trade-o¤s would prefer di¤erent portfolios. TDS1 is more appropriate for more risk aversion hedge fund investors while TDS4 is more appropriate for more risk averse investors.

The most stable portfolio is represented by TDS1 which contains funds with the highest risk aversion estimates among the funds in the top decile portfolio. Its cumulative growth is smoother than any of the other portfolios but it generates the lowest cumulative dollar growth.

[Insert Figure 9 here]

Our interpretation of the cumulative performance of di¤erent out-of-sample portfolios hinges on the underlying risk aversion of fund managers. The results in Figure 9 are the result of a double sort that excludes 90 percent of funds with a low skill estimate. Our conclusions may not apply to all funds. In Figure 10 we therefore sort funds based on the risk aversion estimate $\widetilde{\gamma}$ only. The …gure con…rms our conjecture about the volatility of cumulative dollar growth. The quartile of funds with the lowest structural risk aversion estimate, TG4, are much more volatile than the quartile of funds with the lowest risk aversion estimate, TG1. The quartile of funds with higher risk appetite generate the highest cumulative dollar growth. The TA portfolio appears to be more volatility but have lowest cumulative dollar growth than the TG4 portfolio.

Conclusion

In this paper we develop a comprehensive structural approach to better measure and predict the performance of levered …nancial institutions with complex incentive contracts. The empirical application of the structural model allows us to use previously unexploited information in second moments in a novel way to draw inference about risk-adjusted performance of investment funds with option-

like contractual features. Intuitively, we are able to better distinguish the effect of risk taking and skill on past fund performance, thus providing superior forecasts of hedge fund performance. In the structural model, we carefully motivate our assumptions about the manager's objective and trading technology, and derive the optimal investment strategy and the implied dynamics of assets under management.

We build on and extend the pioneering work of Koijen (2010) on mutual funds by explicitly modelling hedge fund specific contractual features such as (i) high water marks, (ii) equity investor's redemption options and (iii) primer broker contracts that together create option-like payoffs and affect hedge fund's risk taking.

Our second contribution is to apply the model to a large sample of hedge funds. We impose the structural restrictions implied by economic theory to estimate the deep parameters of the model. These restrictions allows us to separately identify true skills from endogenous risk appetite. We document differences between in-sample reduced form regression estimates of performance and the estimates based on the structural model. We link structural parameter estimates to fund characteristics such as investment style, management fees and performance fees. Our third contribution is to document the economic impact of using reduced form estimates. Estimates of managerial ability based on our structural model are shown in-sample to be more accurate than those based on reduced form models. Moreover, out-of-sample the structural risk-adjusted estimates of skill are shown to provide superior forecasts of future fund risk-adjusted performance than traditional reduced form alpha. Funds with low risk aversion estimates generate the largest cumulative dollar growth over time. However, this growth comes at the expense of more pronounced volatility of cumulative wealth. At the same time, funds sorted based on structural estimates of skill outperform funds ranked based on reduced form α in terms of out-of-sample Sharpe Ratio and Information Ratio.

Although we use hedge funds in our empirical application, our results have much broader economic implications. Separating the effect of risk aversion and skill on investment performance is a fundamental problem that not only affects investors in alternative investment funds, but also investors (and regulators of) levered financial institutions such as banks which employ incentive contracts.

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Table 1: This table displays the resulting estimates of the structural model's parameters ,(λ_A, γ),from a simulated distribution (2,500 simulations). The three-year monthly returns are simulated with the following assumed parameters; $\lambda_A \in \{0.1, 0.5, 1.5\}, \gamma \in \{2, 5, 10\}, r = 0.05, \lambda_B = 0.2$,$\sigma_B = 0.2$ and $\sigma_A = 0.1$. Where λ_A denotes true managerial skill , γ denotes coe¢ cient of relative risk aversion , r denotes risk free rate ,λ_B denotes benchmark's price of risk , σ_B denotes benchmark's volatility and σ_A denotes volatility of the hedge fund investment technology. The table provides means and standard deviations of the resulting estimates ; the standard deviations are shown in parentheses.

Model Parameters		Estimated Parameters	
λ_A	$\widetilde{\gamma}$	$\widehat{\lambda}_A$	$\hat{\gamma}$
	2	0.10 (0.02)	2.07 (0.21)
0.1	5	0.10 (0.02)	5.15 (0.52)
	10	0.10 (0.02)	10.31 (1.00)
	2	0.60 (0.33)	2.56 (1.58)
0.5	5	0.60 (0.33)	6.27 (3.74)
	10	0.60 (0.33)	12.42 (7.59)
	2	1.58 (0.60)	2.25 (1.10)
1.5	5	1.59 (0.60)	5.62 (2.60)
	10	1.58 (0.62)	11.13 (5.23)

Table 2: This table displays the resulting estimates of the structural model's parameters ,(α^{*},γ),from a simulated distribution (2,500 simulations). The three-year monthly returns are simulated with the following assumed parameters; $\alpha^{*}\in\{0.01,0.03\},\gamma\in\{2,5,10\},r=0.05,\lambda_{B}=0.2$ $\sigma_{B}=0.2$ and $\sigma_{A}=0.1$. Where α^{*} denotes true alpha skill, γ denotes coe¢ cient of relative risk aversion , r denotes risk free rate ,λ_{B} denotes benchmark's price of risk and σ_{B} denotes benchmark's volatility .The table provides means and standard deviations of the resulting estimates ; the standard deviations are shown in parentheses .

Model Parameters		Estimated Managerial Skill		
α^{*}	$\widetilde{\gamma}$	α^{*}	$\widehat{\alpha}_{OLS}$	$\hat{\alpha_{r}}$
	2	0.0099	0.0059	0.0049
		(0.0015)	(0.0293)	(0.0012)
0.01	5	0.0099	0.0024	0.0020
		(0.0015)	(0.0117)	(0.0005)
	10	0.0099	0.0012	0.0010
		(0.0015)	(0.0059)	(0.0003)
	2	0.0326	0.0471	0.0488
		(0.0147)	(0.0871)	(0.0244)
0.03	5	0.0322	0.0191	0.0193
		(0.0146)	(0.0350)	(0.0091)
	10	0.0327	0.0095	0.0097
		(0.0157)	(0.0175)	(0.0049)

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Table 3: This table displays , for each invesment category, the number of funds (in parentheses) and fund cross-sectional median and 25-75 quantiles (in parentheses) of the annualised excess mean returns over risk free rate , standard deviation , skewness and kurtosis. The statistics are computed by using monthly net-of-fee returns of live and dead hedge funds reported in the BarclayHedge between January 1994 and December 2009.

Investment Objectives	Mean (Ann.)	Std (Ann.)	Skewness	Kurtosis
CTA (1570)	6.27 (1.81 , 12.88)	16.26 (10.44 , 25.39)	0.35 (-0.10 , 0.87)	4.31 (3.41 , 6.11)
Convertible Arbitrage (138)	4.93 (2.47 , 6.60)	5.86 (4.06 , 9.45)	-0.70 (-1.43 , -0.15)	6.13 (4.38 , 11.07)
Distressed Securities (116)	6.10 (3.31 , 8.55)	9.44 (6.51 ,12.57)	-0.28 (-1.14 , 0.10)	6.53 (4.45 , 9.45)
Emerging Markets (473)	8.64 (3.29 , 16.06)	19.67 (11.11 , 29.96)	-0.34 (-1.02 , 0.24)	5.32 (3.90, 8.40)
Equity Long Bias (649)	6.95 (2.97 , 11.54)	15.92 (11.95 , 21.48)	-0.27 (-0.72 , 0.26)	4.69 (3.65 , 6.35)
Equity Long/Short(789)	6.69 (3.09 , 11.15)	11.83 (8.37 , 17.46)	-0.02 (-0.52 , 0.55)	4.60 (3.55 , 6.23)
Equity Market Neutral (152)	2.72 (0.05 , 5.34)	7.29 (5.39 , 10.08)	-0.10 (-0.41 , 0.17)	4.14 (3.05 , 5.58)
Equity Short Bias (37)	2.57 (-2.76 , 8.00)	20.85 (11.93 , 29.20)	0.23 (-0.16 , 0.58)	4.25 (3.37 , 5.90)
Event Driven (199)	6.93 (3.62 , 10.77)	10.85 (7.27 , 14.59)	-0.42 (-1.09 , 0.31)	5.83 (4.42 , 9.78)
Fixed Income (293)	4.42 (0.96 , 8.52)	6.92 (3.89 , 11.71)	-0.66 (-2.07 , 0.42)	7.98 (5.20 , 13.14)
Fixed Income Arbitrage (91)	2.75 (-0.85 , 6.69)	9.46 (5.62 , 13.99)	-1.24 (-2.94 , 0.07)	8.68 (5.12 , 15.90)
Macro (177)	6.02 (2.68 , 11.29)	12.84 (9.39 , 18.46)	0.12 (-0.41 , 0.57)	4.37 (3.59 , 6.34)
Merger Arbitrage (71)	4.57 (3.12 , 6.51)	5.02 (3.53 , 6.50)	-0.42 (-0.95 , 0.21)	5.61 (4.45 , 9.27)
Multi Strategy (186)	7.39 (4.33 , 10.54)	7.37 (4.80 , 10.56)	-0.45 (-1.59 , 0.44)	6.94 (4.60 , 11.34)
Option Traders (41)	7.83 (3.17 , 12.03)	10.31 (7.42 , 15.26)	-0.06 (-1.84 , 1.48)	9.26 (5.91 , 15.60)
Statistical Arbitrage (43)	5.56 (2.42 , 7.94)	7.33 (5.61 , 10.64)	-0.02 (-0.30 , 0.45)	4.56 (3.14 , 6.19)
All Funds (5025)	6.40 (2.48 , 11.66)	13.03 (8.12 , 20.80)	-0.02 (-0.67 , 0.57)	4.88 (3.66 , 7.41)

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Table 4: This table displays number of funds (in parentheses) , as well as annualised alpha , beta exposure to Fung-Hsieh risk factors and its corresponding adjusted R square of the monthtly equal-weighted hedge fund excess returns by investment category. The regression are computed by using monthly net-of-fee returns of live and dead hedge funds reported in the BarclayHedge between January 1994 and December 2009.

Investment Objectives	$\widehat{\alpha}_{OLS}$ (Ann.)	Equity	Eq. Size	B. Term	B. Spread	T. Bond	T. FX	T. Com	Adj. R2
CTA (1570)	9.56	0.02	0.02	0.06	0.02	0.02	0.04	0.04	30.85%
Convertible Arbitrage (138)	5.99	0.12	0.06	0.06	0.13	-0.01	0.00	-0.01	37.63%
Distressed Securities (116)	5.77	0.18	0.13	0.00	0.07	-0.03	0.01	0.00	53.88%
Emerging Markets (473)	9.69	0.53	0.26	0.05	0.15	-0.04	0.01	0.00	45.72%
Equity Long Bias (649)	7.60	0.63	0.40	0.00	0.02	-0.01	0.01	0.01	82.85%
Equity Long/Short(789)	8.63	0.35	0.29	-0.01	-0.02	-0.01	0.01	0.01	63.25%
Equity Market Neutral (152)	3.79	0.02	0.00	0.01	0.00	-0.01	0.01	0.01	2.81%
Equity Short Bias (37)	6.53	-0.85	-0.62	0.01	0.06	0.02	-0.01	-0.02	72.58%
Event Driven (199)	8.52	0.29	0.19	0.00	0.05	-0.03	0.01	0.01	67.50%
Fixed Income (293)	6.35	0.15	0.07	0.04	0.07	-0.02	0.00	0.00	56.02%
Fixed Income Arbitrage (91)	5.53	0.09	0.00	0.05	0.10	-0.01	-0.01	0.00	35.36%
Macro (177)	7.20	0.25	0.16	0.06	0.01	-0.02	0.02	0.02	43.35%
Merger Arbitrage (71)	5.62	0.11	0.05	0.02	0.02	-0.01	0.00	0.00	36.61%
Multi Strategy (186)	8.66	0.12	0.06	0.01	0.06	0.00	0.00	0.00	38.02%
Option Traders (41)	6.42	0.35	0.22	0.02	-0.04	-0.01	0.00	0.05	6.65%
Statistical Arbitrage (43)	5.36	0.11	-0.03	0.01	-0.01	0.00	0.01	-0.01	19.02%
All Funds (5025)	8.41	0.26	0.15	0.03	0.04	0.00	0.02	0.02	58.80%

Table 5: This table displays , by investment category , the number of funds (in parentheses) as well as the fund cross-sectional median and the 25-75 quantiles (in parentheses) of the Fung-Hsieh annualised alpha , model- implied true skill , risk aversion coe¢ cient respectively . The estimations are computed by using monthly net-of-fee returns of live and dead hedge funds reported in the BarclayHedge between January 1994 and December 2009.

Investment Objectives	$\widehat{\alpha}_{OLS}$ (Ann.)	True Skill	Risk Avers.
CTA (1570)	6.86 (1.74 , 13.63)	1.43 (1.24 , 1.64)	8.92 (5.53 , 14.86)
Convertible Arbitrage (138)	5.06 (2.87 , 7.05)	1.95 (1.66 , 2.23)	28.17 (17.22 , 46.11)
Distressed Securities (116)	5.54 (3.01 , 8.75)	1.88 (1.64 , 2.11)	19.21 (12.99 , 29.06)
Emerging Markets (473)	9.35 (4.20 , 16.86)	1.77 (1.60 , 1.99)	8.46 (5.33 , 16.29)
Equity Long Bias (649)	5.68 (2.06 , 10.08)	1.68 (1.54 , 1.83)	9.94 (6.98 , 13.74)
Equity Long/Short(789)	6.05 (2.12 , 10.37)	1.69 (1.51 , 1.89)	13.97 (9.06 , 20.94)
Equity Market Neutral (152)	2.70 (0.19 , 5.24)	1.48 (1.27 , 1.75)	20.06 (13.95 , 29.64)
Equity Short Bias (37)	3.10 (-1.36 , 13.25)	1.18 (1.10 , 1.48)	5.90 (3.72 , 11.50)
Event Driven (199)	6.30 (3.19 , 11.04)	1.87 (1.69 , 2.05)	15.72 (11.34 , 26.22)
Fixed Income (293)	4.50 (1.19 , 8.84)	1.76 (1.50 , 2.34)	23.17 (13.87 , 47.47)
Fixed Income Arbitrage (91)	3.10 (-0.57 , 7.37)	1.69 (1.14 , 2.09)	18.17 (10.78 , 27.99)
Macro (177)	5.92 (2.08 , 10.45)	1.53 (1.39 , 1.70)	11.45 (8.30 , 16.55)
Merger Arbitrage (71)	4.56 (2.85 , 6.50)	1.90 (1.79 . 2.28)	38.11 (27.95 , 60.90)
Multi Strategy (186)	7.01 (4.01 , 10.09)	1.97 (1.73 , 2.40)	26.02 (17.59 , 43.89)
Option Traders (41)	9.80 (4.50 , 13.52)	1.66 (1.42 , 2.02)	13.98 (9.98 , 28.01)
Statistical Arbitrage (43)	4.46 (2.33 , 7.63)	1.61 (1.33 , 1.91)	19.66 (15.24 , 26.80)
All Funds (5025)	6.13 (2.20 , 11.32)	1.66 (1.43 , 1.91)	12.24 (7.36 , 21.44)

Table 6: This table displays number of funds (in parentheses) , as well as annualised alpha , model-implied true skill , risk aversion coe¢ cient , management fee rate and performace fee rates of the monthtly equal-weighted hedge fund excess returns by investment category. The estimations are computed by using monthly net-of-fee returns of live and dead hedge funds reported in the BarclayHedge between January 1994 and December 2009.

Investment Objectives	$\widehat{\alpha}_{OLS}$ (Ann.)	True Skill*	Risk Avers.	Mgmt. Fee	Prfm. Fee
CTA (1570)	9.56	1.87	25.58	2.00%	20.13%
Convertible Arbitrage (138)	5.99	2.04	28.48	1.42%	18.40%
Distressed Securities (116)	5.77	2.10	30.95	1.54%	19.35%
Emerging Markets (473)	9.69	1.81	10.92	1.63%	17.89%
Equity Long Bias (649)	7.60	1.91	15.17	1.34%	17.67%
Equity Long/Short(789)	8.63	2.21	26.92	1.40%	19.52%
Equity Market Neutral (152)	3.79	2.31	75.02	1.41%	19.40%
Equity Short Bias (37)	6.53	1.14	6.98	1.34%	18.56%
Event Driven (199)	8.52	2.34	31.75	1.56%	19.77%
Fixed Income (293)	6.35	2.48	49.78	1.38%	17.86%
Fixed Income Arbitrage (91)	5.53	2.20	39.40	1.54%	20.23%
Macro (177)	7.20	2.07	30.68	1.62%	18.86%
Merger Arbitrage (71)	5.62	2.75	73.75	1.27%	19.21%
Multi Strategy (186)	8.66	2.98	61.96	1.56%	19.05%
Option Traders (41)	6.42	2.00	4.20	1.43%	19.69%
Statistical Arbitrage (43)	5.36	2.45	63.57	1.36%	20.79%
All Funds (5025)	8.41	2.43	39.14	1.49%	19.15%

Table 7: This table displays in sample Fung and Hsieh annualised alpha , model implied true skill and risk aversion coe¢ cient , managment and performance fee rate of portfolios formed by di¤erent strategies. The strategies are the following , TA : Top decile portfolio sorted by FH alpha , TS : Top decile portfolio sorted by model-implied true skill , TDS1 , TDS2 ,TDS3 and TDS4 are the …rst , second , third and fourth quantile of TS portfolio sorted by model-implied risk aversion respectively . The in sample estimations are computed by using monthly net-of-fee returns of live and dead hedge funds reported in the BarclayHedge between January 1994 and December 2009 with 36-month rolling estimation window.

Investment Objective	Portfolio	In Sample Estimates		
		$\widehat{\alpha}_{OLS}$	True skill	Risk Avers.
	TA	29.48	3.54	18.90
	TS	13.00	5.11	207.85
All Investment Styles	TDS1	6.85	6.94	546.09
	TDS2	8.73	4.77	142.11
	TDS3	12.71	4.50	92.70
	TDS4	26.67	4.24	50.14

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Table 8: This table displays in sample annualised alpha , t-statistic of alpha, beta exposure to Fung-Hsieh risk factors , the corresponding adjusted R square, sharpe ratio , maximum drawdown , annualised mean and standard deviation of the monthtly excess returns of portfolios formed by di¤erent strategies with the di¤erent pools of assets ; the all investment style and chosen styles. The strategies are the following , TA : Top decile portfolio sorted by FH alpha , TS : Top decile portfolio sorted by model-implied true skill , TDS1 , TDS2 ,TDS3 and TDS4 are the …rst , second , third and fourth quantile of TS portfolio sorted by model-implied risk aversion respectively, The regression are computed by using in sample equally-weighted monthly returns of individual portfolio between January 1994 and December 2009. The hedge fund data is monthly net-of-fee returns of live and dead hedge funds reported in the BarclayHedge .

Investment Objective	Port.	α_{FH} (Ann.)	Alpha_t	Fung and Hsieh's Betas (Monthly)							Adj R2	Sharpe Ratio	Max. Draw-down	Mean (Ann)	Std(Ann)
		%		Eq	Eq. Size	B. Term	B. Spread	T. Bond	T. FX	T. Com			%	%	%
	TA	29.48	10.75	0.32	0.14	0.05	0.11	0.03	0.03	0.05	0.27	2.30	17.11	29.09	12.60
	TS	13.00	28.89	0.08	0.06	0.01	0.03	0.00	0.00	0.00	0.47	5.37	3.14	13.15	2.44
All Investment Styles	TDS1	6.85	35.93	0.02	0.01	0.00	0.00	0.00	0.00	0.00	0.15	8.46	0.66	6.94	0.82
	TDS2	8.73	24.23	0.04	0.04	0.01	0.02	0.00	0.00	0.00	0.33	5.08	2.21	8.83	1.73
	TDS3	12.71	19.51	0.10	0.10	0.01	0.02	0.00	0.01	0.00	0.41	3.88	3.99	13.01	3.35
	TDS4	26.67	19.90	0.15	0.13	0.01	0.06	0.01	-0.01	0.01	0.30	4.21	8.27	26.65	6.32

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Table 9: This table displays out of sample annualised alpha , beta exposure to Fung-Hsieh risk factors , the corresponding adjusted R square, sharpe ratio , maximum drawdown , annualised mean and standard deviation of the monthtly excess returns of portfolios formed by di¤erent strategies with the di¤erent pools of assets ; the all investment style and chosen styles. The strategies are the following , TA : Top decile portfolio sorted by FH alpha , TS : Top decile portfolio sorted by model-implied true skill , TDS1 , TDS2 ,TDS3 and TDS4 are the …rst , second , third and fourth quantile of TS portfolio sorted by model-implied risk aversion respectively, The regressions are computed by using monthly returns of individual portfolio between January 1997 and December 2009. The portfolios are annually rebalanced. The hedge fund data is monthly net-of-fee returns of live and dead hedge funds reported in the BarclayHedge .

Investment Objective	Port.	α_{FH} (Ann.)	Alpha_t	Fung and Hsieh's Betas (Monthly)							Adj R2	Sharpe Ratio	Max. Draw-down	Mean (Ann)	Std(Ann)
		%		Eq	Eq. Size	B. Term	B. Spread	T. Bond	T. FX	T. Com			%	%	%
All Investment Styles	TA	5.05	1.95	0.42	0.32	0.05	0.08	-0.02	0.01	0.06	0.48	0.47	34.42	5.98	12.69
	TS	4.54	5.51	0.11	0.07	0.02	0.05	-0.02	0.00	0.00	0.52	1.16	15.91	4.88	4.18
	TDS1	3.05	4.30	0.01	0.02	0.02	0.03	-0.01	0.00	0.00	0.18	1.12	13.92	3.11	2.75
	TDS2	3.20	4.00	0.07	0.03	0.01	0.05	-0.02	0.00	0.00	0.44	0.94	14.96	3.55	3.76
	TDS3	4.92	5.81	0.10	0.07	0.02	0.05	-0.01	0.00	-0.01	0.46	1.26	17.98	5.14	4.07
	TDS4	7.18	3.91	0.24	0.15	0.03	0.08	-0.03	0.00	0.02	0.43	0.91	26.43	7.87	8.59
Equity Long Short	TA	5.75	1.97	0.28	0.33	-0.05	0.00	0.03	0.01	0.04	0.26	0.48	34.35	5.81	11.99
	TS	6.14	4.37	0.20	0.20	-0.02	-0.01	-0.01	0.00	0.01	0.40	1.08	10.79	6.92	6.40
	TDS1	3.98	2.58	0.14	0.17	0.01	0.00	-0.03	0.01	-0.01	0.29	0.81	20.96	5.29	6.45
	TDS2	4.56	2.30	0.15	0.14	-0.03	-0.01	-0.01	0.01	0.01	0.14	0.69	17.22	5.22	7.55
	TDS3	8.73	4.32	0.20	0.18	-0.02	0.02	0.00	0.00	0.01	0.25	1.12	12.47	9.21	8.21
	TDS4	7.08	2.87	0.29	0.32	-0.04	-0.05	0.01	-0.01	0.02	0.30	0.76	22.38	7.90	10.40

Continued from Table 9

Investment Objective	Port.	α_{FH} (Ann.)	Alpha_t	Fung and Hsieh's Betas (Monthly)							Adj R2	Sharpe Ratio	Max. Draw-down	Mean (Ann)	Std(Ann)
		%		Eq	Eq. Size	B. Term	B. Spread	T. Bond	T. FX	T. Com			%	%	%
	TA	5.04	2.76	0.27	0.16	-0.01	0.07	-0.05	0.01	0.01	0.53	0.70	34.49	6.59	9.34
	TS	2.51	1.69	0.24	0.12	-0.02	0.05	-0.05	0.00	0.00	0.56	0.49	34.03	3.88	7.88
Event Driven	TDS1	1.94	1.88	0.11	0.07	0.02	0.06	-0.03	0.00	0.00	0.46	0.49	27.56	2.44	4.92
	TDS2	2.55	1.94	0.18	0.11	0.01	0.06	-0.02	0.00	-0.01	0.51	0.47	32.00	3.16	6.64
	TDS3	5.60	3.87	0.21	0.10	0.00	0.07	-0.04	0.00	0.01	0.56	0.86	27.62	6.65	7.66
	TDS4	1.98	0.61	0.43	0.18	-0.14	0.01	-0.10	0.01	0.01	0.46	0.34	52.58	5.28	15.60
	TA	7.17	2.27	0.64	0.64	-0.01	0.04	-0.01	0.01	0.07	0.60	0.50	48.90	8.84	17.68
	TS	4.59	2.34	0.43	0.45	0.00	-0.01	-0.02	0.02	0.02	0.63	0.57	34.12	6.49	11.41
Equity Long Bias	TDS1	5.01	2.96	0.21	0.20	0.02	0.05	-0.03	0.02	-0.01	0.42	0.77	19.44	6.07	7.86
	TDS2	1.74	0.62	0.44	0.47	0.00	-0.05	-0.04	0.01	0.02	0.45	0.32	32.85	4.23	13.27
	TDS3	8.46	3.38	0.48	0.46	0.01	-0.01	-0.01	0.02	0.01	0.53	0.77	33.93	10.04	12.93
	TDS4	2.68	0.72	0.60	0.68	-0.01	0.00	-0.02	0.03	0.04	0.49	0.27	64.73	4.99	18.28
	TA	2.17	1.75	0.03	0.03	0.03	0.03	-0.01	0.01	0.01	0.05	0.56	11.62	2.54	4.47
	TS	3.36	3.28	0.03	0.06	0.02	0.02	0.00	0.01	0.00	0.05	0.94	6.87	3.51	3.70
Market Neutral	TDS1	3.91	4.30	0.04	-0.01	0.00	0.01	-0.01	0.00	0.01	0.03	1.24	8.09	4.08	3.26
	TDS2	1.36	1.07	0.01	-0.05	0.02	0.01	-0.01	0.01	0.00	-0.01	0.34	22.78	1.56	4.44
	TDS3	2.54	1.50	0.06	0.08	0.01	-0.01	-0.03	0.01	0.01	0.05	0.57	13.42	3.54	6.13
	TDS4	5.96	2.20	0.00	0.21	0.04	0.05	0.02	0.01	-0.01	0.07	0.53	18.68	5.28	9.95

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Figure 1: This figure displays payoff to a hedge fund manager plotted against terminal fund value. The underlying parameters are as follows $\alpha = 0.2, m = 0.02$ and $c = 0.02$.

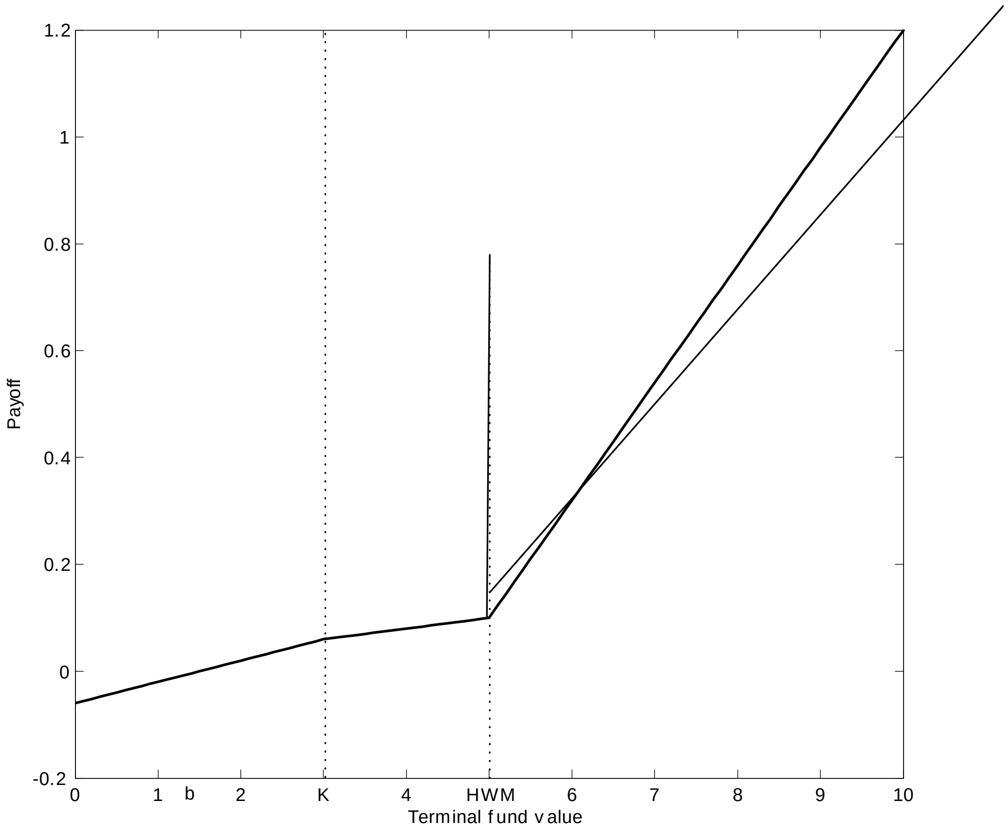

Figure 2: This …gure displays the optimal allocation to risky asset against current fund value. The manager considers an incentive fee, management fee and the presence of put options when making her investmnet decision. The underlying parameters are as follows: $\alpha = 0.2, m = 0.02, c = 0.02, \gamma = 2, \lambda = 0.4, r = 0$ and $t = 0$.Where α denotes performce fee, m denotes management fee, c denotes concern level on short put option positions, γ denotes level of risk aversion, λ denotes Sharpe Ratio and r denotes the risk free rate.

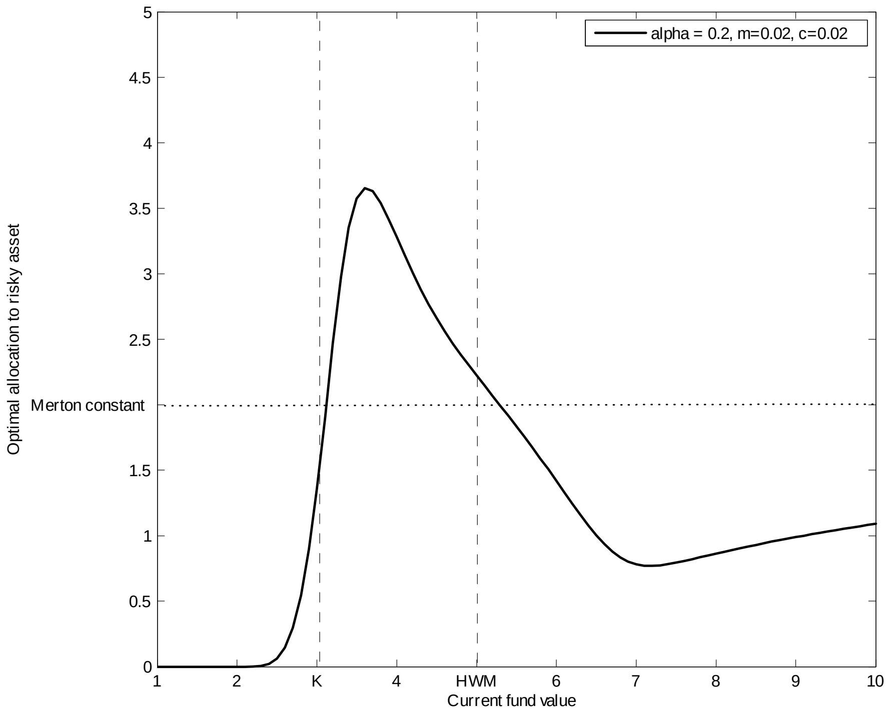

Figure 3: This figure displays the optimal allocation to a risky asset against current fund value. The dashed line represent the decision made by a manager who considers only an incentive fee, while the solid line represents a manager who considers both incentive fee and management fee when making her investmnet decision. The underlying parameters are as follows: $\alpha = 0.2, m = [0, 0.02], c = 0, \gamma = 2, \lambda = 0.4, r = 0$ and $t = 0$.Where α denotes performce fee, m denotes management fee, c denotes concern level on short put oppositions, γ denotes level of risk aversion, λ denotes Sharpe Ratio and r denotes the risk free rate .

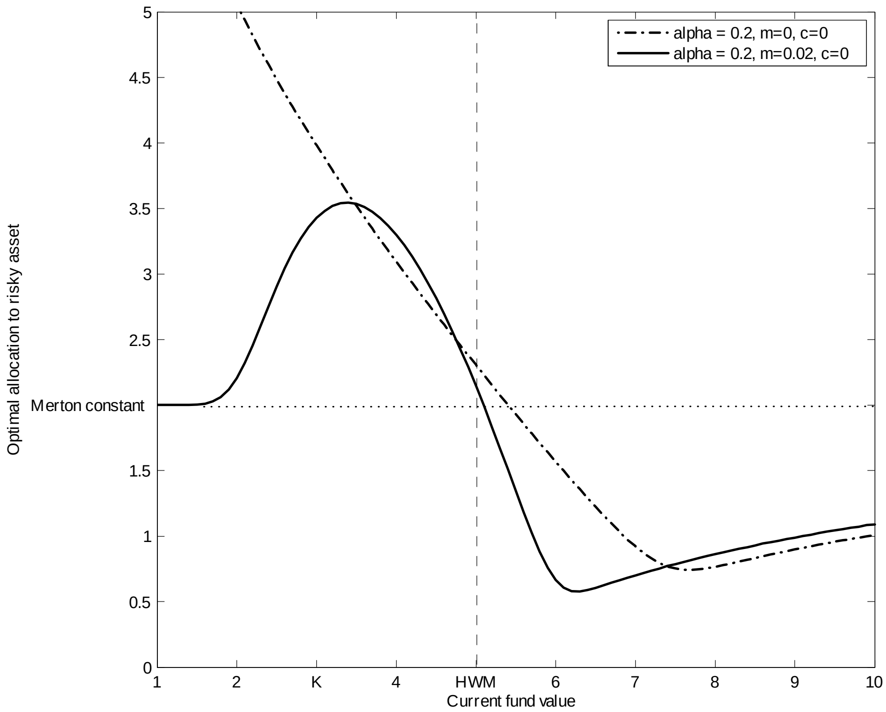

Figure 4: This ...gure displays the scatter plot of OLS Fung and Hsieh alpha on the y-axis and the ratio of current fund value to fund high water mark on the x-axis. Each dot corresponds to the estimated alpha of a fund over 36-month rolling estimation window. The hedge fund data is monthly net-of-fee returns of live and dead hedge funds reported in the BarclayHedge . We exclude funds with less than 36 monthly observations and 40 percent smallest funds by Assets under Management (this is equivalent to the percentile of 25 million USD in 2008) from our fund universe.

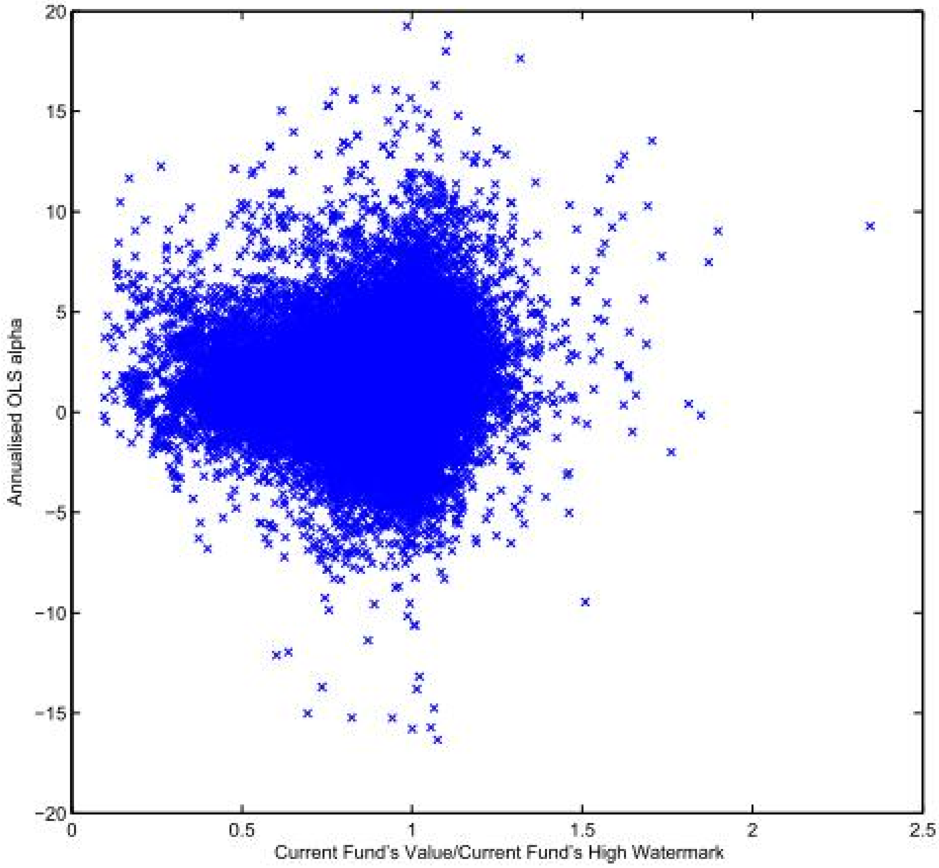

Figure 5: This …gure displays the di¤erence between typical OLS alpha and true alpha against current fund value. The underlying parameters are as follows: $\alpha^* = 0.2, \sigma = 0.1, c = 0.02, \gamma = 2, \lambda = 0.4, r = 0$ and $t = 0$.Where α^* denotes true alpha, σ denotes volatility of alpha generating process, c denotes concern level on short put option positions, γ denotes level of risk aversion, λ denotes Sharpe Ratio and r denotes the risk free rate .

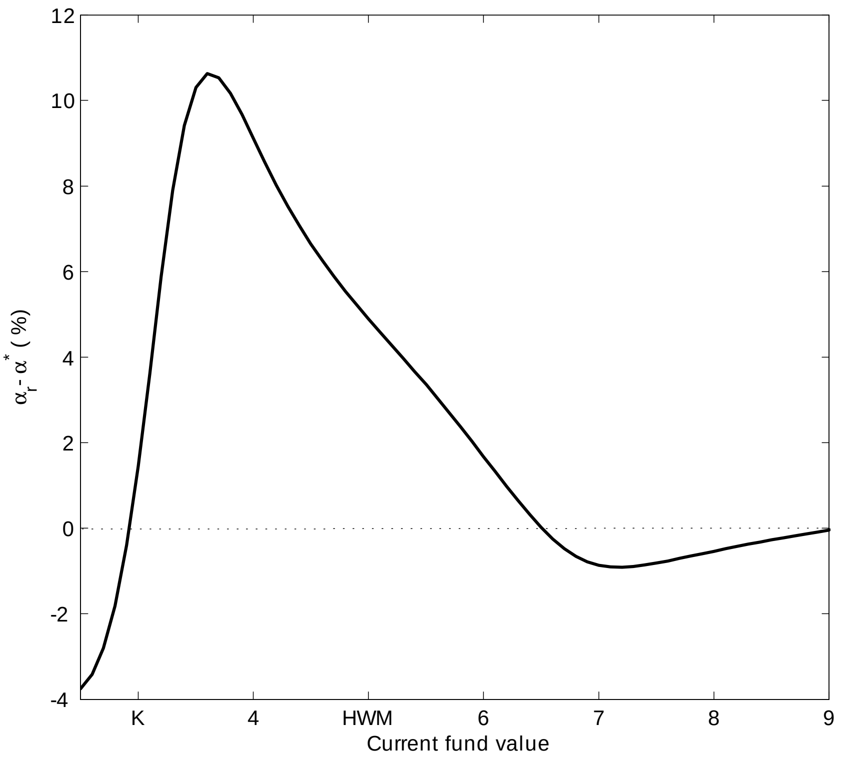

Figure 6: The ﬁgure displays the distribution of alphas based on diﬀerent methodologies. Column (a) presents the distribution of the structural true skill measure, α^*. Column (b) presents the distribution of typical OLS alphas while column (c) presents the distribution of alpha implied from structural restriction on typical OLS alpha. In Panel A the returns are simulated with risk aversion of 2 , while in Panel B and C the risk aversion is 5 and 10 respectively . The other common parameters are r=0.05,λ_B=0.2 , σ_B=0.2 and σ_A=0.2 .Where r denotes the risk free rate ,λ_B denotes benchmark's price of risk and σ_B denotes benchmark's volatility .

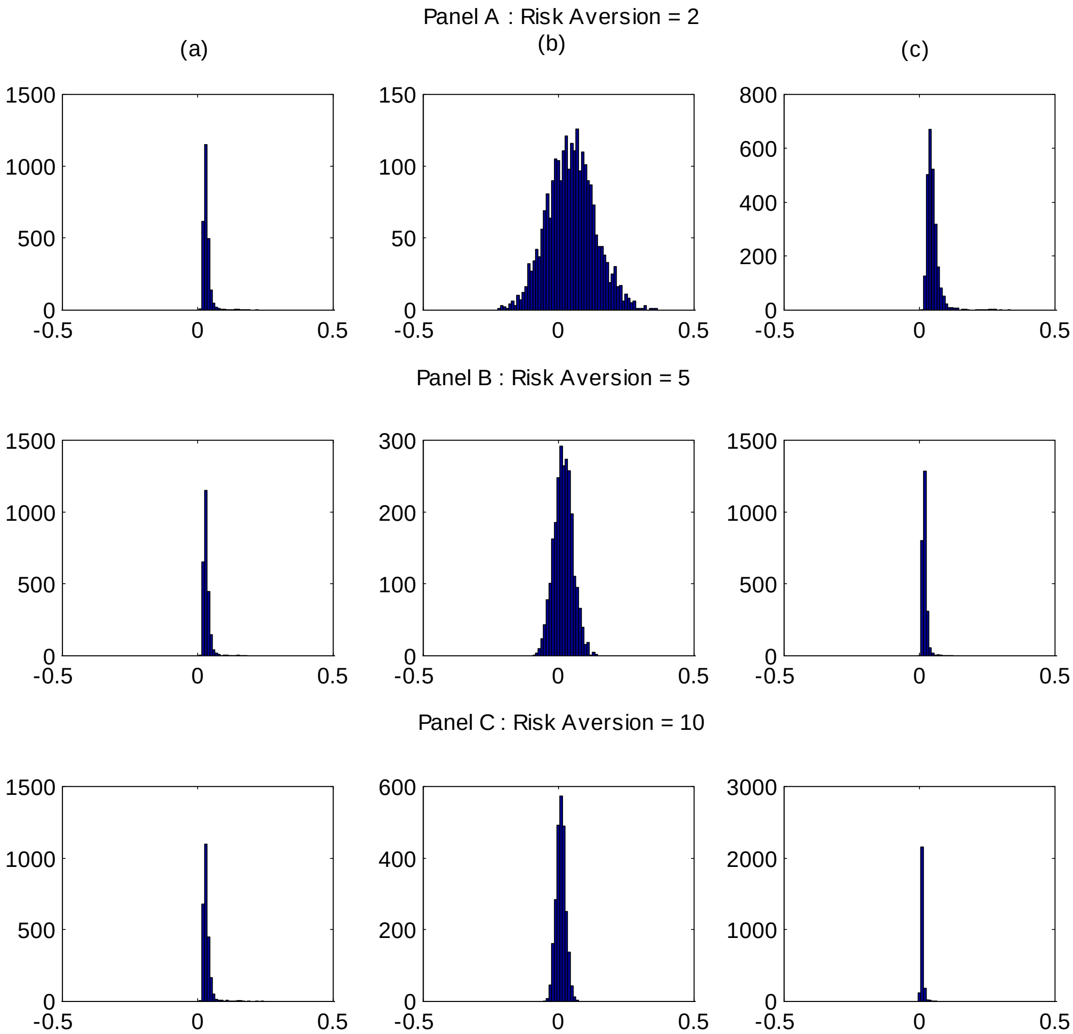

Figure 7: This figure displays the joint distribution of manager specific λ_A and $\tilde{\gamma}$ by strategies. Each dot corresponds to an averaged value of the parameters over each fund's sample period. The entire sample period is from January 1994 to December 2009.

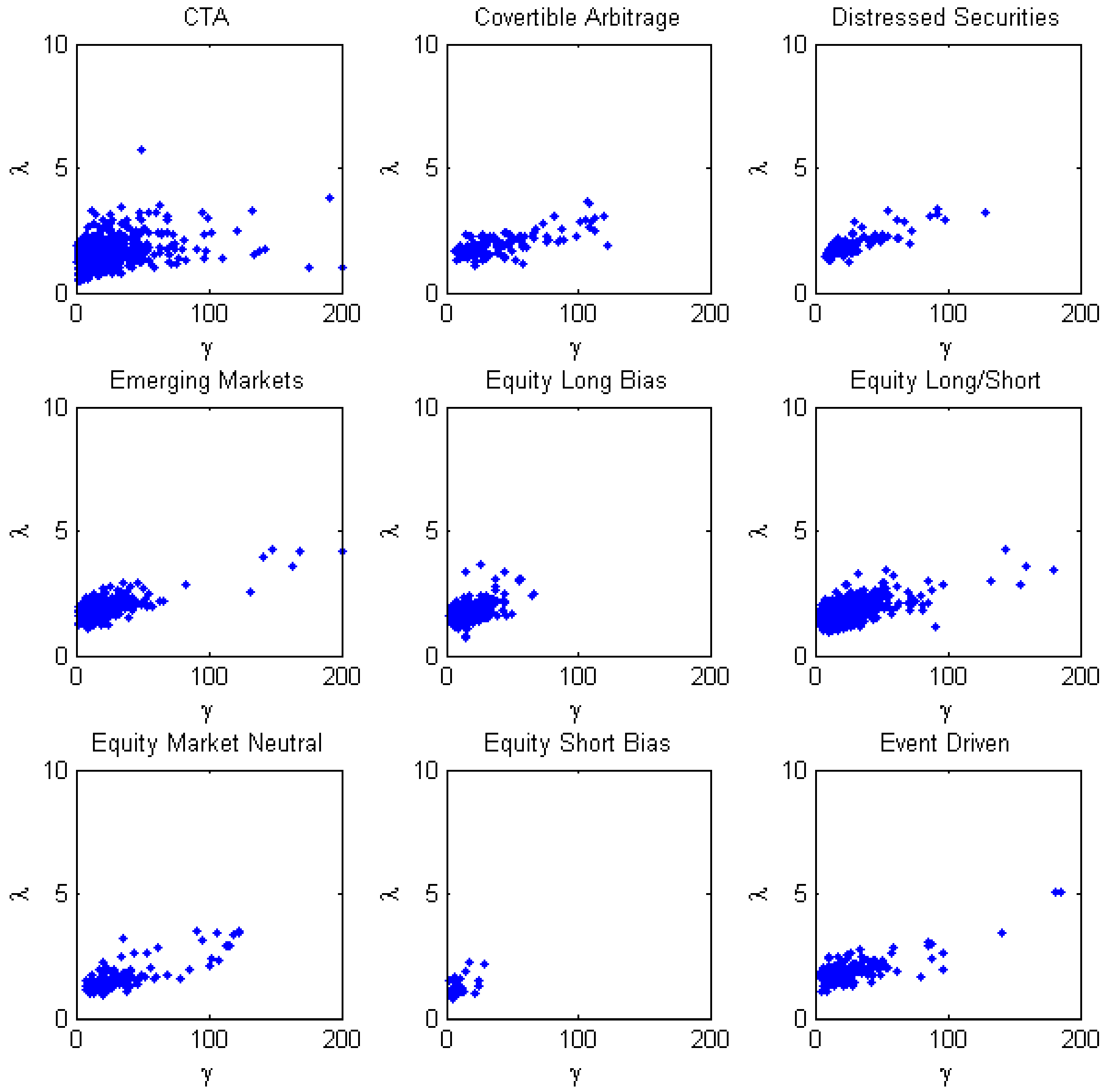

Figure 8: This ...gure displays the joint distribution of manager speci...c λ_A and $\tilde{\gamma}$ by strategies. Each dot corresponds to an averaged value of the parameters over each fund's sample period. The entire sample period is from January 1994 to December 2009.

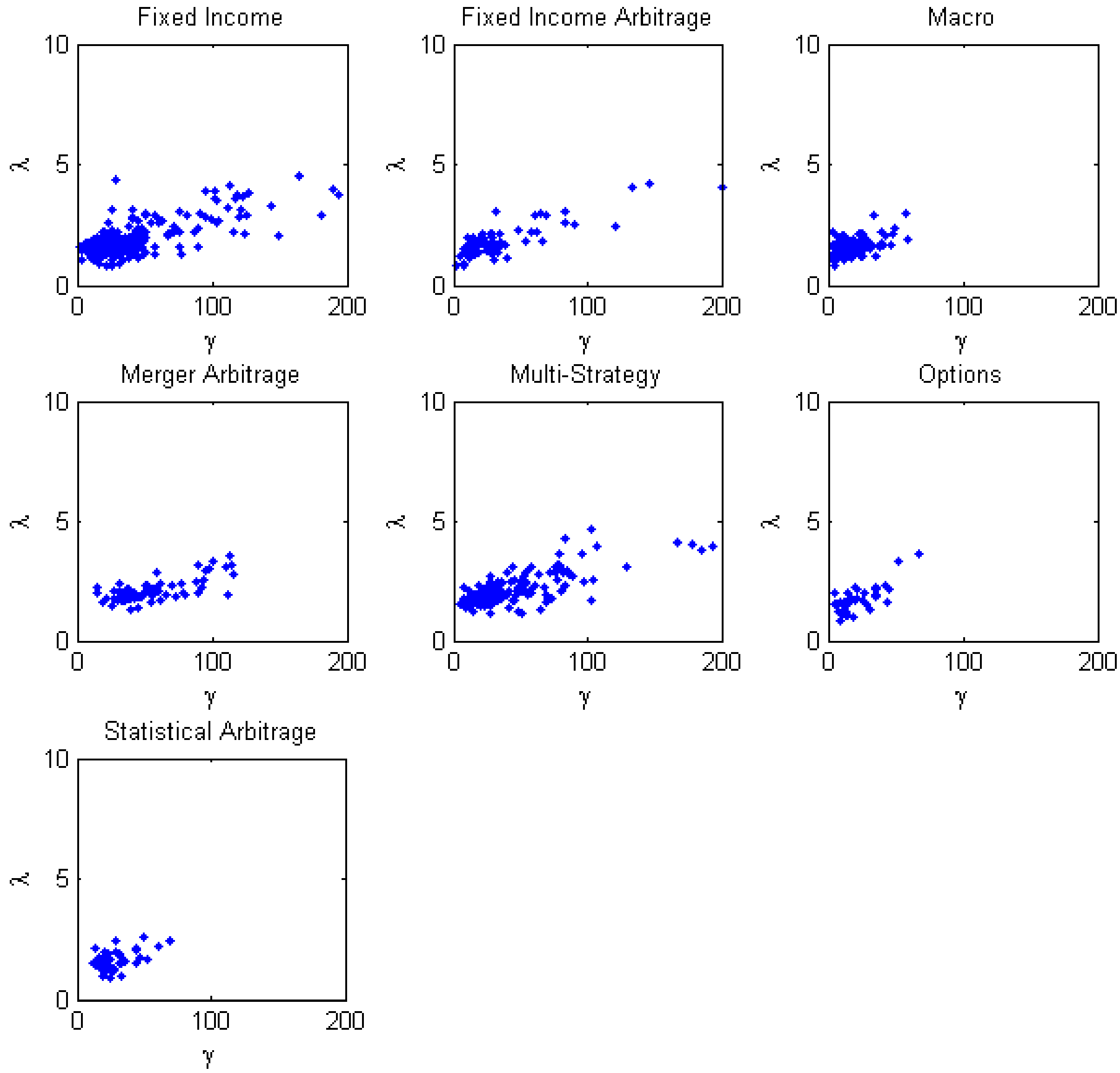

Figure 9: This …gure plots the cumulative wealth of a dollar invested in 6 di¤erent portfolios starting in January 1997 and end in December 2009. The hedge funds used in the allocation are from all investment objectives.The portfolios are the following ; TA : Top decile portfolio sorted by FH alpha , TS : Top decile portfolio sorted by model-implied true skill , TDS1 , TDS2 ,TDS3 and TDS4 are the …rst , second , third and fourth quantile of TS portfolio sorted by model-implied risk aversion respectively. The hedge fund data is monthly net-of-fee returns of live and dead hedge funds reported in the BarclayHedge . We exclude funds with less than 36 monthly observations and 40 percent smallest funds by Assets under Management (this is equivalent to the percentile of 25 million USD in 2008) from our fund universe.

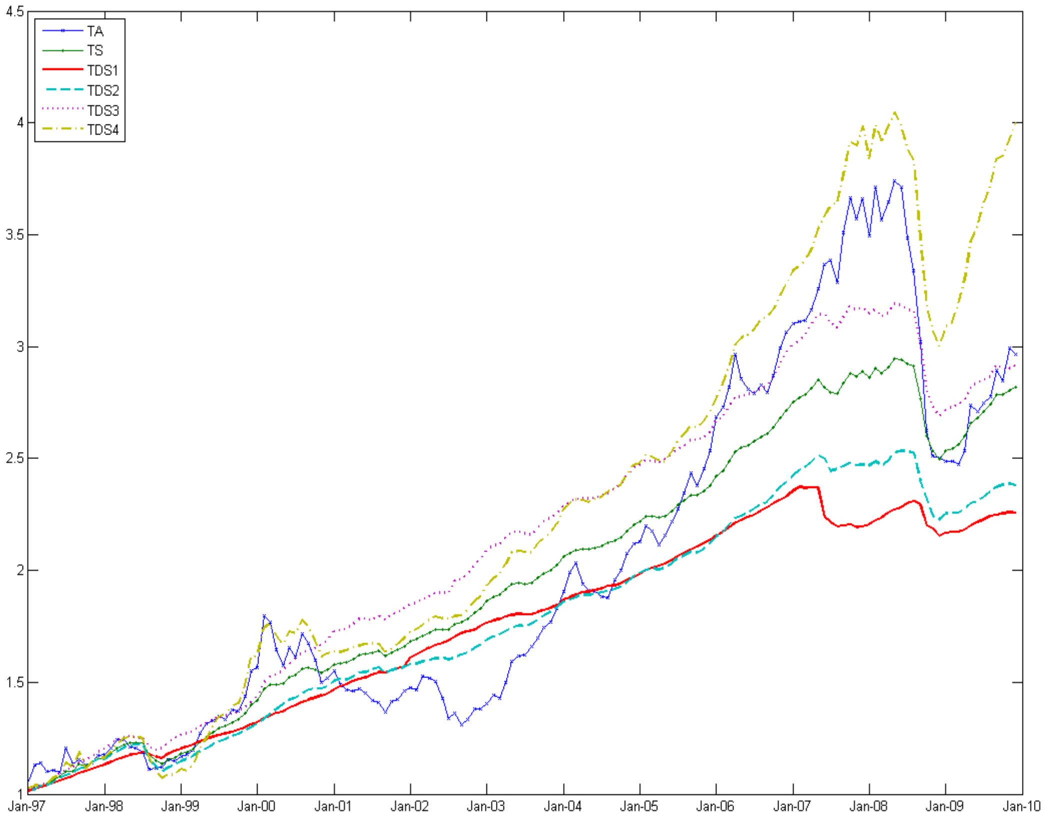

Figure 10: This …gure plots the cumulative wealth of a dollar invested in 5 di¤erent portfolios starting in January 1997 and end in December 2009. The hedge funds used in the allocation are from all investment objectives. The portfolios are the following ; TA : Top decile portfolio sorted by Fung and Hsieh alpha , TG1 , TG2 ,TG3 and TG4 are the …rst , second , third and fourth quantile portfolio sorted by model-implied risk aversion respectively, . The hedge fund data is monthly net-of-fee returns of live and dead hedge funds reported in the BarclayHedge . We exclude funds with less than 36 monthly observations and 40 percent smallest funds by Assets under Management (this is equivalent to the percentile of 25 million USD in 2008) from our fund universe.