Risk and Beta Anatomy in the Hedge Fund Industry

Roberto Savona*
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Abstract

Using a Bayesian time-varying beta model we explore how the systematic risk exposures of hedge funds vary over time conditional on some exogenous variables that managers are assumed to use in changing their trading strategies. In such a setting, we impose a structure on fund returns, betas and benchmark returns, developing a framework that could help explain how expected and unexpected hedge fund returns are correlated with systematic risk factors through the beta dynamics. Such a system proves to be also useful in fund cloning and VaR-based risk monitoring. Major findings of this work, based on the analysis of the CSFB/Tremont indices over the period 01/1994-12/2007, are that: (1) volatility, changes in T-bill, term spread and shocks in liquidity significantly impact on time variation of hedge fund betas; (2) taking into account conditional time variation in betas lead us to conclude that hedge fund industry as a whole did not delivered positive extra-performance over the time period inspected; (4) the proposed model appears to do a good job of replicating the risk/return characteristics of the hedge funds, also delivering better performances in a risk-adjusted basis; (5) simulation-based exercises on VaR predictions suggest that our technology could be a serious candidate in hedge fund risk monitoring systems.

Keywords: Bayesian analysis; Conditional time-varying beta; Hedge Funds; Performance; VaR.
JEL Classification: C11, C13, G12, G13.

* Department of Business Studies, University of Brescia. Address: Dipartimento di Economia Aziendale, Università degli Studi di Brescia, c/da S. Chiara n° 50, 25122 Brescia (Italy). E-mail: savona@eco.unibs.it.

I. Introduction

Understanding the risks in hedge fund strategies is a complex issue of particular relevance to the financial markets. Consider what happened in August 2007. Events in the mortgage market U.S. sub-prime triggered huge losses, firstly, for hedge funds involved in sub-prime mortgages and credit-related instruments, but secondly, also for managers exposed to exchange-traded equities. In a word, extreme losses were experienced by long/short equity strategy as a whole, and not only by those funds who were idiosyncratically invested in sub-prime-based instruments.

In inspecting such market event, many observers have remarked the analogy between the sub-prime crisis with the LTCM case in August 1998, when Russia defaulted on its GKO government bonds. Indeed, both the default events caused widened credit spreads then generating a "margin call spiral", which in turn caused extreme losses due to illiquid portfolio positions. However, Khandani and Lo (2007) note that,

> "*In contrast to August 2007 … the well-documented demand for liquidity in the fixed-income arbitrage space of August 1998 had no discernible impact on the very same strategy.*"

What is changed from 1998 to 2007 is the risk propagation among hedge funds. And looking at risk dynamics of hedge funds seems to be of central importance for both investors and regulators. On the one hand, the concern is with the risk/return profile, which requires the identification of suitable risk factors in order to monitoring the performance of hedge funds. On the other hand, the main focus is on the systemic risk, i.e. on the convergence of risks in hedge fund industry since it can produce destabilizing impacts on financial markets.

From a methodological perspective, a clear understanding of the risks inherent in the hedge fund strategies is particularly challenging. Managers follow portfolio-rebalancing rules which are complex, highly dynamic, also exhibiting different "cycles" in which the risk factors and their corresponding exposures vary over time with all likelihood depending on systematic and idiosyncratic reasons. Fung and Hsieh (1997) firstly explained this concept saying that hedge fund returns are function of strategy (how they trade), location (where they trade), and leverage (how much they trade). More recently, the same authors (Fung, Hsieh, 2007a,b), treating the issue of hedge fund cloning, remarked the need to face at two additional points, namely missing factors and missing time varying risk exposure.

These two elements are of critical importance to capture the essence of the hedge fund dynamics and this paper tries to give a methodological possibility to deal with, inspecting how the systematic risk exposures of the major hedge fund strategies vary over time. The hypothesis we have in mind is that some exogenous variables could act as "primitive signals" that hedge fund managers use in changing their trading strategies. In more depth, we suppose that the systematic risk exposure may modify in response to changes occurred in the financial market conditions and to changes occurred in the systematic risk factors themselves. In such a setting, we impose a Bayesian structure on fund returns, betas and benchmark returns, developing a framework that could help explain how expected and unexpected hedge fund returns are correlated with systematic risk factors through the beta dynamics. Such a beta decomposition proves to be also useful to shed some lights on recent emerging question in the hedge fund industry, namely the fund cloning by the mean of the beta replication.

Using data from CSFB/Tremont indexes over the period 1994-2007, the empirical results show that the time variation of systematic risk exposure can be linked to some fundamental instruments which significantly impact on changes in investment strategies followed by the managers. The implications of this instrument-based conditioning on beta variations appear substantial enough to be extremely skeptics towards traditional econometric approaches in which the systematic risk exposure is assumed constant over time. Indeed, severe rebounds could affect performance measurements: in our comparative analysis we found that unconditional alphas significantly overstate the real extra performance and that hedge fund industry as a whole did not delivered positive extra-performance over the time period inspected. We finally proved that our technology could also be fruitfully used in hedge fund cloning and risk monitoring. On this last point we presented a simulation-based exercise on out-of-sample VaR predictions over the year 2007 confirming the robustness of our model as risk monitoring system.

The structure of the paper is as follows. Section II starts discussing the complexity of hedge fund strategies leading to highlight the reason of the non-linearity in hedge fund returns. Section III introduces our model. Section IV explores the risk factors and the instruments to be used in the model and Section V describes the estimation procedure. Section VI presents the data used in the empirical analysis. In Section VII we report results on hedge fund beta anatomy, while Section VIII reports results on conditional and unconditional performance measurement also exploring the use of our model in cloning hedge fund returns. In Section IX we verify the in-sample model reliability and present the out-of-sample simulation VaR exercise. Section X concludes.

II. Complexity of Trading Strategies and Non-linearity in Hedge Fund Returns

The complex nature of hedge fund strategies reflects on nonlinearity in returns making difficult to uncover *how* the returns are generated and *where* they come from. To reduce this problem Fung and Hsieh (2001) advanced the concept of primitive trading strategies (PTS). Basically, these are option-based benchmarks designed to describe the strategy-driven nonlinearity and contextualized within a clear-cut economic framework tracing back to the Merton's (1981) insight, for which the payoff of a perfect market timer should be identical to the payoff from owning a call option on the market. This isomorphical approximation of hedge fund strategies to option-based trading strategies allows to bypass the problem of unreliability of linear models when passive benchmarks are used. Indeed, since the intrinsic nonlinearity of hedge fund returns is moved onto the explanatory factors, which act as proxies of the complex and often unobservable trading strategies, a simple linear multivariate regression can be effectively used to describe the behaviour of hedge fund returns.

An in depth reasoning about the nature of hedge funds, however suggests that although these benchmarks are intrinsically dynamic and could in principle admit a constant beta model, a more focused inspection of the inner sources of the return nonlinearity suggests that hedge fund exposures may be, notwithstanding, time varying. If, indeed, we consider that the nonlinearity can be emanated, first, by the strategy *per se*, and, second, by the dynamic asset allocation (Fung and Hsieh, 2007b), a model with constant betas allows to control for only the first source of nonlinearity, leaving the second source hidden within the exposure to the rule-based trading strategies. All that points to the importance of considering time variation in risk exposures.

Another related problem is connected to the risk factors. Indeed, since they should represent the strategies of hedge funds and since these could modify over time according to their own "life cycle", new risk factors could emerge in response to new dynamics of hedge fund strategies. On this point, recent empirical evidence, for e.g. Agarwal et al. (2006) or Fung and Hsieh (2006a), has documented that incorporating exogenous variables to hedge fund returns help explain the dynamics of hedge fund strategies. Such finding is of particular importance, because if we assume that the same set of instruments may exerts a significant impact on time varying risk exposures as well as on systematic risk variations, then, such instruments could be used to fully describe the dynamics of hedge fund returns. These variables play the role of, say, "primitive risk signals" (PRS), to be considered as those signals that hedge fund managers use in changing their primitive trading strategies. In doing so, the view of Fung and Hsieh (1997), for which any investment fund's return can be expressed as a function of (1) where it trades (asset class-driven returns), (2) how it trades (strategy-driven returns), and (3) how much it trades (leverage-driven returns) is extended to an additional factor, namely, (4) how it modifies his trade (dynamic strategy-driven returns): time variation in risk factors and their corresponding sensitivities are indeed taken into account.

III. Modelling the Risk Dynamics

To infer how hedge funds change their risk exposure over time in dynamic economic environments, we assume that the managers are predominantly focused on specific trading strategies, to be expressed as linear combination of some systematic risk factors. This linear combination of factors, some of which inherently nonlinear, designs the long-run strategy of the fund, since indeed, over time it is assumed that managers could modify their own strategy (the style benchmark) according to some partly observable primitive risk signals (PRS). Essentially, PRSs can be read as the "impulse variables" that condition the time variation in systematic risk exposure. Moreover, in order to inspect how the beta variation is related to the long-run strategy, the same PRSs are assumed to condition also the benchmark evolution.

The model we propose is in line with Pastor, Stambaugh (2007) and, more closely, with Amisano, Savona (2008). Analytically, the reduced-form scheme arising from this logic is stylized by a three-equation system (portfolio return, beta, and benchmark return) in which:

i) a set of instruments (the PRSs) enter into the beta specification as imperfect covariates, in the sense that: (a) on one extreme, they potentially deliver perfectly the beta, (b) on the other, they do not contribute to explain the beta variation since the process is completely stochastic;

ii) the same set of PRS enters also into the benchmark specification, in order to inspect how differently the instruments impact on benchmark and portfolio returns;

iii) the three equation system are combined by imposing a structure on their innovations, to better examine how expected and unexpected hedge fund returns are correlated with systematic risk factors through the beta dynamics.

Mathematically,

(1) $$r_{p,t} = \alpha_p + \beta_{p,t} r_{b,t} + \varepsilon_{p,t}$$

(2) $$\beta_{p,t} = \mu + \phi\left(\beta_{p,t-1} - \mu\right) + \Gamma' \mathbf{z}_t + \eta_{p,t}$$

(3) $$r_{b,t} = \Lambda' \mathbf{z}_t + u_{b,t} \, .$$

Equation (1) is the excess portfolio returns over the risk-free rate at time *t*, in which α_p denotes the risk-adjusted abnormal return, $\beta_{p,t}$ the systematic risk exposure of the portfolio assumed to be time varying, $r_{b,t}$ the excess benchmark return over the risk-free rate and $\varepsilon_{p,t}$ the unexpected portfolio return.

The equation (2) is the time-varying beta, where ϕ is the persistence beta parameter, μ the unconditional mean reverting beta term, Γ' the transposed vector of sensitivities towards $\mathbf{z}_t$ which is the vector of PRSs at time *t*, and $\eta_{p,t}$ the beta stochastic component to accommodate imperfect PRSs in beta evolution. As one can note, our beta specification is pseudo-stochastic, since it mixes (a) a structural component, assumed to be linear in the state variables (the term $\Gamma'\mathbf{z}_t$), (b) a stochastic component ($\eta_{p,t}$), which represents the unobservable PRS used by the hedge funds in changing their portfolio positions.

Equation (3) is the excess benchmark returns over the risk-free rate, in which $\Lambda'\mathbf{z}_t$ is the expectation in time *t* modeled as a linear function of the same PRSs in (2), with Λ' denoting the transposed vector of sensitivities towards the $\mathbf{z}_t$ vector, and $u_{m,t}$ the unexpected benchmark return at time *t*, then accommodating imperfect PRSs.

Finally, the model assumes that residuals in equations (1), (2) and (3) exhibit the following i.i.d. distribution:

$$\text{(4)} \qquad \begin{bmatrix} \varepsilon_{p,t} \\ \eta_{p,t} \\ u_{b,t} \end{bmatrix} \sim N\left(\begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}, \begin{bmatrix} \sigma_{\varepsilon}^2 & \sigma_{\varepsilon\eta} & \sigma_{\varepsilon u} \\ \sigma_{\eta\varepsilon} & \sigma_{\eta}^2 & \sigma_{\eta u} \\ \sigma_{u\varepsilon} & \sigma_{u\eta} & \sigma_{u}^2 \end{bmatrix} \right).$$

The reason why we impose a structure on the system innovations through the (4) is because the assumption is that superimposed on the residuals there may be a non-negative covariance matrix whose off-diagonal elements help control for unobservable PRSs in describing the dynamics of systematic risk exposures. In a sense, where the PRSs fail to explain the beta dynamics, the innovations try to measure what is, generally, unobservable, namely the measurement error of observable PRSs.

The structure in (4) could have also an economic interpretation when using lagged instruments, which lead to the conditional asset pricing models. Indeed, assuming lagged PRSs as predictors of future benchmark returns, and since these enter into the beta as well as benchmark processes, the model would removes spurious market timing induced by partial predictability of benchmark returns. Indeed, having a positive covariance between benchmark and beta innovations, $\sigma_{\eta u} > 0$, can be interpreted as positive benchmark timing, since the risk exposure increases when unexpected benchmark returns boost, and reduces when they lower. And again, having a positive covariance between portfolio and beta innovations, $\sigma_{\varepsilon\eta} > 0$, can be interpreted as a leverage effect, for which positive portfolio returns increase when beta innovations rises, then amplifying the positive benchmark timing or offsetting it, if the benchmark timing was negative.

In our case, this economic understanding is not possible, since PRSs are contemporaneous and the structure on (4) is technically conceived with the end to reduce the total inaccessibility in the beta stochastic component. Indeed, instead of searching *other* PRSs that may increase the explanatory power of beta variations, we bypass the problem by searching how idiosyncratic portfolio returns, inaccessible beta variation component, and benchmark residuals co-moves together as implied by unobservable/omitted/imperfect PRSs.[1]

IV. Risk Factors and Instruments

IV.1. Systematic Risk Factors

As well pointed out in Fung and Hsieh (2006b), the research on risk factors can be characterized by a bottom-up or top-down perspective. With the first approach one is interested in understanding the risks in *specific* hedge fund styles, while the second approach is devoted to inspect the risk factors of *diversified* hedge fund portfolios. A top-down perspective is then conceived with the end to deal with all the common risks that transversely affect the hedge fund industry as a whole, allowing inspecting the inner sources of risk dynamics and their potential impacts on the markets.

Fung and Hsieh (2004, 2007a,b) address the issue of the top-down approach in modelling the risk factors of hedge funds, proposing a basic model with 7+1 risk factors that are found to be present in empirical studies on many of the major hedge fund styles. Indeed, the authors propose the use of four dominant risk classes:

(I) Trend-Following Risk Factors: three out of the five primitive trend following strategies proxied as pairs of standard straddles and constructed from exchange-traded put and call options as described in Fung and Hsieh (2001), namely **(1)** Bond Trend-Following Factor (BTF), **(2)** Currency Trend-Following Factor (CUTF), **(3)** Commodity Trend-Following Factor (COTF).

(II) Equity-oriented Risk Factors: **(4)** Equity Market Factor, proxied by the Standard & Poors 500 index monthly total return (SP), and **(5)** Size Spread Factor (SIZE), proxied by Wilshire Small Cap 1750 minus Wilshire Large Cap 750 monthly return.

(III) Bond-oriented Risk Factors: **(6)** Bond Market Factor, proxied by the month end-to-month end change in the 10-year treasury constant maturity yield (C10YR), **(7)** Credit Spread Factor (CS), proxied by the month end-to-month end change in the Moody's Baa yield less 10-year treasury constant maturity yield.

(IV) Emerging Market Risk Factor: **(8)** the IFC (or MSCI) Emerging Market Index (EMG).

[1] On the other hand, covariance between portfolio and benchmark innovations, $\sigma_{\varepsilon u}$, is given by the combination of $\sigma_{\eta u}$ and $\sigma_{\varepsilon\eta}$, since the portfolio surprises $\varepsilon_{p,t}$ are linked to unexpected benchmark return via the relation implied in the leverage effect. To make easier the point, consider the case in which η is a linear function in benchmark innovations of the form $\eta = au + e_\eta$, where e_η is the idiosyncratic Gaussian beta stochastic component, and *a* the parameter that measures the linear relation with benchmark surprises. Consider also a process for $\varepsilon_{p,t}$ in the form of $\varepsilon = c\eta + e_\varepsilon$ where e_ε is the idiosyncratic Gaussian beta stochastic component, and *c* the parameter that measures the linear relation with beta surprises. And since $\eta = au + e_\eta$, then $\varepsilon = c(au + e_\eta) + e_\varepsilon$ or, taking the expectation, $E(\varepsilon) = c(au)$ (e_η and e_ε are Gaussian), which clearly proves that the covariance between portfolio and benchmark innovations will reflect the multiplication effect of *c* and *a* parameters. In other terms, the sign of the covariance between portfolio and benchmark innovations will be given by $sign(\sigma_{\varepsilon u}) = sign(c) \cdot sign(a)$.

Factors from (1) to (7) are the original Asset Based Style Factors (ABSF) advocated in Fung and Hsieh (2004), so called because all factors are based on traded securities and their derivatives, while the eighth factor was recently proposed since the authors plausibly suppose that:

> "*When younger emerging equity markets mature and begin to figure more prominently in the opportunity set of hedge fund managers, it may be important to see if a new P(rimitive)T(rading)S(trategy) in some form of an emerging market stock index is needed*"[2].

These eight factors are used to represent hedge fund strategies in an econometric field by running the following regression:

(5)
$$R_{i,t} = A_i + \sum_{k=1}^{8} B_{i,k} F_{k,t} + E_{i,t}$$

where $R_{i,t}$ is the return of the hedge fund *i* for time *t*, A_i is the abnormal performance of hedge fund *i*, $B_{i,k}$ is the factor loading of hedge fund *i* on factor *k*, $F_{k,t}$ is the return of factor *k* for month *t*, and $E_{i,t}$ is the error term.

In this manner, the strategies are considered and inferred as to be fund-specific, since the long-run style benchmark for each fund is its own projection onto the risk factors through the beta sensitivities. The expectation of (5) is then the style benchmark for fund *i* assumed to be linear in the *k* risk factors and that represents the long-run investment philosophy which can be modified in the short-run along the reasoning made in section III. At this point, to make equation (5) coherent with (1) we simply put

(6)
$$R_{b,i,t} = E(R_{i,t})$$

where $R_{b,i,t}$ denotes the benchmark return for fund *i* at time *t*, and $E(.)$ the expectation operator. To express the benchmark return net of the risk free-rate, we finally refer to the following equation

(7)
$$r_{b,i,t} = R_{b,i,t} - r_{f,t}$$

in which $r_{f,t}$ is the risk-free rate at time *t*.

In a sense, what we obtain through the (7) is a univariate version of the multifactor model of Fung and Hsieh (2004) (F-H). Contextualized within our three-equation system, this simplification appears particularly useful, since the time-varying beta could explain how and when the style of a fund moves away from its own "mean reverting" investment philosophy. On this point, consider also that since the style benchmark is the 7+1 F-H risk factor model, then the long-run beta is stationary fixed at the unity.

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[2] Fung and Hsieh (2007a).

IV.2. Instruments as Primitive Risk Factors

As discussed in section II, in order to inspect the dynamic strategy-driven returns of hedge funds (the "how it modifies his trade" factor), risk factor sensitivities are assumed to be time varying and dependent on some partly observable primitive risk signals (PRS); these act as "impulse variables" that managers use in changing their primitive trading strategies. The point is which variables we have to use in proxying such PRSs. Note that in our view the difference between the 7+1 risk factors used in constructing the ABSFs, and the PRSs is definitely subtle. Indeed, if PRSs may possibly be conceived as *other* systematic risk factors, to be used as additional[3] linear explanatory factors of hedge fund returns, this is not at all our view, since we link the PRSs directly to the systematic risk factor sensitivities. In doing so, PRSs enter into the systematic risk factors through the beta process, then controlling also for nonlinearity in hedge fund returns induced by the dynamic asset allocation[4].

In thinking about the PRSs we would envisage those latent factors that almost surely could affect the hedge fund returns, but for which the inner mechanism of such relationship is partly obscured by the complex nature of the dynamic trading rules followed by the managers. This explains why we introduced our complex and nonlinear three-equation system.

Starting from this reasoning we scrutinized all possible variables able to play the role of PRS, referring to empirical findings as well as theoretical explanations advanced in recent papers involved in the issue of the risks in hedge funds. In particular, we chose the following variables:

a) the CBOE Volatility Index (VIX): the index is the weighted average of the implied volatilities of eight OEX calls and puts, with time to maturity of 30 days on average, and provides investors with up-to-the-minute market estimates of expected volatility of the U.S. market. The variable has proven to be a significant factor for hedge fund returns (Amenc, Curtis and Martellini (2003); Billio, Getmansky, and Pellizzon (2008); Chen and Liang (2007); Schneeweis and Spurgin (1999)), and this is because fund managers act as volatility buyers or sellers, depending on the expectation they formulate on future U.S. market returns, in order to control for its impact on portfolio returns;

b) the month end-to-month end change in the change in 3-month T-bill (TBILL): Fama (1981) and Fama and Schwert (1977) show that the variable is negatively correlated with future stock market returns, and as such it is a proxy for expectations of future economic activity. More closely on hedge fund dynamics, TBILL is an important factor also because it reflects tensions in the short-term market liquidity segment, and due to high leveraged exposure of hedge fund portfolios, the sensitivity towards such a variable could be relevant[5];

c) the term spread (TERM), computed as monthly difference between the yield on 10-year Treasuries and 3-month Treasuries: Fama and French (1989) proved that this factor predicts bond and stock returns, mentioning that, if anything, the common variation captured by the term spread is stronger for stocks than for bonds. Hence, it makes sense that hedge funds

[3] In the sense of additional with respect to the 7+1 F-H risk factors.

[4] This is clear by observing equations (1) and (2) together. More precisely, instruments enter into the beta process (equation (2)) through $\Gamma'\mathbf{z}_t$, which in turn reflect into the portfolio return process (equation (1)) as a multiplicative interaction between $\beta_{p,t}$ and $r_{b,t}$.

[5] As discussed in Kambhu, Shuermann and Stiroh (2007), when there are no tensions on market liquidity, traders are able to finance positions, trade in higher volume and smooth price shocks, making the markets more liquid. But in market liquidity turmoil, the market volatility tends to increase, which in turns reflects on variation margin and collateral calls that reduce market liquidity.

change their systematic risk exposures conditional on the term spread. The variable is also useful because it is linked to new financing scheme followed by hedge funds. Indeed, since managers have been recently engaged in "sell-short and buy-long" bond trading rules, through which the fund sell short-term debt to buy higher-yielding, longer-term securities[6], the sensitivity towards the term spread can also reflect such a novel lending practice;

d) the innovations in the S&P'500 monthly standard deviation (INN). This is a new instrument we propose to measure liquidity shocks in the U.S. equity market. The rationale of this variable comes from Brunnermeier and Pedersen (2008), who provide a model that relates the asset market liquidity to the traders funding liquidity. Among the implications of their model, they point that market liquidity declines as fundamental volatility increases[7] and they suppose that fundamental volatility has an autoregressive conditional heteroschedasticity (ARCH) structure. Inspired by this intuition, we propose to base similar arguments on the surprises of volatility process. In other term, we conjecture a different view from Brunnermeier and Pedersen (2008), in which the market volatility follows a mean-reverting process with constant unconditional mean reverting fundamental volatility that evolve according to:

$$v_t - v_{t-1} = c_v\left(v_{t-1} - v_f\right) + s_t \tag{8}$$

where v_t and v_{t-1} are the market volatility at time t and $t-1$, respectively; c_v is the persistence volatility parameter that shrinks the volatility process towards the long-run fundamental volatility v_f, assumed to be constant; s is the volatility surprise at time t assumed to be Gaussian. The logic is that liquidity shocks leads to price volatility which in turns reflects on high margin calls causing possible destabilizing liquidity spirals. Anecdotal evidence can be traced in the October '87 Black Monday, in the first Iraq/U.S. war, in the LTCM debacle, and in the recent sub-prime crisis of end-2007, which all experienced margin increases in S&P 500 futures. In the context of our model, a shock in liquidity can force hedge funds to liquidate portfolio positions in order to meet the new margin requirements, then reflecting in possible dramatic variation in systematic risk exposure. To put this reasoning into perspective, we run equation (8) using annualized monthly standard deviation of the daily S&P 500 index returns over the period 12/1993-12/2006. The results are as follows[8]

[6] When used to financing credit derivative instrument issues, this scheme appears as one of the primary reason underlying the recent hedge fund debacle triggered by the sub-prime crisis. As quoted in the BusinessWeek, December 19, 2007, discussing the Bear Stearn collapse occurred in June 2007, "… *his team developed a novel investment product to attract money-market funds – a new class of investor – to the mortgage market. Their innovation, a particularly aggressive form of collateralized debt obligation, or CDO, became the building blocks of the industry's push to keep growing for longer than it otherwise would have. …(The CDOs) initially branded "Klio Funding," were entities that sold commercial paper and other short-term debt to buy higher-yielding, longer-term securities … Since the Klios offered a refund policy, money-market managers didn't have to worry about whether home buyers would pay back their loans. Their investments were protected even if the owners eventually defaulted on their mortgages*". And as well described in the article, this was a pyramidal self-financing scheme, since the money from each deal was used to get billions in mortgage-backed securities and pieces of other CDOs for the Klios, purchasing many of the assets directly from the other Bear Stearn hedge funds. As a result, a new way for the industry to finance risky sub-prime loans was created, in which the financial engineering encouraged "*lax lending practices by putting too much distance between the borrowers and the ultimate holders of their debt*".

[7] The authors note on this point that this is consistent with the empirical findings of Benston and Hagerman (1974), and Amihud and Mendelson (1989).

[8] The t-value are in parenthesis and denoted in bold font.

$$v_t - v_{t-1} = -0.3024(v_{t-1} - 15.4506) + s_t$$
$$(-\mathbf{5.2391}) \qquad (\mathbf{10.9289})$$

Adjusted R^2	**0.145**
F - statistic	**27.4477**

in which the error term s_t was used as proxy for liquidity shocks.

Finally, in order to derive scale-independent coefficient estimates for PRS sensitivities we standardized each of the four instruments. Consider, also, that using the deviation from the unconditional mean for each PRS is economically meaningful as well, since the signal coming from each PRS is indeed the departure from the unconditional long-term mean.

V. Methodology

V.1. System Estimation

The econometric methodology used in this paper is that introduced in Amisano and Savona (2008) through which the three-equation system are estimated using a Bayesian approach within a state space technology. The reason why we adopted such an approach is because in our problem we observe the hedge fund returns trying to derive a functional relationship among state variables, structural parameters and market prices of risk, being uncertain about the true parameter of the model. This suggests to tackle the inference problem inversely with respect to the classical estimation technique. Indeed, traditional approaches would entail to judiciously choosing parameter values in order to describe the return distribution, which is conditioned over parameters and factors. In a world of certainty about the value of parameters and factors this should be the case, but definitely not for our world, in which we impose uncertainty over parameters and factors. Hence, a suitable approach would be to invert the inference problem, treating the parameters as random variables and, then, extracting information about latent state variables, structural parameters and market prices of risk from observed returns. Formally speaking, this is the Bayesian approach, in which one starts by having some initial ideas about the unknowns (priors), to be represented by a probability distribution over all the possible values. Next, data are collected to improve this understanding (likelihood) and obtain the parameter estimates by combining beliefs with data (posterior). Hence, the Bayesian approach, first, specifies a joint prior distribution; second, identifies the likelihood function; third, computes the joint posterior distribution of the parameters and the data.

Mathematically, let us denote by $\boldsymbol{\theta} = [\boldsymbol{\Sigma}, \alpha, \phi, \mu, \Gamma, \Lambda]$ the parameters of the system, where $\boldsymbol{\Sigma}$ is the covariance matrix of the system innovations in (4), by $p(\boldsymbol{\beta}_{p,T}, \boldsymbol{\theta})$ the prior distribution, in which the values for $\beta_{p,t}$ are modelled as in equation (2), then, the likelihood function $\mathcal{L}$ can be expressed as

$$\mathcal{L} = p(\boldsymbol{r}_{pT}, \boldsymbol{r}_{bT} | \boldsymbol{\theta}) \equiv \int p(\boldsymbol{r}_{pT}, \boldsymbol{r}_{bT} | \boldsymbol{\theta}, \boldsymbol{\beta}_{p,T}) p(\boldsymbol{\beta}_{p,T} | \boldsymbol{\theta}) d\boldsymbol{\beta}_{p,T} \tag{9}$$

where $\boldsymbol{r}_{pT}$, $\boldsymbol{r}_{bT}$ and $\boldsymbol{\beta}_{p,T}$ are the vectors for hedge fund returns, benchmark returns and beta realizations, respectively, measured over the entire time period of length T. The values for beta are obtained as filtered expected values of the time varying coefficients, i.e. the output of the Kalman filtering recursion after processing sample information up to time t[9]. Also the choice for the Kalman filter is not without a justification. Indeed, we found it coherent with our reasoning, since it allows the time varying estimation of the beta in a way that accommodates with the skeptical view we have about the hedge fund returns behaviour. Indeed, as stated in Kim and Nelson (1999), quoting Harrison and Stevens (1976), one nice thing of Kalman filter is that it considers the uncertainty about the future as connected, first, to future random terms and also to uncertainty about current parameter values and, second, to the model's ability to link the present to the future.

V.2. Priors

As discussed in the previous section, through the Bayesian approach we essentially mix priors with data in order to improve the understanding process. This is, say, a neat philosophical choice in inspecting how hedge fund returns behave over time. We indeed move from a skeptical view about "what the data can tell us", while supposing that other extra-sample information could give useful insights. To do this, a Bayesian observer starts from an idea about how the hedge fund managers behave, then, he modifies that idea depending on what the numbers say. In this data processing apparatus, the problem is how much weight we should put on, first, priors and, second, data. In other term, is it more convenient to give more weight on prior beliefs or on observed sample data?

To answer this question, we observed the data making prior estimates of the system using the OLS technology, then deriving the posterior by modulating the shrinkage towards the priors according to the model reliability, as measured by, (1) the variability of each parameter, and (2) the R-squared of the benchmark regression, both measured in the pre-sample. In this way, we modulated the dogmatic-skeptical range with which the priors are transformed into posterior belief.

In this procedure, the prior estimation for the beta process was complicated by the fact that in the pre-sample we did not observed its time-varying evolution. Then, we started assuming a linear relationship between beta and PRSs in the form of $\beta_{p,t}(z_t) = b_{0p} + B'_p z_t$, where b_{0p} is the average (or mean reverting equivalent) beta parameter and B'_p is the vector with dimension equal to that of the vector of PRSs denoted by z_t and whose elements measure the response of the conditional beta to the PRS variations. And since we imposed a process for hedge fund excess returns in the form of equation (1), then, $r_{p,t} = \alpha_p + (b_{0p} + B'_p z_t) r_{b,t} + \varepsilon_{p,t}$. This simple algebra gave us the way to get the priors. Indeed, after the time-varying beta $\beta_{p,t}(z_t) = b_{0p} + B'_p z_t$ was estimated, we run the following OLS equation:

(10) $$\beta_{p,t}(z_t) = m + f(\beta_{p,t-1}(z_t) - m) + \Gamma' \boldsymbol{z}_t + e_{p,t}$$

where m, f and Γ' are the priors for the mean reverting beta term, the persistent parameter, and the vector of sensitivities towards the PRSs, respectively.

[9] Our model is a state space system in which equations (1) and (2) are, respectively, the measurement and the transition (or state) equations, and where equation (3) characterises the benchmark evolution based upon PRSs. It is just this equation that complicates the system. Indeed, two critical points arise in our model. The first is connected to the fact that the benchmark return is endogenously specified (by equation (3)) and enters into the measurement equation, while the second refers to the model parameters, which interact in a non-linear way. In order to handle these complexities, our Bayesian approach is developed according to the procedure detailed in Amisano and Savona (2008), in which posterior distribution is simulated using a Markov Chain Monte Carlo (MCMC)-based technique, namely, the Gibbs sampling-data augmentation procedure.

Finally, to modulate the dogmatic-skeptical range with which the priors were transformed into posterior belief, we used the estimated parameter covariance matrix of (10) as proxies for the parameter variances together with the R-squared of the benchmark equation. In particular, the benchmark's R-squared was used as shrinkage factor for Γ', namely the higher the explanatory power, the higher the weight. The economic reason underlying this technicality is linked to the assumption we made about the way with which we suppose the managers change their systematic risk exposure over time. Indeed, we assume that managers modulate the systematic risk of their portfolios in part by observing how the benchmark returns are related to the PRSs and in part on the basis of their own private and stochastically inaccessible signals[10]. In doing this, managers could be more confident in following PRSs or private signals based upon their own investment philosophy, and in this regard, they have a measure of the potential benefit, which is linked to the R-squared of the benchmark equation, when using PRSs, and to the covariances among the shocks of portfolio returns, the beta variations and the benchmark returns, when using private information.

VI. Data

For the empirical analysis in this paper, we used the hedge fund index monthly returns from CSFB/Tremont over the period 01/1994-12/2007. These are asset-weighted indexes of funds with a minimum of $10 million of AUM, a minimum one-year track record, and current audited financial statements. An aggregate index is computed from this universe, and ten sub-indexes based on investment style are also computed using a similar method. Indexes are computed and rebalanced on a monthly frequency, and the universe of funds is redefined on a quarterly basis.

The time period was split into three intervals, the first from January 1994 to December 1997, the second from January 1998 to December 2006, and the third from January to December 2007. We used the first sub-sample as "pre-sample" for priors estimation, the second sub-sample as "estimation sample" to estimate our system, and the third as "validation sample" in out-of-sample analysis. Univariate descriptive statistics for the indices (annualized Mean, Min, Max, annualized Standard Deviation, Skewness, excess Kurtosis and first-order autocorrelation) and for each of the three sub-sample, are reported in Table 1.

The data shows considerable heterogeneity in the historical risk and return characteristics of the various categories of hedge fund investment styles, also denoting a considerable time variation over the time-periods inspected. This is particularly evident by observing the Min-Max values computed across styles for each statistics. In the period 01/1994-12/1997 we note, for example, that the annualized mean returns varied from 0.0128, for Dedicated Short Bias, to 0.1993, for Global Macro, and the annualized volatility ranged from 0.0296, for Fixed Income Arbitrage, to 0.1861, for Emerging Markets. Again, in the period 01/1998-12/2006, the annualized mean returns ranged from –0.0203, for Dedicated Short Bias, to 0.1182, for Long/Short Equity, and the volatility from 0.0229, for Equity Market Neutral, to 0.1804, for Dedicated Short Bias. In the 2007 we finally observe variations in the mean and the standard deviation from 0.0381 (Fixed Income Arbitrage) to 0.1886 (Emerging Markets), for the first, and from 0.0193 (Equity Market Neutral) to 0.1485 (Dedicated Short Bias), for the second.

[10] This explains why the PRSs enter both into the beta and the benchmark equations.

Table 1: Descriptive Statistics of CSFB/Tremont indexes

	Mean	Min	Max	StdDev	Skew	Kurtosis	$\rho_{t,t-1}$
Pre-sample: from 1994/01 to 1997/12							
Hedge Fund Index	0.1507	-0.0413	0.0699	0.0918	0.0056	0.0014	0.0061
Convertible Arbitrage	0.0933	-0.0252	0.0231	0.0389	-1.1317	0.8062	0.7340
Dedicated Short Bias	0.0128	-0.0691	0.0983	0.1443	0.2293	-0.3483	0.0766
Emerging Markets	0.1334	-0.0998	0.1642	0.1861	0.1990	0.3270	0.3628
Equity Market Neutral	0.0952	-0.0115	0.0326	0.0393	0.3060	-0.3590	0.2686
Event Driven	0.1431	-0.0129	0.0368	0.0429	-0.0254	-0.6124	0.2652
Distressed	0.1664	-0.0240	0.0410	0.0576	-0.2833	-0.7168	0.2867
Multi-Strategy	0.1315	-0.0126	0.0393	0.0456	0.1382	-0.6121	0.1575
Risk Arbitrage	0.0976	-0.0167	0.0239	0.0298	-0.4321	0.2663	0.0323
Fixed Income Arb	0.0903	-0.0200	0.0202	0.0296	-1.6182	2.9935	0.3966
Global Macro	0.1993	-0.0707	0.1060	0.1422	0.1755	0.1585	-0.1245
Long/Short Equity	0.1229	-0.0390	0.0703	0.0845	0.0916	-0.0191	0.2501
Managed Futures	0.0525	-0.0935	0.0946	0.1161	-0.3717	1.5541	-0.0639
Multi-Strategy	0.0958	-0.0347	0.0361	0.0545	-0.9099	0.8950	-0.1356
Min	**0.0128**	**-0.0998**	**0.0202**	**0.0296**	**-1.6182**	**-0.7168**	**-0.1356**
Max	**0.1993**	**-0.0115**	**0.1642**	**0.1861**	**0.3060**	**2.9935**	**0.7340**
Mean	**0.1132**	**-0.0408**	**0.0612**	**0.0788**	**-0.2591**	**0.3096**	**0.1795**
StdDev	**0.0472**	**0.0303**	**0.0418**	**0.0502**	**0.5842**	**1.0078**	**0.2376**
Estimation Sample: from 1998/01 to 2006/12							
Hedge Fund Index	0.0877	-0.0755	0.0853	0.0685	-0.0003	5.1926	0.2035
Convertible Arbitrage	0.0855	-0.0468	0.0357	0.0493	-1.3969	3.5839	0.5229
Dedicated Short Bias	-0.0203	-0.0869	0.2271	0.1804	0.9914	2.4994	0.1276
Emerging Markets	0.0877	-0.2303	0.1534	0.1477	-1.5172	9.1919	0.2635
Equity Market Neutral	0.0967	-0.0085	0.0248	0.0229	0.3391	-0.2634	0.3427
Event Driven	0.1001	-0.1177	0.0327	0.0599	-3.8793	25.8667	0.3364
Distressed	0.1141	-0.1245	0.0391	0.0644	-3.8008	25.0761	0.2838
Multi-Strategy	0.0930	-0.1152	0.0466	0.0647	-2.8561	17.3872	0.3581
Risk Arbitrage	0.0660	-0.0615	0.0381	0.0453	-1.1464	6.1482	0.3012
Fixed Income Arb	0.0515	-0.0696	0.0205	0.0389	-3.3434	18.1310	0.3774
Global Macro	0.1040	-0.1155	0.1016	0.0874	-0.7128	7.2210	0.2611
Long/Short Equity	0.1182	-0.1143	0.1301	0.1071	0.2358	4.4874	0.1432
Managed Futures	0.0779	-0.0862	0.0995	0.1199	0.1829	0.0133	0.0957
Multi-Strategy	0.0905	-0.0476	0.0276	0.0367	-1.4548	6.1312	0.1894
Min	**-0.0203**	**-0.2303**	**0.0205**	**0.0229**	**-3.8793**	**-0.2634**	**0.0957**
Max	**0.1182**	**-0.0085**	**0.2271**	**0.1804**	**0.9914**	**25.8667**	**0.5229**
Mean	**0.0823**	**-0.0929**	**0.0759**	**0.0781**	**-1.3113**	**9.3333**	**0.2719**
StdDev	**0.0343**	**0.0520**	**0.0609**	**0.0456**	**1.6204**	**8.7164**	**0.1150**
Validation Sample: from 2007/01 to 2007/12							
Hedge Fund Index	0.1202	-0.0153	0.0316	0.0503	-0.3507	-0.4773	-0.0141
Convertible Arbitrage	0.0515	-0.0148	0.0218	0.0421	-0.2608	-1.0961	0.1281
Dedicated Short Bias	0.0684	-0.0494	0.1031	0.1485	1.3121	1.5884	-0.0210
Emerging Markets	0.1886	-0.0237	0.0548	0.0788	-0.1020	0.2256	-0.2764
Equity Market Neutral	0.0890	-0.0039	0.0165	0.0193	-0.1028	0.5334	0.0537
Event Driven	0.1261	-0.0188	0.0324	0.0540	-0.7932	0.3769	-0.0887
Distressed	0.0813	-0.0173	0.0208	0.0421	-1.0513	0.0203	0.2621
Multi-Strategy	0.1585	-0.0203	0.0431	0.0663	-0.4482	0.2148	-0.2313
Risk Arbitrage	0.0853	-0.0080	0.0322	0.0445	0.6554	-0.5243	0.0543
Fixed Income Arb	0.0381	-0.0196	0.0185	0.0356	-0.8307	1.0355	0.2317
Global Macro	0.1621	-0.0062	0.0410	0.0429	0.6665	1.4249	-0.1730
Long/Short Equity	0.1304	-0.0171	0.0373	0.0622	-0.1020	-1.0669	0.0836
Managed Futures	0.0668	-0.0479	0.0513	0.1348	-0.2742	-1.6753	0.1527
Multi-Strategy	0.0975	-0.0140	0.0302	0.0479	-0.1951	-0.9172	0.0911
Min	**0.0381**	**-0.0494**	**0.0165**	**0.0193**	**-1.0513**	**-1.6753**	**-0.2764**
Max	**0.1886**	**-0.0039**	**0.1031**	**0.1485**	**1.3121**	**1.5884**	**0.2621**
Mean	**0.1046**	**-0.0197**	**0.0382**	**0.0621**	**-0.1341**	**-0.0241**	**0.0181**
StdDev	**0.0446**	**0.0134**	**0.0220**	**0.0367**	**0.6388**	**0.9857**	**0.1634**

Interesting findings arises also inspecting higher moments, since we note that as a whole the industry strengthened the negative skewness combined with excess kurtosis from the first to the second time period, with the notably exception for Equity Market Neutral, which exhibited a positive skewness with negative excess kurtosis for both the sub-periods. However, in 2007 the things changed, since as a whole negative skewness was linked to negative excess kurtosis. Also in this case we had the notable exception of one style, which exhibited positive skewness with negative excess kurtosis, namely the Event Driven-Risk Arbitrage. Finally, the positive autocorrelation seems to be prevalent for most of the hedge fund styles for the first and particularly for the second sub-period, while in 2007 on average we obtained a not significant different from zero value.

Hence, the picture arising from Table 1 shows high across and over time variation in hedge fund risk/return profiles, in which higher moments and autocorrelations suggest to take into account departure from normality. Negative skewness with excess kurtosis could indeed indicate a significant tail (or extreme event) risk, as well as positive autocorrelation could blind the true volatility of the funds then reflecting in possibly biased risk-adjusted performance metrics, as it is the case for the Sharpe ratio (Lo (2002)).

VII. Beta anatomy of Hedge Fund Styles

For each CSFB/Tremont Index we run the three-equation system according to the prior elicitation discussed in Section V.2. We used the 7+1 F-H risk factor model prediction to proxy the long-term style benchmark, the 4 PRSs as instruments for beta and benchmark processes along the line discussed in section IV, and the 30 days Treasury Bill rate for the risk-free rate. The results are in Table 2.

Table 2: Beta Estimates

	Mean Reverting β		PRS sensitivities				β		
	Persistence	Long-Run β	VIX	TBILL	TERM	INN	Vol	Explained Variance:	
	ϕ	μ	$\gamma 1$	$\gamma 2$	$\gamma 3$	$\gamma 4$		E(β)	η
Hedge Fund Index	0.4021	1.033	0.0413	0.0701	-0.2429	-0.2185***	0.4500	47.01%	52.99%
Convertible Arbitrage	-0.0687	1.7696***	0.041	-0.2378**	-0.8161***	-0.0588	0.8380	69.53%	30.47%
Dedicated Short Bias	-0.2444	0.987***	-0.0985**	-0.1036**	0.1982***	-0.0255	0.2230	33.64%	66.36%
Emerging Markets	0.1904	1.1321***	-0.0496	0.1009***	-0.0105	0.0687	0.1606	28.30%	71.70%
Equity Market Neutral	0.0928	1.2896***	0.1191***	-0.0987**	-0.3736***	-0.1868***	0.4398	58.56%	41.44%
Event Driven	0.1344	0.7415***	-0.0399	-0.0569***	-0.2323***	-0.079**	0.3191	46.70%	53.30%
Distressed	0.6649***	0.3383***	0.0402	-0.0429	-0.028	-0.2531***	0.3037	1.26%	98.74%
Multi-Strategy	-0.0461	0.7652***	0.1198***	-0.0433	-0.4188***	-0.0359	0.4366	87.23%	12.77%
Risk Arbitrage	-0.2719	0.5702***	0.299***	-0.0103	-0.2697***	-0.0143	0.3287	78.79%	21.21%
Fixed Income Arb	0.8007***	0.2822***	0.0737	0.0325	-0.0595	-0.1468***	0.6453	60.70%	39.30%
Global Macro	-0.0712	2.4736***	0.0478	-0.1548	-0.8424***	-0.1801	0.7764	84.29%	15.71%
Long/Short Equity	0.6983	0.3029	0.0774***	0.0052	-0.0382	-0.2365***	0.3889	29.41%	70.59%
Managed Futures	-0.4601	1.3121***	0.5064***	-0.0139	0.2803***	-0.0029	0.4426	65.28%	34.72%
Multi-Strategy	-0.0677	1.5918***	0.2223***	0.017	-0.4426***	0.0305	0.5223	44.44%	55.56%
Mean	**0.1253**	**1.0421*** **	**0.1000** **	**-0.0383**	**-0.2355** **	**-0.0957*** **	**0.4859**	**52.51%**	**47.49%**
StdDev	**0.3861**	**0.6223**	**0.1560**	**0.0895**	**0.3305**	**0.1060**			
t-value	**1.2138**	**6.2656**	**2.3995**	**-1.6021**	**-2.6659**	**-3.3772**			

***, **, * denote significance at 0.01, 0.05, and 0.1 level, respectively.

On average, the data in Table 2 suggest that hedge funds appear as strongly based on their own style benchmark though they moves away from its own investment philosophy. The long-run beta is indeed very closed to the unity and the overall mean beta volatility (Vol) is 0.4859, indicating significant time variation of betas. Convertible Arbitrage seems to be the most dynamic, with a volatility of 0.8380, followed by Global Macro with a value of 0.7764; on the other hand, Emerging Market seems to be the most conservative, with a volatility of 0.1606. Based on these findings it make sense to conjecture that over the period 01/1994-12/2006 Convertible Arbitrage and Global Macro experienced significant changes in their investment styles.

Inspecting the mean reversion in beta, we observe that, first, Global Macro exhibits a statistically significant value of 2.4736 which suggest high long-run leverage in the systematic risk exposure; second, the aggregate Hedge Fund Index and Long/Short Equity do not reach statistical significance, maybe indicating time variability over the long run beta. As regards to the persistence parameter, Event Driven-Distressed and Fixed Income Arbitrages are the only indices exhibiting a significant positive value greater than 0.5, indicating a mean reversion in beta. Namely, they seem to be characterized by a long-run, partially constant, investment philosophy towards which reverting each time a move away from it occurred for whatever reason. And this is somewhat confirmed by observing the beta volatility of the two indices, in particular for Event Driven-Distressed (0.3037).

PRSs played a significant role as well. On average, the beta variation explained by mean reversion term and PRSs together, as measured by the R-squared against the mean reverting term and the PRSs, accounted for 52.51 per cent $\left(E(\beta)\right)$, ranging from 1.26 per cent for Event Driven-Distressed, for which inaccessible stochastic component (η) played a major role, to 87.23 per cent for Event Driven-Multi-strategy, proving that structural component in beta variations really matter.

Only the TBILL appears as not significant in the beta dynamics, although Convertible Arbitrage, Dedicated Short Bias, Equity Market Neutral, Event Driven, exhibited significant negative sensitivities, and Emerging Markets a positive one. For the first 4 indices the negative sensitivity could indicate a short-term financing scheme for their dominant asset classes. Such a view should imply that when TBILL rise, which in turn reflects in more high short-term interest rates, the funds tend to reduce their exposure due to high financing costs. For Emerging Markets, the positive sensitivity requires a deeper inspection of the exposure towards the 7+1 F-H risk factors. Unreported data on the model estimates[11] indicate that the index is significantly exposed towards C10YR ($B_{\text{C10YR}} = -2.2291$), CS ($B_{\text{CS}} = 5.1598$), and EMG ($B_{\text{EMG}} = 0.4569$), and the sensitivity towards CS is the reason we attribute to the positive TBILL coefficient. Indeed, since the index is significantly exposed to credit sensitive instruments, the higher the short-term interest rates, the higher the CS exposure, then reflecting in boosting the beta, and vice versa.

The term spread is the most important PRS, since it significantly impacts on beta variation for 9 out 14 indices. On average, the mean coefficient among all the hedge fund categories is –0.2355, significant at 0.05 level, indicating a possible “sell-short and buy-long” scheme for which the funds sell short and buy long-term bond as well as other asset class positions, both long and short. This is the case for all the 9 indices that exhibit significant sensitivity except for Dedicated Short Bias and Managed Futures, which sensitivity is indeed positive. For these indices we have a reversed “sell-short and buy-long” scheme for which the funds do finance their investments selling long-term bonds[12].

The VIX is a significant PRS for 7 indices, and except for Dedicated Short Biases the relationship with the beta variations is significantly positive, indicating that leverage in beta rises when expected volatility tends to increase, namely hedge funds seem to be net volatility buyers. This is particularly

[11] The results are available upon request.

[12] The meaning we attribute to the term spread is partially different from that used in understanding how the positive relationship between term premium and future equity and bond returns reflect on equity and bond allocations, but, as it is obvious, also such an implication play a key role as well.

true for Managed Futures, which exhibits the higher coefficient among the categories (the value is 0.5064) and also across the other PRSs of the index the VIX is in magnitude the more important instrument. The negative coefficient of Dedicated Short Biases indicates that the index is net volatility seller, signifying that the systematic risk exposure lowers in high volatility times. This suggests that Dedicated Short Biases may follow an hedging strategy to reduce the negative impact of volatility on portfolio returns.

Finally, liquidity shock measured by the INN instrument appeared significant for 6 hedge fund indices. For all these six cases, the coefficient is negative, indicating that when INN rises, then reflecting a shock in liquidity, the beta lowers as a result of reduced leverage of the funds. This signifies that in market liquidity turmoil, hedge funds find difficult to finance their positions and this probably because of raised margin and collateral calls. This seems to be particularly the case for Event Driven-Distressed and Long/Short Equity, since the coefficients are the higher with values of –0.2531 and –0.2365, respectively. Other indices that appear significantly exposed to shocks in liquidity are the aggregate Hedge Fund Index, the Equity Market Neutral, the Fixed Income Arbitrage, and Event Driven.

VIII. Performances

VIII.1. Conditional and Unconditional Alphas

In our framework, the alpha of equation (1) is a conditional Bayesian alpha, since the process for beta is pseudo-stochastic, based on PRSs, and estimated according to the Bayesian approach. A natural question is, then, how performance measurement changes using our approach with respect to the traditional, and frequentist, approach. To this end Table 3 reports the unconditional alphas obtained through the OLS 7+1 F-H risk factors model[13] and our conditional Bayesian alphas. As is clear, without taking into account conditional time variation in imperfect betas, hedge fund indices as a whole seem to deliver positive extra performance over their own style benchmark. The overall unconditional mean alpha is indeed significantly positive with a value of 4.08 per cent on a annual basis. Except for Emerging Markets, Event Driven-Risk Arbitrage and Long/Short Equity the unconditional alphas appear positive and significantly greater than conditional Bayesian measures. On average, we get a biased extra performance measure of 5.15 per cent over the unbiased conditional Bayesian alpha. Again, for Equity Market Neutral, Global Macro, and Multi-Strategy we have a “reversal in sign”, that clearly indicates the danger in valuing performance of hedge funds in an unconditional and constant beta setting. Differently from the unconditional alphas, the conditional performance measurement leads to conclude that the hedge fund industry as a whole did not delivered positive extra-returns over the period 01/1998-12/2006, the overall mean alpha is in fact not significantly different from zero. Only Event Driven, Event Driven-Multi-Strategy, Event Driven-Risk Arbitrage outperformed their own benchmark excess return. Global Macro was the worst performer, with significant negative alpha of –12.77 per cent, while Event Driven-Multi-Strategy appeared as the top performer, with a positive alpha of 3.72 per cent.

[13] Since the 7+1 F-H risk factor model is used here to measure the risk-adjusted performance of hedge funds, we run the equation (5) net of risk-free, namely

$$\begin{aligned} R_{i,t} - r_{f,t} &= A_i + B_{i,1}\left(\mathrm{SP}_t - r_{f,t}\right) + B_{i,2}\left(\mathrm{SIZE}_t\right) + B_{i,3}\left(\mathrm{C10YR}_t - r_{f,t}\right) + B_{i,4}\left(\mathrm{CS}_t\right) + \\ &+ B_{i,5}\left(\mathrm{BTF}_t - r_{f,t}\right) + B_{i,6}\left(\mathrm{CUTF}_t - r_{f,t}\right) + B_{i,7}\left(\mathrm{COTF}_t - r_{f,t}\right) + B_{i,8}\left(\mathrm{EMG}_t - r_{f,t}\right) + E_{i,t} \end{aligned}.$$

Standard errors were calculated using the Newey-West (1987) covariance estimator with 4 lags.

Table 3: Annualized Unconditional and Conditional Bayesian Alpha

	Unconditional Alpha (a)	Conditional Bayesian Alpha (b)	(a) *minus* (b)
Hedge Fund Index	0.0277	-0.0422**	0.0698
Convertible Arbitrage	0.0492	-0.0469***	0.0961
Dedicated Short Bias	0.0468	-0.0048	0.0516
Emerging Markets	-0.0147	-0.0063	-0.0084
Equity Market Neutral	0.0744***	-0.0294***	0.1038
Event Driven	0.0555**	0.0257***	0.0297
Distressed	0.0680***	0.0146	0.0534
Multi-Strategy	0.0494**	0.0372***	0.0122
Risk Arbitrage	0.0345**	0.0349***	-0.0004
Fixed Income Arb	0.0297*	0.0022	0.0275
Global Macro	0.0551*	-0.1277***	0.1828
Long/Short Equity	0.0315	0.0351	-0.0036
Managed Futures	0.0104	0.0030	0.0074
Multi-Strategy	0.0546***	-0.0446***	0.0991
Mean	**0.0408*** **	**-0.0107**	**0.0515*** **
DevStd	**0.0233**	**0.0450**	**0.0544**
t-value	**6.5450**	**-0.8859**	**3.5443**

***, **, * denote significance at 0.01, 0.05, and 0.1 level, respectively.

VIII.2. Performance of Beta-Driven Hedge Fund Clones

As argumented our time varying beta modelling represents a possible remedy to the problem of missing time varying risk exposure pointed out in Fung and Hsieh (2007b), since the benchmark portfolio is the hedge fund return projection onto the 7+1 F-H risk factors, using long-run constant expositions. The point is interesting not only for the understanding process of the risk dynamics of these financial vehicles, but also for the collateral issue involving the hedge fund cloning. Indeed, our model could be used to obtain “passive replication strategies” based on liquid underlying assets aiming to replicate hedge fund returns or their systematic risk.

The rationale of the searching in hedge fund clones is, by the way, an old story (Fung and Hsieh (2007b): as a strategy matures, industry competition erodes its idiosyncratic features leaving behind the systematic strategy core.

To explore the possibility offered by our model in this issue, we computed hedge fund clones using the expected beta times the style benchmark, which in turns is the 7+1 F-H risk factor model projection. This allows to control for time variation in systematic risk exposure, using the PRSs as the rule-based dynamic risk loadings to be used in modulating the 7+1 F-H risk factor exposure. Table 4 reports performance summary of hedge fund indices and corresponding clones over the estimation sample 01/1998-12/2006.

Firstly, note that correlation between hedge fund indices and corresponding clones is on average 0.6139, indicating a relatively good job in cloning risk/return characteristics of hedge funds. For certain categories the correlation is not particularly high, as for Multi-Strategy (0.3323), Global Macro (0.3505), and Convertible Arbitrage (0.3864), while for other the value is well above the 0.5.

Table 4: Performance Summary of Hedge Fund Indices versus Hedge Fund Clones

	$\rho_{(HF, Clone)}$	Mean$_{yr}$			StdDev$_{yr}$		
		HF (1)	Clone (2)	(2) *minus* (1)	HF	Clone	(2) *minus* (1)
Hedge Fund Index	0.7143	0.0727	0.1361	0.0634	0.0685	0.0713	0.0028
Convertible Arbitrage	0.3864	0.0705	0.1230	0.0526	0.0491	0.0366	-0.0124
Dedicated Short Bias	0.6818	-0.0354	-0.0838	-0.0484	0.1802	0.1230	-0.0572
Emerging Markets	0.8537	0.0727	0.1341	0.0615	0.1478	0.1623	0.0144
Equity Market Neutral	0.4311	0.0816	0.1076	0.0259	0.0224	0.0217	-0.0007
Event Driven	0.7068	0.0851	0.0829	-0.0022	0.0600	0.0360	-0.0240
Distressed	0.6378	0.0991	0.1023	0.0032	0.0645	0.0350	-0.0295
Multi-Strategy	0.7923	0.0779	0.0584	-0.0195	0.0647	0.0463	-0.0184
Risk Arbitrage	0.7182	0.0510	0.0264	-0.0246	0.0451	0.0259	-0.0192
Fixed Income Arb	0.6343	0.0364	0.0509	0.0145	0.0390	0.0268	-0.0122
Global Macro	0.3605	0.0889	0.2902	0.2013	0.0874	0.1228	0.0353
Long/Short Equity	0.7576	0.1031	0.0837	-0.0194	0.1070	0.0579	-0.0491
Managed Futures	0.5877	0.0628	0.1156	0.0528	0.1199	0.0984	-0.0215
Multi-Strategy	0.3323	0.0754	0.1150	0.0396	0.0366	0.0231	-0.0135
Mean	**0.6139**	**0.0673**	**0.0959**	**0.0286***	**0.0780**	**0.0634**	**-0.0147****
StdDev	**0.1697**			**0.0611**			**0.0236**
t-value				**1.7516**			**-2.3241**
		$\eta(12)$SR			Prob>0		
		HF	Clone	(2) *minus* (1)	HF	Clone	(2) *minus* (1)
Hedge Fund Index		0.9671	1.5300	0.5628	0.6759	0.7500	0.0741
Convertible Arbitrage		0.6740	2.2158	1.5418	0.7685	0.8981	0.1296
Dedicated Short Bias		-0.2661	-0.8976	-0.6315	0.4444	0.4352	-0.0093
Emerging Markets		0.3727	0.5835	0.2108	0.6389	0.6667	0.0278
Equity Market Neutral		1.8944	2.8590	0.9646	0.8796	0.9907	0.1111
Event Driven		1.0340	1.4800	0.4460	0.7870	0.7870	0.0000
Distressed		1.0104	2.4963	1.4860	0.7963	0.7963	0.0000
Multi-Strategy		0.9294	0.7825	-0.1469	0.7500	0.7685	0.0185
Risk Arbitrage		0.5817	0.4643	-0.1175	0.7315	0.8056	0.0741
Fixed Income Arb		1.2956	1.8929	0.5973	0.7500	0.8148	0.0648
Global Macro		0.6888	2.1511	1.4623	0.7315	0.8241	0.0926
Long/Short Equity		0.6860	1.2952	0.6092	0.6481	0.7222	0.0741
Managed Futures		0.4916	0.9597	0.4681	0.5278	0.5833	0.0556
Multi-Strategy		1.4192	5.2878	3.8686	0.8056	0.9352	0.1296
Mean		**0.8413**	**1.6500**	**0.8087****	**0.7097**	**0.7698**	**0.0602*****
StdDev				**1.0886**			**0.0470**
t-value				**2.7796**			**4.7874**

***, **, * denote significance at 0.01, 0.05, and 0.1 level, respectively.

On average, our Bayesian time varying hedge fund clones significantly outperformed the hedge funds. The annualized overall mean return of the clones is significantly greater than that of the hedge funds, while the annualized standard deviation was significantly lesser, then reflecting in a annualized autocorrelation adjusted Sharpe Ratio (Lo (2002)[14] equal to 1.6500, which doubles that of the hedge funds, equals to 0.8413. Based on the adjusted Sharpe Ratio results, Multi-Strategy

[14] To control for autocorrelation in compute the Sharpe ratio we followed Lo (2002). The author documents that the positive autocorrelation in hedge fund returns can overstate the Sharpe ratio. He then recommends using the autocorrelation adjusted Sharpe ratio using,

$$\eta(q)SR \quad \text{with} \quad \eta(q) = \frac{q}{\sqrt{q + 2\sum_{k=1}^{q-1}(q-k)\rho_k}}$$

where SR is the regular Sharpe ratio on a monthly basis, ρ_k is the k-th autocorrelation for hedge fund returns, and $\eta(q)SR$ is the annualized autocorrelation adjusted Sharpe ratio with $q = 12$. From the expression is ease to note that when returns are independently and identically distributed, the annualized Sharpe ratio is $\sqrt{12}SR$, which may overstate the true Sharpe ratio if the returns are positively autocorrelated as $\eta(q)$ is less than q.

clone appeared as the best performer with 5.2878 while Dedicated Short Bias was the worst performer with –0.8976.

Hence, by confirming recent evidence in hedge fund cloning literature (for e.g. Hasanhodzic and Lo (2007)), our empirical findings prove that hedge-fund returns can be both cloned and outperformed. Except for Event Driven and Dedicated Short Biases the clones are all successful, with performances that significantly exceed their hedge fund counterparts in a risk-adjusted basis. Moreover, since our cloning procedure is essentially based on a instrument-based beta variation rule, we also reduce complexity in replicating complex dynamic investment strategies of hedge fund. And this is done taking into account time variation in the systematic risk exposure and non-linearity in hedge fund returns.

IX. In-Sample Model Reliability and Out-Of-Sample Risk Prediction

After having explored the implications of our approach in terms of beta anatomy and cloning possibilities, it is now temping to, first, verify the in-sample model reliability of our Bayesian time-varying beta model (BB-Model) compared with the constant beta 7+1 F-H risk factor model (F-H-Model). In Table 5 we report the corresponding adjusted R-squared computed over the estimation sample.

Table 5: In-Sample Adjusted R-Squared

	Adj. R^2 F-H-Model (a)	Adj. R^2 BB-Model (b)	(b) *minus* (a)
Aggregate Hedge Fund Index	0.4766	0.5871	0.1105
Convertible Arbitrage	0.0677	0.1377	0.0700
Dedicated Short Bias	0.5145	0.5836	0.0690
Emerging Markets	0.7060	0.7733	0.0674
Equity Market Neutral	0.1260	0.3231	0.1971
Event Driven	0.5945	0.6934	0.0989
Distressed	0.4844	0.6844	0.2000
Multi-Strategy	0.5773	0.6174	0.0402
Risk Arbitrage	0.4453	0.4880	0.0426
Fixed Income Arbitrage	0.2214	0.5680	0.3466
Global Macro	0.1389	0.1179	-0.0210
Long/Short Equity	0.4934	0.7245	0.2311
Managed Futures	0.2673	0.3462	0.0789
Multi-Strategy	0.0940	0.1086	0.0146
Mean	**0.3719**	**0.4824**	**0.1104*** **
DevStd	**0.2122**	**0.2338**	**0.0993**
t-value			**4.1601**

***, **, * denote significance at 0.01, 0.05, and 0.1 level, respectively.

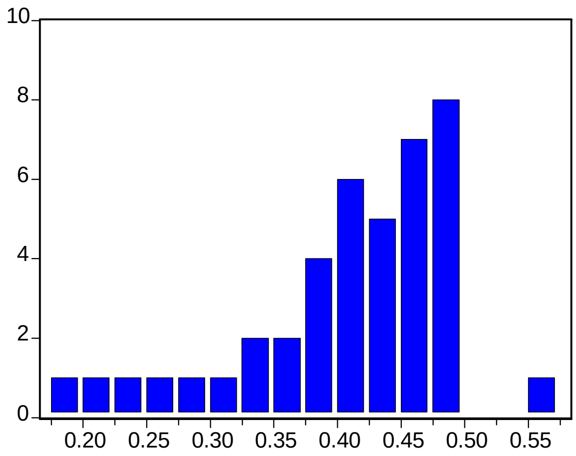
As is clear by the data, our model significantly outperforms the OLS alternative. On average, the BB-Model explains 0.1104 over the F-H-Model and only for Global Macro the adjusted R-squared worsen with our model. The larger gain is with Fixed Income Arbitrage and Long/Short Equity, for which the adjusted R-squared delivered by F-H-Model and BB-Model are 0.2214 versus 0.5680 and 0.4934 versus 0.7245, respectively. But also for Event Driven-Distressed, Equity Market Neutral and the aggregate index we get substantial improvement, proving that Bayesian time-varying beta model is better than simple 7+1 F-H risk factors model with constant beta. Hence, in-sample diagnostics provide justification to our beta modelling.

To complete the robustness check of our model we also analyzed the out-of-sample risk prediction in a Value At Risk setting. Our three-equation system is particularly useful in this regard, since only the PRSs are required to forecast benchmark returns, beta variation and portfolio returns. And since our system also imposes a structure on covariance innovations, a simulation-based VaR approach can be easily employed to predict, at certain confidence level, maximum losses hedge funds could experience in market turmoil scenarios. The key elements are indeed the system innovations.

Analytically, using parameter estimates computed over the period 01/1998-12/2006, we simulated the system errors over the period 01/2007-12/2007 using the Cholesky factorization in order to maintain the estimated correlation structure. And instead of, first, setting a confidence level and, second, computing the corresponding VaR, we proceeded using a reversal approach, i.e., starting from each return occurred over the out-of-sample period, we calculated the percentile of simulated system errors that exactly mach the expected with the actual return for each indices and for every month. In a sense, this approach is like to answering the question of how good our system is in predicting hedge fund losses over the confidence level mass while reducing tail event or, worse, unpredicted extreme events. In fact, percentiles confined within the 0.01-0.99 level indicate that the model is statistically robust in predicting potential maximum losses; and indeed, the narrower the difference between matching percentile and error expectation (0.5 percentile), the better the model in predicting the risk in hedge fund strategies. Consider, also, that since the validation sample contains the August 2007 sub-prime crisis, this exercise is particularly interesting as stress test.

Computationally, we generated 10,000 scenarios for the three-equation system errors, taking the corresponding covariance structure estimated in the period 01/1998-12/2006. Limiting the analysis of the matching percentile corresponding to the negative returns occurred over the validation period, in Figure 1 we report the entire distribution with corresponding descriptive statistics. As we can observe, the mean is 0.4119, which is very closed to the distribution expectation. Min and Max also confirm the out-of-sample robustness of the model in predicting unexpected losses, since the actual negative returns never exceed the VaRs at 0.1940 (Min) or 0.5523 (Max) level.

Figure 1: VaR implied Percentile Distribution



Percentiles of 41 pooled negative returns:	
Mean	0.4119
Median	0.4311
Max	0.5523
Min	0.1940
StdDev	0.0822
Skew	-0.9964
Kurt	3.4904

Interestingly, focusing on sub-prime induced impacts, we extracted from the overall 41 pooled negative returns those occurred in the July-September period. Descriptive statistics in Table 6 confirm again the robustness of our approach, since that the actual losses never exceed the 0.2115 and 0.5523 confidence levels.

Table 6: VaR implied Percentiles in July-September 2007

Number Of Negative Returns	July 2007	August 2007	September 2007
1	0.4660	0.4152	0.3153
2	0.4692	0.4840	
3	0.4541	0.5523	
4	0.4366	0.3810	
5	0.3465	0.4445	
6	0.2115	0.3888	
7	0.4954	0.4079	
8		0.3587	
9		0.2438	
10		0.4935	
Mean	**0.4113**	**0.4170**	**0.3153**
Max	**0.4954**	**0.5523**	**0.3153**
Min	**0.2115**	**0.2438**	**0.3153**

Overall, out-of-sample forecasting tests confirm the usefulness of our three-equation system in determining the downside risk, and more closely, extreme event risk in a VaR context. Such application could be functional in particular for hedge fund counterparts, such as brokers, banks and investors, for assessing the capital-at-risk for engaging in servicing, financing and investing hedge fund industry.

X. Conclusion

The recent important ramifications of global financial markets exploded in connection with August 2007 events have inspired the writing of this paper. As pointed out in Khandani and Lo (2007), a substantial implication of those events is that the notion of "hedge-fund beta" is now a reality. Putting in other terms, the risk propagation within hedge fund classes occurred with the sub-prime crisis is a clear message that common factors significantly impact on the dynamics of hedge fund returns. However, the technology underlying the hedge-fund beta anatomy is still in its infancy and largely unexplored, also in connection with the corresponding replication possibilities. In this work we tried to fill up this gap.

Our objective was to explore a new methodological alternative moving from a world of uncertainty, where we have only some ideas on the risks inherent in the hedge fund strategies to be mixed with empirical evidence possibly coming from the data. This is why we developed our approach within a Bayesian framework. And due to severe limitations relative to possible missing time varying risk exposure and missing factors, we proposed a time varying beta model based on some, say, primitive risk factors which directly impact on variation of systematic risk exposure. This new technology allows to, first, answering the question involving the "how the hedge funds modify their trade" and, second, detecting those factors which act as input variables the managers use in changing their trading strategies, then offering a real possibility in the hedge fund (beta) cloning.

Different interesting findings arise from the empirical analysis carried out on CSFB/Tremont indices over the period 01/1994-12/2007. First, we prove that volatility, changes in T-bill, term spread and shocks in liquidity significantly impact on time variation of hedge fund betas. Second, the time variation in betas is essential to understand how hedge fund returns behave over time and, consequently, to correctly measuring the performance on a risk-adjusted basis. On this point, our analysis demonstrates that unconditional alphas significantly overstate the real extra performance;

indeed, our results suggest that the hedge fund industry as a whole did not delivered positive extra-performance over the time period inspected. Fourth, collateral uses of our model offer interesting opportunities in hedge fund cloning and risk monitoring. On the one hand, by using the structural component in beta time variations we replicate the risk/return characteristics of the hedge funds quite well also delivering better performances in a risk-adjusted basis. On the other, simulation-based exercises on VaR predictions suggest that our technology could be a serious candidate in hedge fund risk monitoring systems.

However, severe limitations still remain on the understanding of the life cycles of the hedge funds. The evolving trends of the strategies lead to the emergence of new risk factors for which a more explicit link with the hedge fund portfolio dynamics needs to be established. In this study we introduced the idea of imperfect betas, through which we are able to partially observe how the risk factors impact on beta variation. However, we are convinced that much work on searching and modelling these primitive risk factors could help reduce the inaccessible component of the beta dynamics.

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