Hedge Fund Managers: Luck and Dynamic Assessment

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I. Introduction

Today, investing in mutual funds is expected to underperform passive investment strategies. As a result, many private and institutional investors have turned their attention to hedge funds: private investment partnerships that use advanced investment strategies, derivatives, leverage, and short-selling to aggressively manage a portfolio of international and domestic investments. Hedge fund managers pride themselves on their ability to produce what they refer to as " absolute alpha" or " absolute return." That is, returns not due to primary asset class performance. Their aim is not to track and beat a given stock or bond benchmark, but to focus on pure performance generation. Although we find that performance is due to management decisions based on the manager's skills, statistical analysis shows that many funds retain significant exposure to different types of market risk factors. Therefore, it is essential that investors determine if these strategies are sensitive to market changes and if they can generate "pure alpha" thanks to manager skills exclusively. This explains the growing attention on hedge fund performance and their factor exposures.

Owing to the theory of Capital Asset Pricing Model (CAPM) or Arbitrage Pricing Theory (APT), fund performances are mainly assessed using a parametric model with the hypothesis of linearity and constant coefficients. Fung and Hsieh (2001,2004a) uses methodologies to replicate trend-following strategies. Agarwal and Naik (2000) suggests using option-based returns approaches in order to capture non-linearities. And Bollen and Whaley (2009) employed two econometric techniques that focused on risk exposures. Their optimal change point methodology looks for a discrete number of dates in which factor loadings shift. However, this methodology only accepts one single shift in parameters for each fund. Patton and Ramadorai (2013) provided an extension of Bollen and Whaley (2009) study. Thus, in the literature, there are two approaches in order to take into account hedge fund managers' dynamic allocations. The first postulates that the relationship between hedge fund returns and market indices are non-linear. The second assumes that betas are not constant during the period studied.

In this paper, we follow the second approach. We introduce an econometric model for hedge fund returns that considers this specific point, allowing us to relax traditional parametric models. Moreover, to this we added a new model: the False Discovery Rate approach (FDR), developed by Barras *et al* (2010). Here the concept of "proportion of true alphas" is introduced and applied to mutual funds. A framework is developed, which precisely estimates the fraction of mutual funds that truly outperforms their benchmarks. Barras, *et al* find that only 0.2% of the population of mutual funds generate genuine positive " alpha" in recent years.

We extend this analysis to the world of hedge funds and look to determine the " proportion of true alpha" worldwide. We then apply this approach on the intercept and betas, which according to our model, are defined according to market exposures. Thus, we are able to consider alphas and betas in a different way. We examine the proportion of the fund population that shows a change in market exposures, as well as the proportion of skills, unskilled and zero-alpha funds. Our reason for using this approach focuses on validating three main assumptions.

First, if alpha refers to the performance of hedge fund managers, we should not see constant positive alphas across different time periods. For all funds, depending on the manager experience, we should witness some intervals of positive alpha that correspond to periods when hedge fund managers have enough experience to take solid positions and in this way, generate alpha. During periods where these same managers are not able to anticipate market events based on lack of experience, poor performance should result.

The second assumption focuses on the dynamics of market exposures. Intuitively, if a hedge fund manager changes his or her position dynamically, a change in betas that alters the hedge fund risk should result.

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Finally, there is the question of luck that Barras *et al* (2010) analyze in the context of mutual funds. What is the proportion of hedge fund managers that generate " alpha" based on their skills and not luck?

In our study, the proportion of " skilled" or " unskilled" funds is higher than with a static linear factor model. The ability of our model to capture the dynamic part of alpha that reflects a hedge fund manager forecasting skill can explain this difference. Nevertheless, the results are different depending on the strategy studied. Some strategies, like emerging market or event driven, obtain a percentage of true alphas that is more or less the same as those derived from our time-varying coefficient or static linear models. Other strategies, like equity long/short, CTA, or short bias reveal a significant difference. Essentially, the majority of hedge funds are zero-alpha funds as Barras *et al* (2010) argue for mutual funds.

In our research, we also find that some strategies obtain a better percentage of true alphas when the market is stressed versus when it is stable, and vice versa. This confirms our assumption about the performance of hedge fund managers. After having investigated the performance of hedge fund managers, we focus our analysis on risk behavior and look to understand if a strategy with a common increasing trend toward market exposure during a crisis is possible. We find that the credit spread and the bond risk factors necessitate careful examination, even though each strategy is marked by heterogeneous exposure behavior.

The merger of a time-varying coefficient model and the FDR approach represents a new methodology that provides another useful analysis of hedge fund selection. The use of a multiple hypothesis test analyzes the proportion of skilled funds conditional to the sample study. Given that portfolio managers often define and manage a peer group, this method is a closer reflection of reality as it determines the percentage of skilled funds conditional to a defined peer group.

The following paper is organized as follows: Section 2 reviews related literature about hedge fund modeling and the dynamics in beta. Section 3 reviews the data and summarizes the risk factors defined in Fung and Hsieh (2001, 2004). In Section 4, our methodology is outlined. Section 5 reports the results of our time-varying coefficient model, as well as the application of the FDR to alpha and beta, which offers a new tool for hedge fund analysis. Section 6 concludes.

II. Literature review

Following the work of Fung and Hsieh (1997), many articles were written on hedge fund trading strategies and characteristics, focused on regressing returns on a range of factors (see, for instance, Agarwal and Naik (2000), Mitchell and Pulvino (2001)). Agarwal and Naik (2000) extend this analysis by acknowledging that funds may follow dynamic, non-linear trading strategies. Using stepwise regression to identify independent variables, they conclude that a put or a call option is the most significant factor in determining performance for 54% of funds they analyze. However, Fung and Hsieh (2002) introduce option strategies into a Sharpe-style model and find that, in most cases, these strategies play only a marginal role. The authors argue that the reason is based on their use of active and advanced straddle strategies rather than plain vanilla options. Fung and Hsieh (2004) prove that their seven-factor model strongly explains variation in hedge fund returns while at the same time avoids multicollinearity. Moreover, their results are similar to those obtained with the Agarwal and Naik (2004) option-based factor model.

In addition to the seven factors included in their paper, Fung and Hsieh adds an eighth on their website.[1] These factors are:

- *Three Trend-Following Factors*: Bond, Currency and Commodity[2] which capture a non-linear exposure.
- *Two Equity-oriented Risk Factors*: S&P500 minus risk free rate[3] and Size Spread Factors defined by the Russell 2000 index monthly total return less S&P500 monthly total return.
- *Two Bond-oriented Risk Factors*: Bond Market Factor represented by the monthly change in the 10-year treasury constant maturity yield, and a Credit Spread Factor formed by the monthly change in the Moody's Baa yield less 10-year treasury constant maturity yield.
- *One Emerging Market Risk Factor*: The MSCI Emerging market minus the risk free rate.

Mitchell and Pulvino (2001) investigate merger-arbitrage strategies and produce useful and explicit links between hedge fund strategies and observable asset returns. In their work, they find that manager investment-styles change over time, which impacts hedge funds more than mutual funds, accounting for another important distinction between the two.

Brealey and Kaplanis (2001) present evidence that prove, within each category, hedge funds tend to make similar changes to their factor exposures. Similarly, Fung *et al* (2006) estimate factor exposures during times of crises. By studying vendor-provided fund-of-fund indices and performing a modified-CUSUM test, they identify structural break points in fund factor loadings. Results show that break points coincide with extreme market events.

Both Brealey and Kaplanis (2001) and Fung and Hsieh (2006) implement a normality hypothesis, rarely verified by hedge fund data. For strong evidence of non-normality, see Agarwal and Naik (2000a) and Fung and Hsieh (1999). Kat and Lu (2002), Brooks and Kat (2002) show that, although hedge funds offer high mean returns and low standard deviations, returns also exhibit third and fourth moment attributes, as well as positive first-order serial correlation. Their distributional characteristics differ depending on the type of hedge fund strategies implemented (Anson, 2006).

Most recently, Bollen and Whaley (2009), study two econometric techniques that consider changes in risk exposure. They find significant changes in the risk factor parameters of about 40% of their hedge fund sample. Patton and Ramadorai (2013) provide an extension to this analysis. Their model outperforms the change point regression approach and demonstrats that variations in leverage cost, the performances of carry trade, and commonly employed benchmarks are important drivers of hedge fund risk factors.

III. Database and Factors

For this study, we use both the Center for International Securities and Derivatives Markets (CISDM) and HedgeFund.net databases. CISDM's database covers January 2004 to July 2007 and includes dead funds. The full sample contains approximately 9800 funds (hedge funds, CTA, and funds-of-funds). HedgeFund.net is the largest commercial database of active hedge fund, fund-of-fund, and CTA products, with over 8500 (approximately 3000 funds-of-funds and 5500 hedge funds), covering May 1975 to October 2008. Together, the databases covered roughly 10,000 hedge funds and 1900 CTAs.

For every fund, the returns (net of management and performance-based fees), the strategy, and the fund type[4] are collected. Fung and Hsieh (1997) and Brown and Goetzmann (2003) identify between five and eight investment styles; Bianchi Drew, Veeraraghavan, and Whelan (2005) identify only three. Hedge fund database providers distinguish between eleven and thirty-one investment styles. In our study, we compare the thirty strategies used by HedgeFund.net with the twenty-three strategies used by the CISDM. We then apply the twenty-three strategies that are presented by both providers.

We can divide hedge funds into several groups with an associated major risk factor. The strategy used in every group can also have a specific exposure to other risk factors, meaning risk exposure can drastically change depending on the approach employed. Defining these factors is therefore a complex exercise. In our research, we use all eight risk factors as defined by Fung and Hsieh (2004) that we describe in the literature review section.[5]

IV. Methodology

IV.1. FALSE DISCOVERY RATE

In this section, we offer a brief review of the important elements of the Barras *et al* (2010) FDR approach and explain why we used this method in our research.

Barras *et al* (2010) suggests an approach[6] that provides valuable insights on the prevalence of outstanding managers in the whole fund population and not only for the best fund.

Consider the problem of testing simultaneously M (null) hypotheses, of which M_0 are true. R is the number of hypotheses rejected and is an observable random variable.

	Declared non-significant (NS)	Declared significant (S)	Total
True null hypotheses (T)	TNS	TS	M_0
Non-true null hypotheses (NT)	NTNS	NTS	$M - M_0$
	$m - R$	R	

TNS, TS, NTNS and NTS are unobservable random variables. The proportion of errors committed by falsely rejecting null hypotheses can be viewed through the random variable $Q = \dfrac{TS}{TS + NTS}$. Benjamini and Hochberg (1995) define the FDR Q_e to be the expectation of Q:

$$Q_e = E\left[Q\right]E\left[\frac{TS}{TS + NTS}\right] = E\left[\frac{TS}{R}\right].$$

It is this quantity that Barras *et al* (2010) exploit in order to determine the "true" proportion. Their approach simultaneously estimates the prevalence and location of multiple overperforming funds within a group, examining fund performance from a more general perspective.

We consider two hypothesis testing problems that use this methodology. The first is a multiple hypothesis testing problem that deals with the proportion of " true alpha". The second examines the proportion of changes in market exposure.

IV.2. FACTOR MODEL

This section outlines a model that considers time-varying exposure dynamics as well as hedge fund returns characteristics, including non-normality, limited history (ranging from a few months up to 150 months), and systematic risk captured by a high number of factors.

We recommend using a semi-parametric model that relies on the estimation procedure of Fan and Zhang (1999), which overcomes these obstacles. The first assumption in this model is that beta is a function of time approximated by a Taylor series. The use of a kernel, whose variable depends on time, relaxes the assumption of normality and hedge fund returns. It also allows the use of independent factors, whereas the size of the tracks is short. This can significantly reduce the modeling bias and avoid the " curse" of dimensionality.

The choice of bandwidth is critical in our study as several multiple hypothesis tests are used, covering a large number of funds. It is not possible to manually determine the optimal bandwidth for each fund. An estimation procedure that relegates the calculation of the optimal bandwidth to a position of secondary importance is needed. Fan and Zhang (1999) illustrates that determining the optimal bandwidth is easy within their two-step procedure.

Below we present the model and its assumptions, and explain how the bandwidth and confident interval are calculated.

The time-varying coefficient model (TVCM hereafter) assumes the following conditional linear structure:

$$Y_t = \sum_{j=1}^{p} \beta_j\left(t\right) X_{jt} + \varepsilon_t = \alpha\left(t\right) + X\beta\left(t\right) + \varepsilon_t,$$

for a given covariates $\left(t, X_1, \ldots, X_p\right)'$ and variable Y.

Different methods are suggested for conducting statistical inferences, such as the construction of confidence interval for $\beta_i\left(t\right)$ different methods have been suggested. We opte for the so-called nave bootstrap procedure presented by Colin and Chiang (2000)[7].

In kernel regression, it is well known that selecting bandwidths is more important than selecting kernel function. In practice, bandwidths may be selected by examining the plots of the fitted curves. In our study, however, an automatic bandwidth selection is necessary. One of the greatest advantages of the two-step estimator is its ability to remain largely insensitive to the choice of initial bandwidth. The authors suggest to use cross-validation or generalized cross-validation to determine the bandwidth $\hat{h}$ for the one-step fit. They then use $\hat{\hat{h}} = 0.5\hat{h}$ as the initial bandwidth. Moreover, Colin and Chiang (2000) suggest applying the " leave-one-subject-out" cross-validation bandwidth.

IV.3. APPLICATIONS

Having introduced the FDR approach and the time-varying coefficient model (TVCM), we turn to the applications. Here we focused on two areas: performance of hedge funds as related to alpha and risk exposures.

First, a multiple hypothesis test is built that determines, by strategy, the proportion of true alpha during all periods and during two crises (*i.e.* the long term capital management (LTCM) and the equity bubble crises, respectively). We are most concerned with (1) the security selection ability, and (2) the capacity to anticipate market events and/or manage them (*i.e.* forecast ability).

The estimates provided by our TVCM are not a single value over the period studied, but rather a full path. For the security selection ability, we examine the whole period and create a t-statistic for each fund by taking the mean of each track, as well as the standard deviation[8].

For the forecast ability, we examine two strong market events as noted above: the LTCM crisis and the equity bubble crisis. We choose three consecutive months to ensure we are effectively covering this time period, focusing on July-September 1998 for the LCTM crisis and February-April 2000 for the equity bubble event. Using this three-month data, we build two t-statistics by crisis based on the differences between the second and first month, and the third and second month. By doing so, we are able to determine how capable managers were at reacting quickly.

To analyze the dynamic allocation from hedge fund managers, we then focus on another multiple hypothesis testing problem that examines changes in market exposures. Since a slight variation does not necessarily represent a change in allocations, we build a t-statistic in the same way we have for the crisis period and test whether the change in exposure was superior to 10%[9]. These results allow us to examine the proportion of funds that shows changes in exposure. To understand which of these are the highest impacted betas, we calculate the median of the percentage change for each beta.

The methodology we employ has several advantages for the hedge fund analysis process. First, we are able to analyze the skill level of managers during a precise, short period of time. Second, the FDR approach calculates the percentage of skilled or unskilled funds conditional to the sample study. Third, since portfolio managers often define and manage a peer group, this method determines the percentage of skilled funds conditional to a defined peer group, thereby better reflecting reality. Finally, we do not need to compare our estimate with an index or a mean performance from a hedge population, nor give a specific value for alpha, but we do statistically test the percentage of true alpha conditional to our population.

Lastly, we consider the volatility of estimated alpha. While the majority of academic literature that analyzes whether hedge funds generate alpha only considers estimated alpha, in financial products analysis it is commonplace to examine performance and risk factors (for example, volatility). Why would manager performance be different?

Within our methodology, we thus use the ratio-estimated alpha and the standard deviation of estimated alpha, which is most applicable for assessing manager performance. We then compare the results using two different regression techniques: first, our TVCM and second, a static linear factor model with the Newey-West (1987) heteroscedasticity and autocorrelation consistent estimator. We regress the net-of-fee monthly excess return (in excess of the risk-free rate) of a hedge fund on the excess returns earned by traditional buy-and-hold and primitive trend-following strategies as defined above[10].

V. Empirical Results

Mutual fund managers generally use a buy-and-hold strategy, which means they purchase a range of financial products as per their investment strategy and then hold them according to the time horizon (or investment horizon)[11]. Mutual funds are therefore often assimilated to funds with relative performance. Barras *et al* (2010) illustrate that only 0.2% of mutual funds generate positive alpha, and the majority of funds are considered zero-alpha. This begs the question: are the results the same for hedge funds?

Estimating a static linear factor model with the Newey-West (1987) heteroscedasticity and autocorrelation consistent estimator, we determine a " static" alpha that does not capture the particularities of hedge fund strategies. Using this, we find that the majority of hedge funds are zero-alpha funds, regardless of strategies.

We then apply the TVCM, capturing hedge fund manager skills to obtain a non-negligible increase of positive alpha funds. The results demonstrate that some strategies achieve a better percentage of positive alpha when the market is stable, whereas other strategies obtain a stronger percentage during market stress. We follow-up by focusing on risk factors to determine where there is an increase to a specific risk factor.

The results illustrate that the majority of hedge funds are often marked by an increase in credit spread, as well as bond market risk factors during market stress. These findings are in line with Almeida and Garcia (2008) who conclude that the credit risk factor is the most heavily loaded, followed by the bond risk factor.

The following section of this paper examines the results of seven out of twenty-four strategies. Findings are separated into three sub sections, starting with performance, exposures and finally liquidity

V.1. PERFORMANCE

Results are divided into two categories: those that obtain roughly the same percentage using the static factors model (SFM) and the TVCM model, and those strategies that illustrate a difference. Emerging markets, equity market neutral, event driven, and global macro strategies make-up the first group; the second is compromised of the CTA, equity long/short, and short bias strategies.

First Group: Same proportions depending on the model:

An analysis of the emerging market strategy as applied by hedge funds in our database reveals a strong proportion of stock picker-skilled funds, with approximately 12% generating positive alpha. This demonstrates that the majority of managers are fundamental bottom-up stock pickers. The proportion of dynamic skilled funds is very positive during both measured periods of crisis, with 40% of positive alpha funds. Results thus confirme that emerging market equity hedge fund managers viewed volatility as real opportunity.

The percentage of true alpha for hedge funds that employ equity market neutral strategies during LTCM reaches 0%. During the equity bubble crisis, this strategy did not perform well. In our study, a small 4% of positive alpha is exhibited during the first period, accelerating to 16% in the second. These percentages corroborate Patton (2009) whose own results raised questions about whether market neutral strategies are really market neutral.

Event driven multi-strategy approaches reveal the lowest percentage of skilled-funds, with 0% for the SFM and 2.5% for the TVCM. Examining data from the two crises confirms these results, with 0% of positive alpha funds during LTCM. These findings are not surprising, however, as both crises created several opportunities[12] not captured in the period studied (for example, a flood of corporate bankruptcies emerged during the dot-com burst in 2001-2002). On the other hand, this strategy is employed amongst funds that have the smallest proportion of unskilled managers, thereby confirming the convergence of hedge funds and private equity[13]. The adaptability of these two manager categories allowed them to survive changing market conditions and still prosper along with their investors.

Finally, global macro managers reveal one of the largest groups of unskilled funds, with a proportion of stock picker-skilled funds equal to 5% using the TVCM and 1% with the SFM. Unsurprisingly, the percentage of positive alpha during LTCM increased to 26%, confirming the assumption that global macro managers have the most extensive investment universe, which enables them to find opportunities. The equity bubble crisis furthers this theory, with a notable percentage of positive alpha funds at 18%.

Second Group: different proportions depending on the model:

Table 1. Estimated proportions of zero-alpha, unskilled, and skilled funds from merge database

This table displays the estimated proportions of zero-alpha, unskilled, and skilled funds for each strategy after applying the False Discovery Rate methodology developed by Barras *et al* (2010). These results come from the merge between the CISDM and the HegdeFund.net databases. The funds cover the LTCM and equity bubble periods and have a track record with a minimum of 36 months. We estimate alphas with the time-varying coefficient model defined in Section 6. We compute the average of estimated alphas which represents the stock-picker ability and the indicators defined in Section 7 during the 2 crises: α_{L1} and α_{L2} for LTCM and α_{B1} and α_{B2} for the Equity Bubble which represents the different market timer abilities. We also gave the result using a linear factor model based on the Newey-West (1987) heteroscedasticity and autocorrelation consistent estimator. We do not give results for Single Strategy because of too few data. Results about other strategies are available upon request.

Strategy	Model	α			α_{L1}			α_{L2}			α_{B1}			α_{B2}		
	used	π_A^+	π_0	π_A^-	π_A^+	π_0	π_A^-	π_A^+	π_0	π_A^-	π_A^+	π_0	π_A^-	π_A^+	π_0	π_A^-
2*Eq. Long/ Short	TVCM	18.6%	58.8%	22.6%	16.0%	61.9%	22.1%	22.8%	62.2%	15.0%	17.0%	58.8%	24.2%	17.0%	58.8%	24.2%
	Nwest	3.8%	93.5%	2.7%												
2*Emerging Markets	TVCM	12.6%	41.5%	45.9%	44.2%	42.6%	13.2%	38.9%	43.8%	17.3%	44.4%	39.2%	16.4%	43.6%	39.2%	17.3%
	Nwest	12.3%	87.5%	0.2%												
2*Eq. Market Neutral	TVCM	11.6%	74.1%	14.2%	0.0%	90.4%	9.6%	0.0%	92.2%	7.8%	4.3%	83.2%	12.5%	16.4%	83.2%	0.5%
	Nwest	8.6%	89%	2.4%												
2*Event Driven M. S.	TVCM	2.5%	97.5%	0.0%	0.0%	97.5%	2.5%	0.0%	99.8%	0.2%	0.9%	90.7%	8.4%	0.9%	90.7%	8.4%
	Nwest	0%	100%	0%												
2*Global Macro	TVCM	5.2%	67.0%	27.8%	26.1%	69.1%	4.8%	26.2%	66.8%	7.0%	18.5%	59.9%	21.6%	18.5%	59.9%	21.6%
	Nwest	1%	96%	3%												
2*Short bias	TVCM	35.2%	9.5%	55.2%	71.4%	0.0%	28.6%	71.4%	0.0%	28.6%	49.0%	19.0%	31.9%	49.0%	19.0%	31.9%
	Nwest	5.3%	63.6%	31.2%												
2*CTA	TVCM	18.8%	53.1%	28.1%	17.0%	60.2%	22.8%	17.0%	60.2%	22.8%	27.2%	55.3%	17.5%	27.2%	55.3%	17.5%
	Nwest	2%	97%	1%												

Let us begin with CTA. Here, we find a strong difference in estimated alpha between the static factors model (SFM) and our time-varying coefficient model. The SFM find a small percentage of positive and negative alpha funds, with 2% and 1%, respectively. Meanwhile, the TVCM reveals roughly 19% and 28%, respectively. And while the CTA cope well during both crises, it exhibits a strong percentage (27%) of positive alpha funds during the equity bubble. Moreover, while all other hedge fund strategies were struggling, CTAs experienced one of its best performances during the summer of 1998[14].

Equity long/short funds exhibit approximately the same results as the CTA, except with respect to the equity bubble crisis. Additionally, equity long/short strategies reveal a better percentage of positive alpha funds using the TVCM at 24%. The SFM, on the other hand, shows 4% of positive and 3% of negative alpha funds. Certain equity long/short funds specialize in specific sectors, like technology, and unsurprisingly, the forecast ability of managers is more impactful during the equity bubble than LTCM. Generally, however, the proportion stays relatively consistent throughout, thereby proving manager's ability to pivot from the short to the long position, and vice versa.

Finally, we consider the short bias. Using the SFM, short bias reveals 5% skilled funds, as compared to TVCM's 35%. This latter percentage represents less than the 71% of positive alpha funds found during LTCM. During the equity bubble crisis, 27% of positive alpha funds are revealed, confirming there is strong dynamism inherent to the strategy.

V.2. EXPOSURES

During the two events - the equity bubble crisis and LTCM - CTA shows a slight increase in the credit spread, and emerging market risk factors equaled 2%. This sensitivity only affects a small percentage of the population studied, however. The majority of CTAs possess a relatively stable exposure.[15]

During the equity bubble and LTCM, the emerging market strategy reveals greater dynamism than previously seen with approximately 25% and 55% of the population studied exhibiting an increase in credit spread and bond market risk factors. The credit spread risk factor is the most sensitive factor during LTCM. Four of the eight other factors show sensitivity during the equity bubble crisis[16].

A small percentage of the population applying equity long/short strategies show an increase or decrease in exposure throughout the two crises. Sensitivity to the credit spread risk factor and to commodities factors during LTCM is found, whereas emerging risk factors proves the most sensitive during the equity bubble crisis.

Equity market neutral strategies proves the most robust. Yet, for a minority of the population studied, a credit spread is revealed and the commodities factors exhibits the largest sensitivity during LTCM. Over the course of the equity bubble, the emerging market factor shows the greatest sensitivity.

A small portion of the event driven multi-strategy approach exhibits instability during the crisis, validating convergence between managers as debt managers began to pursue longer-term investments via private equity funds. Therefore, only the credit spread, emerging market and commodities factors for LTCM, and the emerging risk factor for the equity bubble crisis, shows an increase in positive alpha.

Less than 10% of the global macro strategy reveal an increase or decrease in general exposure. Credit spread risk factors stays the most sensitive here during LTCM, whereas the size of the spread and the risk factors for emerging markets are marked by a change in exposure[17].

Short bias produces the best percentage of exposure variation. More than 60% of the studied population show an increase in different market risk factors. Credit spread is present during LTCM, while size spread proves a negligible sensitivity to bond, commodity and emerging market risk factors during the equity bubble.

V.3. LIQUIDITY

Our research reveals that approximately 9% of funds show an increase in liquidity over the course of LTCM. CTA strategy reveals the same liquidity during both crises. For emerging market strategies, LTCM decreases the liquidity and the equity bubble increases liquidity. Short bias presents the most interesting data. Here, a significant percentage of funds increases liquidity when the market is stressed, thereby confirming it as a strong strategy during market turmoil. For the other strategies - *i.e.* global market, event driven multi-strategy, equity long/short, and equity market neutral - they remain robust against the liquidity factor, regardless of the crisis.

V.4. THE SUBPRIME MORTGAGE CRISIS

For the sake of comparison, we have also extended our analysis to the latest crisis using the same databases through to March 2010. We begin our empirical analysis with an estimate of hedge fund manager performances (alpha) using the time-varying coefficient model over the period March 2007-2010. Table 4 shows estimated proportions of unskilled and skilled funds by strategy $\left(\pi_0, \pi_A^-, \pi_A^+\right)$, as defined in Sections 5 and 7.2.

A completely different result is obtained in comparison to the other crises studied. During the subprime mortgage crisis, the proportion of negative, zero, and positive funds are roughly the same. Approximately half of the hedge funds are negative alpha funds, one-quarter is zero, and the remaining quarter is positive. We therefore estimate that the majority (75%) of funds across all strategies are zero or negative alpha.

The roughly 23% of strategies with zero-alpha represents a sharp decrease when compared to the other crises. The subprime mortgage disaster strongly increased the proportion of negative alpha funds, but surprisingly, also leads to a substantial increase of positive alpha funds (between 12.4% for equity long/short to 34.4% for short bias). This growth in negative alpha funds is explained by the fact that many hedge funds operated with too little capital and used short-term financing to

Figure 1. Variation in Market Exposures during Turmoils: Equity Long/Short

The number of funds covering the period is equal to 2525. The bar figures illustrate the proportion of funds having more than 10 percent decrease (blue or π_A^-), constant (white or π_0), and increase (red or π_A^+) market exposure during the 2 crises. Each crisis is divided in 2 period (see Section 7: methodology). The second figures (Factor Radar Chart) indicates the strategy's sensitivities (percentage change) to various factors in regards to the 2 crises.

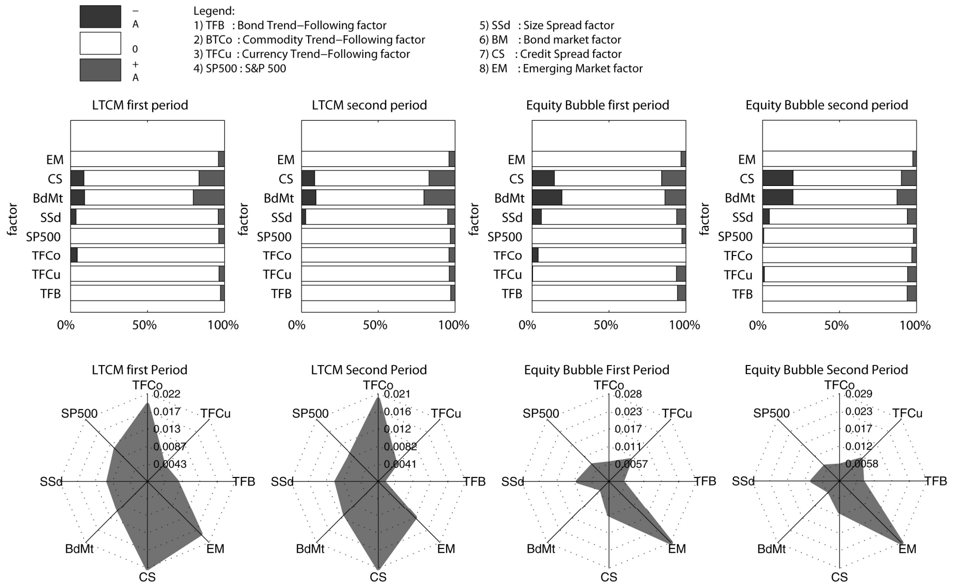

Figure 2. Variation in Market Exposures during Turmoils: Equity Market Neutral

The number of funds covering the period is equal to 519. The bar figures illustrate the proportion of funds having more than 10 percent decrease (blue or π_A^-), constant (white or π_0), and increase (red or π_A^+) market exposure during the 2 crises. Each crisis is divided in 2 period (see Section 7: methodology). The second figures (Factor Radar Chart) indicates the strategy's sensitivities (percentage change) to various factors in regards to the 2 crises.

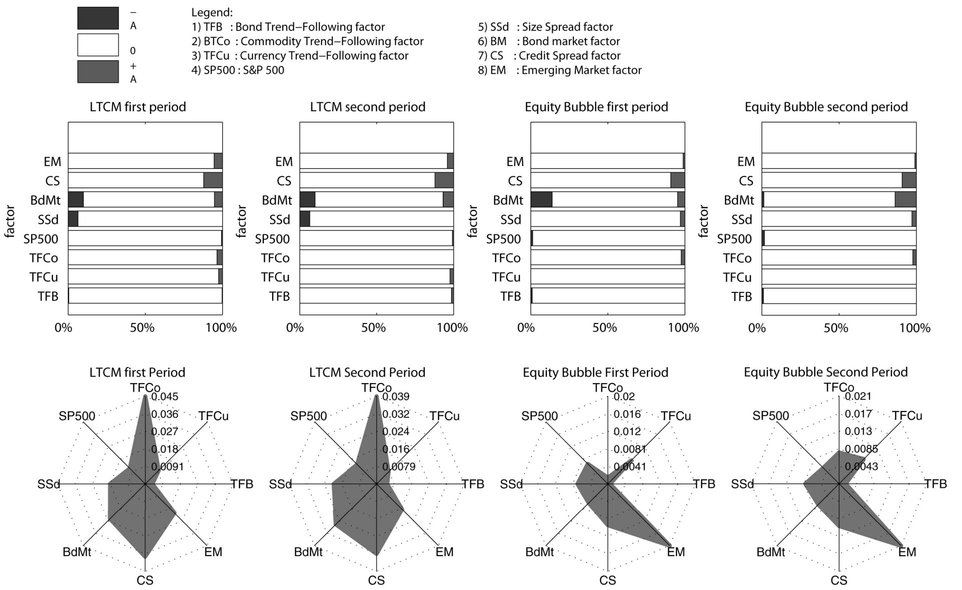

Figure 3. Variation in Market Exposures during Turmoils: Event Driven Multi Strategy

The number of funds covering the period is equal to 293. The bar figures illustrate the proportion of funds having more than 10 percent decrease (blue or π_A^-), constant (white or π_0), and increase (red or π_A^+) market exposure during the 2 crises. Each crisis is divided in 2 period (see Section 7: methodology). The second figures (Factor Radar Chart) indicates the strategy's sensitivities (percentage change) to various factors in regards to the 2 crises.

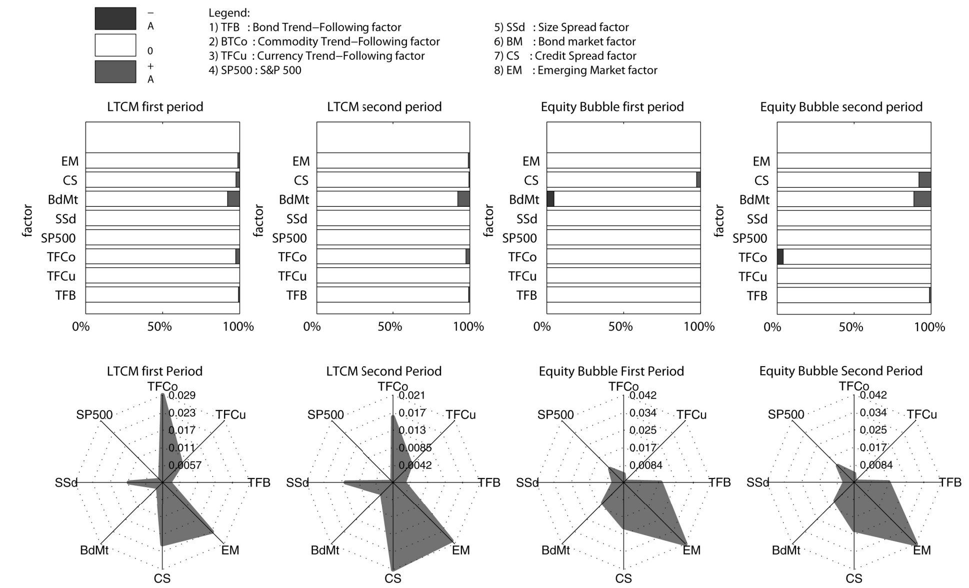

Figure 4. Variation in Market Exposures during Turmoils: Short Bias

The number of funds covering the period is equal to 56. The bar figures illustrate the proportion of funds having more than 10 percent decrease (blue or π_A^-), constant (white or π_0), and increase (red or π_A^+) market exposure during the 2 crises. Each crisis is divided in 2 period (see Section 7: methodology). The second figures (Factor Radar Chart) indicates the strategy's sensitivities (percentage change) to various factors in regards to the 2 crises.

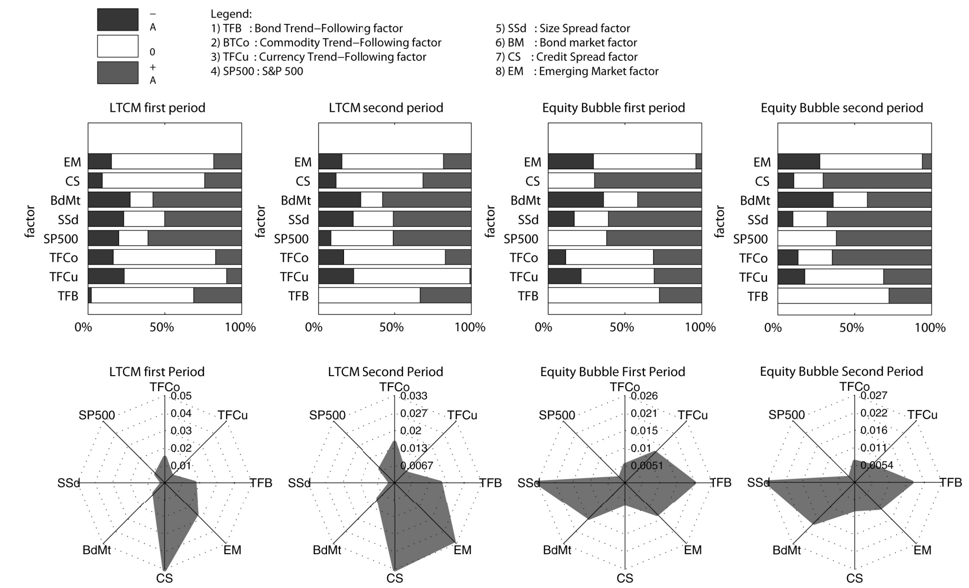

Table 2. Liquidity factor: estimated proportions of funds that show a change in liquidity during the two crisis

See Appendix I for definitions of fund types. This table displays the estimated proportions of funds that show a change in liquidity for each strategy after applying the False Discovery Rate methodology developed by Barras *et al* (2010). These results come from the merge between the CISDM and the HegdeFund.net databases. The funds used at minimum cover the LTCM and equity bubble period which represent a track record with a minimum of 36 months. We use the liquidity factor provided by Pastor and Stambaugh (2003) which is available on the website of Lubos Pastor: http:\\ faculty. chicagobooth.edu\ lubos.pastor\ research. We estimate the liquidity factor with the time-varying coefficient model defined in Section 6. We compute the average of estimated alphas which represents the stock-picker ability and the indicators defined in Section 7 during the 2 crises: α_{L1} and α_{L2} for LTCM and α_{B1} and α_{B2} for the Equity Bubble which represents the different market timer abilities.

Strategy	Model	Liq_{L1}			Liq_{L2}			Liq_{B1}			Liq_{B2}		
	used	π_A^+	π_0	π_A^-	π_A^+	π_0	π_A^-	π_A^+	π_0	π_A^-	π_A^+	π_0	π_A^-
2*Eq. Long/ Short	TVCM	0.0%	100%	0%	0.0%	100%	0%	1.9%	95.8%	2.3%	1.9%	95.8%	2.3%
2*Emerging Markets	TVCM	9.8%	86.4%	3.8%	11.1%	87.6%	1.3%	10.1%	81.8%	8.1%	10.1%	81.8%	8.1%
2*Eq. Market Neutral	TVCM	0.5%	99.5%	0.0%	0.5%	99.5%	0.0%	0.0%	100%	0%	0.0%	100%	0%
2*Event Driven M. S.	TVCM	6.9%	88.4%	4.7%	6.9%	88.4%	4.7%	0%	100%	0%	0%	100%	0%
2*Global Macro	TVCM	4.8%	89.9%	5.3%	5.4%	89.9%	4.7%	0.0%	96.8%	3.2%	0.0%	96.8%	3.2%
2*Short bias	TVCM	13.8%	76.2%	10.0%	23.6%	66.7%	9.8%	23.8%	76.2%	0.0%	23.8%	76.2%	0.0%
2*CTA	TVCM	8.4%	88.0%	3.6%	9.4%	87.0%	3.7%	0.0%	99.4%	0.6%	0.0%	99.4%	0.6%

fund subprime mortgages. When they could no longer sell these mortgages, many were forced out of business. Hedge funds that did not have an exposure to subprime mortgages found interesting opportunities, however, which serves to explain the increase of positive alpha funds.

VI. Conclusion

Hedge funds cover a wide range of strategies that assess risk radically differently. Similarities, however, do exist. Hedge fund managers strive to focus on positive returns (independent of market conditions), the use of leverage, and their structural fees. To analyze hedge funds, an econometrics model is needed to account for their characteristics and to ignore the ad hoc error distribution assumption and center on the dynamic in beta, or non-linearity exposures to the market.

To overcome these obstacles, we opt for a time-varying coefficient model and include a full set of factors as defined in Fung and Hsieh (2001, 2004). This model enables us to define alphas and betas as functions that depend on time and avoid parametric assumptions. It also enables us to cover the best overall risk factors as our model is based on the factors of Fung and Hsieh (2004).

Additionally, the merger of our TVCM model and the FDR approach results in a new methodology, applicable for hedge fund analysis. This model allows us to separate out manager skills into two components illustrated by the stock, bonds or fund-picking, and by their ability to anticipate market events. It also permits us to see changes in beta exposure, or in the manager reactions to changing market conditions.

Table 3. Proportion of Unskilled and Skilled Funds during the Subprime Mortgage Crisis

We measure with the time-varying coefficient model over the period 31/03/2007 to 31/03/2010. The table displays the estimated proportions of zero-alpha, unskilled, and skilled funds (π_0, π_A^-, π_A^+) for each strategy.

Strategy	Number of funds	π_A^-	π_0	π_A^+
Equity Long/ Short	2000	75.26%	12.32%	12.42%
Convertible Arbitrage	123	55.1%	23.3%	21.6%
CTA	1096	47%	28.3%	24.6%
Event Driven Multi Strategy	439	50.%	22.5%	27.5%
Emerging Market	342	51.2%	26.92%	21.88%
Fixed Income	507	55.4%	19.3%	25.3%
Global Macro	813	55.4%	22.6%	22%
Short Selling	28	40.6%	25%	34.4%
Equity Market Neutral	436	49.61%	27.29%	27%

Second, the FDR approach allows us to evaluate the proportion of skilled funds, conditional our sample study, while eliminating the different biases inherent to hedge fund databases. We determine the proportion of skilled funds by using a ratio composed of estimated alpha and corresponding volatility.

While Barras *et al* (2010) illustrate that only 0.2% of mutual funds generated positive alpha, and therefore the majority are considered as zero-alpha funds, the results for hedge funds are different. Hedge fund managers seek absolute returns and aim to outperform the market, whatever the market conditions.

Our study shows that a static factor model fails to capture this dynamic. In contrast, our model reveales a higher proportion of both positive and negative alpha funds. For positive alpha funds, the minimum percentage we find is 2.5% for event driven multi-strategy funds. The maximum is 18.5% for CTA and equity long/short strategies. The minimum percentage for negative alpha funds is find at 0% for event driven multi-strategy approaches, and 46% for the emerging market strategy.

In addition, some strategies in our study standd out as their percentage of true alpha is higher when the market is stressed than when it is stable, and vice-versa. Therefore, even if a strategy is defined as non-directional, the risk exposure can increase during market turmoil.

Another advantage of our methodology is its ability to analyze changes in risk factors. Examining each strategy, we determine the percentage change of all eight factors and we evaluate the persistence of betas parameters. Our results reveal that for all hedge funds, two exposures stand out in the down-state market: credit spread and bond risk factors. Our research on the changes in factorial exposure and the proportion of funds provides us with a tool for risk managers, particularly for stress-testing.

Finally, our study revealed that, with the appropriate toolbox, it is worth it to invest in hedge funds independent of market conditions. ■

1 http://faculty.fuqua.duke.edu/ dah7/.

2 We thank William Fung and David Hsieh for providing their factors which are downloadable on http://faculty.fuqua.duke.edu/ dah7/DataLibrary/TF-FAC.xls .

3 3-month USD LIBOR

4 This database combines four main group, Hedge Funds, Funds of Funds, CTA, and CPO.

5 For more details about the construction of these factors see Fung and Hsieh, 1997, 2001, 2004a.

6 Kosowski, Naik and Teo (2005) offer another approach. Using a bootstrap procedure, they examined whether hedge fund performance is explainable by luck and if it persists at annual horizons. Their methodology examined the skills of the best fund chosen from alpha-ranked funds.

7 Another paper of Galindo, Kauermann, and Carroll (2000) suggest another bootstrap method based on the wild-bootstrap of Härdle and Marron (1991)

8 The *t*-statistic distributions for individual Hedge Funds are generally non-normal. In order to overcome the non-normality, we use the same approach as Barras *et al* (2010), consisting of the use of a bootstrap to more accurately estimate the distribution of *t*-statistics for each Hedge Funds (and their associated *p*-values).

9 This methodology is simply a linear relation between two independent variables which, under the condition of normality for $\hat{\beta}_{jt} \quad j = 1, \ldots, N_j$; N_j being the number of funds, assure that the linear relation follows also a normal distribution.

10 Kat and Lu (2002), Brooks and Kat (2002) show that the net-of-fees monthly returns of the average individual Hedge Funds exhibit positive first-order serial correlation which is due, according to the authors, to marking-to-market problems. We have removed serial correlation by applying the same methodology as used in Brooks and Kat paper (2001), called the simple Blundell-ward filter; see Geltner (1991, 1993) for an extensive discussion of the motivations for and methodologies to unsmooth returns series.

11 refer to the time between making an investment and needing the funds.

12 Invests in mergers, spin-offs, reorganizations, and other announced events.

13 see Gonzales-Heres and Beinkampen (2006)

14 Approximately 10 percent in August and 7.5 percent in September according to CSFB/Tremont Managed Futures

15 The graph for the CTA strategy is available upon request.

16 The graph for the Emerging Market strategy is available upon request.

17 The graph for the Global Macro strategy is available upon request.

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