DSE
Dipartimento Scienze Economiche

Working Paper

Department of Economics
Ca' Foscari University of Venice

Monica Billio
Mila Getmansky
Loriana Pelizzon

Dynamic Risk Exposure in Hedge Funds

ISSN: 1827/336X
No. 18/WP/2007

This paper can be downloaded without charge from the Social Science Research Network (SSRN) electronic library at: http://ssrn.com/abstract=1020011

Working Papers
Department of Economics
Ca' Foscari University of Venice
No. 17/WP/2007
ISSN 1827-3580

Dynamic Risk Exposure in Hedge Funds[1]

Monica Billio
University of Venice and SSAV, Scuola Studi Avanzati in Venezia

Mila Getmansky
Isenberg School of Management, University of Massachusetts

Loriana Pelizzon
University of Venice and SSAV, Scuola Studi Avanzati in Venezia

Abstract
We measure dynamic risk exposure of hedge funds to various risk factors during different market volatility conditions using the regime-switching beta model. We find that in the high-volatility regime (when the market is rolling-down) most of the strategies are negatively and significantly exposed to the Large-Small and Credit Spread risk factors. This suggests that liquidity risk and credit risk are potentially common factors for different hedge fund strategies in the down-state of the market, when volatility is high and returns are very low. We further explore the possibility that all hedge fund strategies exhibit idiosyncratic risk in a high volatility regime and find that the joint probability jumps from approximately 0% to almost 100% only during the Long-Term Capital Management (LTCM) crisis. Out-of-sample forecasting tests confirm the economic importance of accounting for the presence of market volatility regimes in determining hedge funds risk exposure.

Keywords
Hedge Funds; Risk Management; Regime-Switching Models, Liquidity
JEL Codes
G12, G29, C51

Address for correspondence:
Monica Billio
Department of Economics
Ca' Foscari University of Venice
Cannaregio 873, Fondamenta S.Giobbe
30121 Venezia - Italy
Phone: (++39) 041 2349170
Fax: (++39) 041 2349176
e-mail: billio@unive.it

1 We thank Vikas Agarwal, Lieven Baele, Ben Branch, Stephen Brown, Laura Frieder, Bruno Gerard, David Hsieh, William Fung, Will Goetzmann, Robin Greenwood, Ravi Jagannathan, Nikunj Kapadia, Hossein Kazemi, Camelia Kuhnen, Martin Lettau, Bing Liang, Laura Lindsay, Andrew Lo, Narayan Naik, Geert Rouwenhorst, Stephen Schaefer, Tom Schneeweis, Matthew Spiegel, Heather Tookes, Marno Verbeek, Pietro Veronesi, Rebecca Zarutskie and seminar participants at the NYU Stern School of Business, Cornell, Rutgers Business School, University of Waterloo, Hebrew University, Brandeis University, State University of New York-Albany, University of Massachusetts-Amherst, University of Connecticut, Tilburg University, Sorbonne University-CES Paris 1, Goethe University, ENS CACHAN, European Finance Association Conference (EFA), European Summer Symposium in Financial Markets (ESSFM), Second Italian Conference in Econometrics and Empirical Economics, International Workshop on Computational and Financial Econometrics, and European Conference of the Econometric Community (EC^2) for valuable comments and suggestions.

The Working Paper Series
is availble only on line
(www.dse.unive.it/pubblicazioni)
For editorial correspondence, please contact:
wp.dse@unive.it

Department of Economics
Ca' Foscari University of Venice
Cannaregio 873, Fondamenta San Giobbe
30121 Venice Italy
Fax: ++39 041 2349210

1 Introduction

The last decade has seen an increase in the number of hedge funds and the availability of hedge fund data both on individual hedge funds and on hedge fund indexes. Unlike mutual funds, hedge funds engage in dynamic strategies, use leverage, take concentrated bets, bet on volatility and have non-linear payoffs. The tremendous increase in the number of hedge funds and the availability of hedge fund data has attracted a lot of attention in the academic literature, which has been concentrated on analyzing hedge fund styles (Fung and Hsieh (2001) and Mitchell and Pulvino (2001)), performance and risk exposure (Fung and Hsieh (1997), Brealey and Kaplanis (2001), Edwards and Caglayan (2001), Agarwal and Naik (2004), Bali, Gokcan and Liang (2007), Gupta and Liang (2005), and Schneeweis, Karavas, and Georgiev (2002)), liquidity, systemic risk and contagion issues (Getmansky, Lo, and Makarov (2004), Chan, Getmansky, Haas, and Lo (2005) and Boyson, Stahel and Stulz (2006)).

The aim of this paper is to analyze time-varying and state-dependent risk exposures for various hedge fund strategies and obtain reliable estimates for predicted exposures of hedge fund returns. The innovative aspect of this paper is that we study hedge fund risk exposure conditional on different levels of mean and volatility of the market risk factor, characterized by the S&P 500.

Understanding and modeling hedge fund risk exposures is fundamental for both hedge fund investors and regulators. For example, the recent subprime mortgage crisis of August 2007 exposed new types of risk for hedge funds, and currently there is a discussion of a potential role of regulators to diminish the effects of this crisis. This crisis also emphasized the importance of credit and liquidity for hedge fund returns. For investors, a knowledge of hedge fund exposures is essential in order to analyze risk-adjusted hedge fund performance and to perform optimal asset allocation. Regulators are concerned about risks that are common across different hedge fund strategies. These risks can be responsible for financial trouble in the hedge fund industry and can act as catalysts for a spillover to other financial sectors, i.e., systemic risk. Moreover, regulators are worried if this joint risk across hedge fund strategies is associated with a particular state or regime of the equity market. In addition, regulators are concerned about an event where all different hedge fund strategies move to a high volatility state due to liquidity or non-market related shocks. This can lead to the downfall of all hedge fund strategies at the same time and potential spillovers to financial markets.

Our approach provides a framework that can be used to address these issues and can be applied in stress-testing analysis.

Hedge funds may exhibit non-normal payoffs for various reasons such as their use of options, or more generally dynamic trading strategies. Unlike most mutual funds (Koski and Pontiff (1999) and Almazan et al. (2004)), hedge funds frequently trade in derivatives. Further, hedge funds are known for the "opportunistic" nature of their trading strategies and a significant part of their returns arise from taking state-contingent and volatility bets.

There is currently a limited understanding of the real non-linear exposure to risk factors of the different hedge funds strategies. In the hedge fund literature, the analysis of risk exposure is based on three main approaches. The first approach is based on the classical linear factor model applied to mutual funds. The second, introduced by Fung and Hsieh (1997), is based on a predetermined structure of the risk factors (quintile analysis or extreme event analysis). The third approach is based on option-like payoffs, also called Asset-Based Style Factors (ABS-Factors), introduced by Fung and Hsieh (2001) and Agarwal and Naik (2004). We add to the literature by proposing a new way of capturing dynamic risk exposure in hedge funds based on volatility changes of the market risk factor.

In this paper, consistent with the asset pricing perspective proposed by Bekaert and Harvey (1995), we suggest analyzing the exposure of hedge fund indexes with a factor model based on regime-switching volatility, where non-linearity in the exposure is captured by factor loadings that are state-dependent. The regime-switching approach is able to identify when the market risk factor is characterized by normal, down-market or up-market conditions, and the state dependent factor loadings are able to capture the exposure of hedge funds to risk factors in these different volatility states.[1] To our knowledge this is the first attempt to analyze hedge fund exposure considering that the market risk factor is characterized by stochastic volatility, i.e., calculating hedge fund exposure to the market factor by explicitly accounting for the change in volatility of the market factor. This feature is relevant because hedge funds bet on volatility, and factor loadings are affected by the volatility of the risk factors.

The importance of using regime-switching models is well established in the financial economics literature and examples are found in Bekaert and Harvey's (1995) regime-switching asset pricing model, Ang and Bekaert's (2002) and Guidolin and Timmermann's (2006) regime-switching asset allocation models, Lettau, Ludvigson, and Wachter's (Forthcoming) regime-switching equity premia model, and Billio and Pelizzon's (2000, 2003) analysis of VaR

[1] The expected returns and volatilities for each state are endogenously defined from the data. Section 3 and Table 2 show that the return pattern of the S&P 500 could be easily captured with three regimes, where up-market regime has a mean of 5.79% and a relatively low volatility 1.52%. The normal regime has a mean of 0.85% and a volatility of 2.49%. The down-market regime captures market downturns and has a mean of -2.02% and a volatility of 4.51%.

calculation, volatility spillover and contagion among markets. Moreover, regime-switching models have been successfully applied to constructing trading rules in equity markets (Hwang and Satchell (2007), equity and bond markets (Brooks and Persand (2001)), and foreign exchange markets (Dueker and Neely (2004)). Chan et al. (2005) apply regime-switching models to the CSFB/Tremont hedge fund indexes to analyze the possibility of switching from a normal to a distressed regime in the hedge fund industry. The implementation of the regime-switching methodology is similar in spirit to ours; however, in our paper we propose a regime-switching *beta* model to measure the exposure of hedge fund indexes to different regimes that characterize market risk factors. Such exposure cannot be measured with the simple regime-switching model used by Chan et al. (2005) because this model does not account for market risk factor regimes.

Our approach maintains the spirit of Fung and Hsieh (1997) and Agarwal and Naik (2004), but we differ from these studies in the focus of our investigation. Specifically, rather than using ABS factors to capture dynamic strategies, we allow for dynamic factor loadings with different betas, where factor loadings are endogenously determined. In this way we capture, with a formal model, the idea of Fung and Hsieh (1997) to separate factors into different quintiles based on historical performance and try to access the exposure of hedge fund returns to factors in each of the quintiles. However, the use of quintiles implies the exogenous definition of states. Rather, we let the model to determine the states. Our analysis shows that hedge fund exposure to risk factors is related to a mixture of strategies based on options. The framework is also flexible, as we do not need to define *a priori* the strategy that hedge funds may follow, but in line with the classical Sharpe-style analysis approach (Sharpe, (1992)), the data highlight the dynamic exposure to risk factors. Therefore, we have different factor loadings for hedge fund strategies during different market regimes.

Our analysis confirms that hedge funds change their exposure based on different market conditions. Bollen and Whaley (2007) show that allowing for switching in risk exposure is essential when analyzing hedge fund performance. We show that the exposures change over time for all strategies, confirming the time-varying risk exposure of hedge funds. Factor loadings with respect to systematic risk factors vary in different regimes for almost all hedge fund indexes, validating the non-linear exposure to the market risk factor. We find that in many cases (i.e, emerging markets, distressed, event driven multi-strategy and risk arbitrage strategies) hedge fund exposure to the S&P 500 in the down-state of the S&P 500 is greater than in the normal state of the market. Moreover, our framework can capture the phase-locking property of hedge funds introduced by Chan et al. (2005).[2] For example, we observe

[2]The term "Phase-locking" behavior is borrowed from the natural sciences, and refers to a state in which otherwise uncorrelated actions suddenly become synchronized.

that for all strategies in the normal market regime, factor loadings are very low or zero for some particular risk factors, including the S&P 500; however, factor loadings become very large in the down-market or up-market regimes.

Our model is able to capture changes in factor loadings depending on the volatility of the market and exposure to risk factors that, for a certain period of time, are negligible and are not captured by linear models. More specifically, we find that exposures to Large-Small (Fama-French Factor), Government Credit, and MSCI Emerging Market Debt are mostly characterized by zero or small exposure during the normal state and significant exposure during market downturns. Moreover, our results show that risk factor exposures conditional on market regimes are quite different among hedge fund indexes.

The above results suggest, first, that by using regime-switching models investors can identify and select hedge funds and hedge fund indexes with favorable market exposure in each regime and in particular in market downturns. They will also be more informed about transition probabilities between different regimes and probabilities of being exposed to several market factors.

Second, our results suggest that the common exposures of different hedge fund indexes to risk factors in the down-state of the market are the exposure to the Large-Small risk factor (which may potentially capture liquidity risk in line with Acharya and Pedersen (2005)), Credit Spread (i.e., credit risk) and change in VIX. This suggests the possibility of a systematic risk among the hedge fund family that is not generated by direct market exposure. The systematic risk is attributed to liquidity and credit risks, two typically non-linear phenomena, and is more relevant during market downturns that are usually characterized by large volatility. This aspect is important for regulators who would like to access systematic exposure of hedge funds.

Third, our analysis shows that the idiosyncratic risk factor of hedge funds is largely characterized by changes from a low volatility regime to a high volatility state that are not directly related to market risk factors. We further explore the probability that all hedge fund strategies exhibit idiosyncratic risk in a high volatility regime. This could be interpreted as a proxy measure for contagion between different hedge fund strategies. Specifically, we calculate the joint probability of being in a high volatility state for all hedge funds. We find that the joint probability jumps from approximately 0% in May 1998 to 4% in June 1998 to 13% in July 1998 to 96% in August 1998, the month of the Long-Term Capital Management (LTCM) collapse. It started to subside in October 1998. The peak in the joint probability coincides with the liquidity crisis precipitated by the collapse of the LTCM. The results suggest that the LTCM crisis not only affected market risk factors, but also, after controlling for market and other factor exposures, affected idiosyncratic volatility of hedge funds. This provides evidence that even after accounting for market and other factor exposures, the LTCM crisis precipitated contagion across the hedge fund industry.

Robustness analysis and out-of-sample forecasting experiments confirm the economic importance of accounting for the presence of market regimes for determining hedge fund risk exposure.

The rest of the paper is organized as follows. In Section 2 we develop a theoretical framework and define a series of beta regime-switching models that can be used to analyze different hedge fund style indexes. Section 3 describes data and presents results for the one-factor and multifactor beta regime-switching models. Section 4 presents analysis on omitted factors. Section 5 presents analysis on evolution of the idiosyncratic risk factor. Section 6 provides robustness checks. We compare our approach to OLS, asymmetric beta and threshold models. We also adjust for potential illiquidity and smoothing in the data and check that regime-switching approach is applicable to individual hedge funds as well as indexes. Section 7 conducts an out-of sample analysis. Section 8 concludes.

2 Theoretical Framework

Linear factor models such as the capital asset pricing model (CAPM) and the arbitrage pricing theory (APT) have been the foundation of most of the theoretical and empirical asset pricing literature. Formally, a simple one-factor model applied to hedge fund index returns could be represented as:

$$R_t = \alpha + \beta I_t + \omega u_t \tag{1}$$

where R_t is the return of a hedge-fund index in period t, I_t is a market factor, for example, the $S\&P500$ in period t, and u_t is IID.

In this model, we can identify the exposure of hedge fund returns to a factor I. Unfortunately this theory constrains the relation between risk factors and returns to be linear. Therefore it cannot price securities whose payoffs are nonlinear functions of the risk factors, i.e., hedge fund returns that are characterized by the implementation of dynamic strategies. For this reason we propose a more flexible and complete model for capturing this feature: a regime-switching model.

A Markov regime-switching model is one in which systematic and un-systematic events may affect the output due to the presence of discontinuous shifts in average return and volatility. The change in regime should not be regarded as predictable but rather as a random event.

More formally, the model could be represented as:

$$R_t = \alpha + \beta(S_t)I_t + \omega u_t \quad (2)$$

$$I_t = \mu(S_t) + \sigma(S_t)\epsilon_t \quad (3)$$

where S_t is a Markov chain with n states and transition probability matrix $\mathbf{P}$. Each state of the market index I has its own mean and variance. Hedge fund mean returns are related to the states of the market index and are defined by the parameter α plus a factor loading, β, on the conditional mean of the factor. Hedge fund volatilities are also related to the states of the market index I and are defined by the factor loading, β, on the conditional volatility of the factor plus the volatility of the idiosyncratic risk factor ω.[3] In both cases β could be different conditional on a state of the risk factor I.

For example, if $n = 3$ (state labels are denoted as 0, 1 or 2), the model can be represented as follows:

$$R_t = \begin{cases} \alpha + \beta_0 I_t + \omega u_t \; if \; S_t = 0 \\ \alpha + \beta_1 I_t + \omega u_t \; if \; S_t = 1 \\ \alpha + \beta_2 I_t + \omega u_t \; if \; S_t = 2 \end{cases} \quad (4)$$

where the state variable S depends on time t, and β depends on the state variable:

$$\beta(S_t) = \begin{cases} \beta_0 & \text{if } S_t = 0 \\ \beta_1 & \text{if } S_t = 1 \\ \beta_2 & \text{if } S_t = 2 \end{cases} \quad (5)$$

and the Markov chain S_t (the regime-switching process) is described by the following transition probability matrix $\mathbf{P}$:[4]

[3] In all Markov states, we assume normality of the error terms and homoskedasticity within regimes. These hypotheses are not at all restrictive since, as it will be clear in the Section 3.2.1 and Figures 1 and 2, the resulting return distributions are non-normal and heteroskedastic.

[4] P_{ij} is the transition probability of moving from regime i to regime j.

$$\mathbf{P} = \begin{bmatrix} p_{00} & p_{01} & p_{02} \\ p_{10} & p_{11} & p_{12} \\ p_{20} & p_{21} & p_{22} \end{bmatrix} \tag{6}$$

with $p_{02} = 1 - p_{00} - p_{01}$, $p_{12} = 1 - p_{10} - p_{11}$ and $p_{22} = 1 - p_{20} - p_{22}$. The parameters p_{00}, p_{11} and p_{22} determine the probability of remaining in the same regime. This model allows for a change in variance of returns only in response to occasional, discrete events. Despite the fact that the state S_t is unobservable, it can be statistically estimated (see for example Hamilton (1989, 1990)).

Our specification is similar to the well-known "mixture of distributions" model. However, unlike standard mixture models, the regime is not independently distributed over time unless transition probabilities p_{ij} are equal to $1/n$, where n is the number of states. The advantage of using a Markov chain as opposed to a "mixture of distributions" is that the former allows for conditional information to be used in the forecasting process. This allows us to: (i) fit and explain the time series, (ii) capture the well known cluster effect, under which high volatility is usually followed by high volatility (in the presence of persistent regimes), (iii) generate better forecasts compared to the mixture of distributions model, since regime-switching models generate a time-conditional forecast distribution rather than an unconditional forecast distribution, and (iv) provide an accurate representation of the left-hand tail of the return distribution, as the regime-switching approach can account for "short-lived" and "infrequent" events.[5]

Moreover, our formal model allows us to make dynamic forecasts. More specifically, once parameters are estimated, the likelihood of regime changes can be readily obtained, as well as forecasts of β_t itself. In particular, because the k-step transition matrix of a Markov chain is given by $\mathbf{P}^k$, the conditional probability of the regime S_{t+k} given date-t data $\mathcal{R}_t \equiv (R_t, R_{t-1}, \ldots, R_1)$ takes on a particularly simple form when the number of

[5]The Markov switching model is more flexible than simply using a truncated distribution approach, as at each time t, we have a mixture of one or more normal distributions, and this mixture changes every time. Using the truncated distribution will lead to a non-parametric estimation, where the down-state of the market is exogenously imposed, and it is hard to make inferences about beta forecast and conditional expectations. Instead, we use a parametric model to help us separate the states of the world. We are able to infer time-varying risk exposures of hedge funds, make forecasts, calculate transition probabilities from one state to another and calculate conditional expectations.

regimes is 2 (regime 0 and 1):

$$\begin{aligned} \text{Prob}\,(S_{t+k}=0|\mathcal{R}_t) &= \pi_1 \ + (p_{00}-(1-p_{11}))^k \Big[\text{Prob}\,(S_t=0|\mathcal{R}_t)-\pi_1\Big] & (7) \\ \pi_1 &\equiv \frac{(1-p_{11})}{(2-p_{00}-p_{11})} & (8) \end{aligned}$$

where $\text{Prob}\,(S_t = 0|\mathcal{R}_t)$ is the probability that the date-t regime is 0 given the historical data up to and including date t (this is the filtered probability and is a by-product of the maximum-likelihood estimation procedure). More generally, the conditional probability of the regime S_{t+k} given date-t data is:

$$\begin{aligned} \text{Prob}\,(S_{t+k}=0|\mathcal{R}_t) &= \mathbf{P}^{k\prime}\mathbf{a}_t & (9) \\ \mathbf{a}_t &= \Big[\ \text{Prob}\,(S_t=0|\mathcal{R}_t)\ \ \text{Prob}\,(S_t=1|\mathcal{R}_t)\ \ ..\text{Prob}\,(S_t=n|\mathcal{R}_t)\Big]^\prime & (10) \end{aligned}$$

Using similar recursions of the Markov chain, the conditional expectation of β_{t+k} can be readily derived as:

$$\begin{aligned} \text{E}[\beta_{t+k}|\mathcal{R}_t] &= \mathbf{a}_t^\prime\mathbf{P}^k\boldsymbol{\beta} & (11) \\ \boldsymbol{\beta} &\equiv [\ \beta_0\ \ \beta_1\ \ ..\beta_n]^\prime & (12) \end{aligned}$$

Time-varying betas can be easily determined by using equation 11 and setting k=0. This gives us the framework for analyzing time-varying risk exposures for hedge funds for different factors. Moreover, this framework can be used to calculate expected time-varying risk exposures for hedge funds for various factors, by setting k to be more than 0. For example, if k=1, we can calculate the evolution of expected one-month beta exposures to different factors.

The model described in equations 2 and 3 could be extended in several ways. For example, we propose a regime-switching model with non-linearity in the volatility of residuals and in the intercept coefficient:

$$R_t = \alpha(Z_t) + \beta(S_t)I_t + \omega(Z_t)u_t \tag{13}$$
$$I_t = \mu(S_t) + \sigma(S_t)\epsilon_t \tag{14}$$

In this model, additional non-linearities are captured by the intercept and residuals. Z_t is another Markov chain which proxies for all other non-linearities not captured by non-linear relationship between a particular hedge fund (index) and the risk factor I.

Usually more than one factor affects hedge fund returns. Our regime-switching beta model could be easily extended to a multifactor model.

The first extension is a model in the same spirit as the model developed by Agarwal and Naik (2004) with a non-linear exposure to the S&P 500 and a linear exposure to other risk factors. More formally:

$$R_t = \alpha(Z_t) + \beta(S_t)I_t + \sum_{k=1}^{K} \theta_k F_{kt} + \omega(Z_t)u_t \tag{15}$$
$$I_t = \mu(S_t) + \sigma(S_t)\epsilon_t \tag{16}$$

where θ_k is the linear factor loading of the hedge fund index on the k-th risk factor and F_{kt} is the return on the k-th risk factor at time t.

However, this model does not consider the possibility that the exposure to other risk factors could be affected by the regime that characterizes the S&P 500. To capture this feature, we propose a multifactor beta switching model with non-linearity in residuals:

$$R_t = \alpha(Z_t) + \beta(S_t)I_t + \sum_{k=1}^{K} \theta_k(S_t) F_{kt} + \omega(Z_t)u_t \tag{17}$$
$$I_{1t} = \mu(S_t) + \sigma(S_t)\epsilon_t \tag{18}$$

This model allows us to detect the exposure of hedge fund indexes to different factors conditional on the state that characterizes the market index factor that in our empirical analysis is represented by the S&P 500.

Goodness-of-fit for our non-linear models is measured using McFadden's (1974) pseudo-R^2 approach. In this approach, the unrestricted (full model) likelihood L_{UR} is compared to the restricted (constant only) likelihood L_R as follows:

$$Pseudo - R^2 = 1 - \frac{logL_{UR}}{logL_R} \tag{19}$$

Pseudo-R^2 measure has also been used by Boyson, Stahel and Stulz (2006) to compare different hedge fund risk models. The ratio of the likelihoods measures the level of improvement made by the unrestricted model with respect to the restricted model. A likelihood falls between 0 and 1, so the log of a likelihood is less than or equal to zero. If a model has a very low likelihood, then the log of the likelihood will have a larger magnitude than the log of a model with high likelihood. A small ratio of log likelihoods indicates that the unrestricted model has a far better fit than the restricted model. The pseudo-R^2 measures an improvement of the unrestricted model with respect to the restricted model. Thus, when comparing two models on the same data, McFadden's pseudo-R^2 is higher for the model with the greater likelihood. However, even though it ranges from 0 to 1 with higher values indicating a better model fit, pseudo-R^2 is not a measure of explained variability, which is captured by a classical OLS R^2.

3 Empirical Analysis

3.1 Data

For the empirical analysis in this paper, we use aggregate hedge-fund index returns from the CSFB/Tremont database from January 1994 to March 2005. For out-of-sample analysis, we extend the dataset until October 2006. The CSFB/Tremont indexes are asset-weighted indexes of funds with a minimum of $10 million of assets under management, a minimum one-year track record, and current audited financial statements. An aggregate index is computed from this universe, and 10 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. We use net-of-fee monthly excess return (in excess of LIBOR). This database accounts for survivorship bias in hedge funds (Fung and Hsieh (2000)). Table 1 describes the sample size, β with respect to the S&P 500, annualized mean, annualized standard deviation, minimum, median, maximum, skewness and kurtosis for monthly CSFB/Tremont hedge-fund index returns as well as for the S&P 500.

[INSERT Table (1) about here]

For our empirical analysis, we evaluate the exposure of hedge fund indexes to the market index, the S&P 500; therefore, we concentrate only on hedge fund styles that either directly or indirectly have S&P 500 exposure. For example, we concentrate on directional strategies such as Dedicated Shortseller, Long/Short Equity and Emerging Markets as well as non-directional strategies such as Distressed, Event Driven Multi-Strategy, Equity Market Neutral, Convertible Bond and Risk Arbitrage.

Categories greatly differ. For example, annualized mean of excess return for the Dedicated Shortseller category is the lowest: -6.48%, and the annualized standard deviation is the highest at 17.63%. Distressed has the highest mean, 7.32%, but relatively low standard deviation: 6.69%. The lowest annualized standard deviation is reported for the Equity Market Neutral strategy at 2.94% with an annualized mean of 4.08%. Hedge fund strategies also show different third and fourth moments. Specifically, non-directional funds such as Event Driven Multi-Strategy, Risk Arbitrage and Convertible Bond Arbitrage all have negative skewness and high kurtosis. The exception is the Equity Market Neutral strategy, which has a low positive skewness and kurtosis. Directional strategies such as Dedicated Shortseller, Long/Short Equity have positive skewness and small kurtosis. Emerging Markets has a slight negative skewness of -0.65 and a small kurtosis. The market factor is characterized by high annualized excess return of 5.52% and high standard deviation of 15.10% during our sample period. Moreover, the distribution of the market factor is far from normal and is characterized by negative skewness.

3.2 Beta Regime-Switching Models

In the following sub-sections, all switching regime models have been estimated by maximum likelihood using the Hamilton's filter and the econometric software GAUSS.

Because of the limited dataset, we prefer to adopt a two-step procedure. We first characterize the S&P 500 behavior by a switching-regime model and then, conditional on this result, we estimate our one-factor and multi-factor models.

Finally, in all our estimations we compute the robust covariance matrix estimator (often known as the sandwich estimator) to calculate the standard errors (see Huber (1981) and White (1982)). The estimator's virtue is that it provides consistent estimates of the covariance matrix for parameter estimates even when a parametric model fails to hold, or is not even specified. In all tables we present the t-statistics obtained with the robust covariance matrix estimators, which allows us to take into account a possibility that data may deviate to some extent from the specified model.[6]

[6]For the switching-regime models the standard deviations obtained with the usual covariance matrix

3.2.1 S&P 500 regimes

In this section we first verify the presence of the S&P 500 regimes in the data, and then analyze the exposure of different hedge fund indexes to the different states of the S&P 500 market index by implementing the model described in equation 3.

In order to determine the number of regimes used in the estimation, we estimated and tested models with different number of regimes and ultimately decided that using three regimes is optimal for our analysis. Using three regimes is also consistent with the literature that well recognizes the presence of normal, rolling-up or downturn regions in the returns of the equity market.[7] The results of the estimation are shown in Table 2.

[INSERT Table (2) about here]

Table 2 shows that the return pattern of the S&P 500 could be easily captured with three regimes, where regime 0 has a mean of 5.79% and a relatively low volatility of 1.52%. We denote this regime as the up-market state, which has a very low probability of remaining in the same regime in the following month: P_{00}=28%. Regime 1 has a mean statistically different than zero and equal to 0.85% and a volatility of 2.49%, and we call it a normal state. This is a persistent regime, and the probability of remaining in it is 98%. The last regime captures market downturns and has a mean of -2.02% and a volatility of 4.51%. The probability of remaining in this regime is 74%.

The model estimation allows us to infer when the S&P 500 was in one of the three regimes for each date of the sample using the Hamilton filter and smoothing algorithms (Hamilton, 1994).

We observe that in the first part of the sample, the S&P 500 returns are frequently characterized by the normal regime 1, in particular from July 1994 to December 1996 (91.7% of time in normal regime and 8.3% in the market downturn). The period from 1997 through 2003 is characterized primarily by two other regimes: up-market (30.4%) and down-market (64.6%). This outcome is generated mainly by high instability of the financial markets starting from the Asian down-market in 1997, well captured by regime 2, the technology and internet boom, well captured by regime 0, the Japanese down-market of March 2001, September 11, 2001 and the market downturn of 2002 and 2003, captured mostly by regime 2. The last part of the sample from 2003 through 2005 is characterized by the normal regime 1 (100%). It is important to note that the three-regime approach does not imply simply

estimator and the robust covariance matrix estimator are similar.

[7] Goetzmann et al. (2007) show that an optimal strategy for hedge funds might be selling out-of-the-money puts and calls, ensuring that during normal regimes, hedge fund managers obtain a positive cash flow, and have a large exposure in extreme events.

splitting the data sample into large negative, large positives or close to the mean returns. The regime approach allows us to capture periods where the return distribution belongs to large volatility periods characterized by large downturns or more tranquil periods. In all these different regimes we may face positive or negative returns.[8]

In addition to analyzing the change in the S&P 500 returns, and probability of being in a particular regime, we derive both conditional and unconditional distributions for the S&P 500 for all three regimes as well as for the total time series.

[INSERT Figure (1) about here]

Figure 1 depicts unconditional distributions of the S&P 500 overall, in down-market, normal and up-market regimes. First, it is worthwhile to note that during the time period analyzed in the paper, the market clearly experienced three distinct regimes: up-market, normal and down-market. Moreover, the total distribution is skewed, and distribution of being in a down-market state is characterized by fat tails. Figure 1 also depicts conditional distributions of different regimes, conditional on starting in regime 2, a down-market regime. The resulting total distribution closely overlaps regime 2 distribution, especially in the left tail. Therefore, once in down-market, the market is more likely to stay in down-market (74%), and both conditional regime 2 and total distribution are fat-tailed.

[INSERT Figure (2) about here]

Figure 2 shows conditional distributions of the S&P 500 overall, in down-market, normal and up-market regimes first conditional on an up-market regime and second conditional on a normal regime. Interestingly, conditional on being in an up-market, there is a certain probability of staying in an up-market (28%), but there is also a large left-tail probability of moving to a down-market (67%). It looks like the up-market regime is often transitory, frequently followed by a down-market regime. Conditional on being in a normal regime, the total distribution is almost identical to the conditional probability of a normal regime. Therefore, if a market is in the normal regime, it is more likely to be persistent (98%). The conditional distributions for all regimes are very close to normal in this case. Nevertheless, there is a small probability of 2% of moving to an up-market regime that is more likely (67%) followed by a down-market.

[8] This approach is closely compared to an alternative threshold approach where a sample is split into positive and negative returns, following Fung and Hsieh (1997). These two approaches are carefully compared in Section 6. More specifically, the regime-switching approach allows us to endogenously determine changes in market return distributions without exogenously splitting the data into positive and negative returns.

Overall, the results confirm that during the period of January 1994 to March 2005, the S&P 500 was clearly characterized by three separate regimes. In the paper, we are interested in clearly understanding the exposure of each hedge fund strategy to the market in all these regimes. In other words, we are interested in finding the exposure of hedge fund returns to all parts of this distribution. Using the results in Figures 1 and 2, it is clear that not accounting for three separate regimes and only concentrating on a normal regime will underestimate the left tail of the distribution and thus bias hedge fund market risk exposure.

3.2.2 One-factor model

After having characterized the process for the S&P 500, we analyze the exposure of different hedge fund strategies to different S&P 500 regimes. The analysis is based on the model presented in equation 13 and results are shown in Table 3.

[INSERT Table (3) about here]

We find different factor loadings with respect to the S&P 500 regimes for almost all hedge funds indexes. The only exception is the Convertible Bond Arbitrage strategy. Regarding the more directional strategies (Dedicated Shortseller and Long/Short Equity), we do find significant exposures to the S&P 500 regimes, but the factor loadings vary a lot for different regimes. In particular, Dedicated Shortseller shows a large negative exposure of -1.26 to the S&P 500 in normal times. This relationship is maintained for the down-market period; however, the exposure is reduced in half for the up-market state of the market. Long/Short Equity strategy aims to go both long and short on the market during the normal regime. Our analysis shows that the exposure to the market during the normal regime is three times as high as the exposure during the other two regimes. There is, therefore, an attempt of this strategy to reduce the exposure to the market downturns, but the exposure remains still positive, as shown in Table 3.

The Emerging Markets strategy shows a peculiar positive exposure mostly when the market is characterized by the down-market state and is relatively large in normal time. A potential explanation of this large exposure in market downturns can come from the fact that many emerging markets do not allow short-selling and lack availability of option instruments to be used for hedging. Therefore, the exposure result for the Emerging Markets strategy is similar to writing a put option on the S&P index.

For Equity Market Neutral we find a positive exposure in regime 0, i.e., when the market is rolling up. The exposure is zero in normal times and when the market is mostly characterized by a downturn. This result is in line with the fact that the Market Neutral strategy can neutralize the effects of normal movements of the market, but when the market is suddenly moving to another regime facing a phase-locking phenomenon, the exposure becomes positive.

The other three strategies are related to the Event Driven categories. The exposures to the S&P 500 are positive and quite similar in different states of the market, especially for the Event Driven Multi-Strategy, which has a slightly higher exposure during the market downturn. Distressed security strategy presents a larger exposure in normal times. The Risk Arbitrage Strategy presents a positive exposure in the normal regime and when the market is rolling up and an almost zero exposure in the down-market regime.

In addition to showing that hedge fund exposure differs over various market regimes, a regime-switching framework allows us to calculate time-varying risk exposure of hedge funds implied by the data, i.e., time-varying betas with respect to various factors including the S&P 500 for various hedge fund strategies. Time-varying betas can be easily determined using equation 11 by assuming that k=0. This gives us the framework for analyzing time-varying risk exposures for hedge funds for different factors. Time-varying market risk betas are depicted for several hedge fund strategies in Figure 3.

[INSERT Figure (3) about here]

First, note that the market exposure changes over time for all strategies, confirming that hedge funds are implementing dynamic strategies. Figure 3 depicts the evolution of market betas for Hedge fund index, Long/Short Equity and Emerging Markets strategies. For the Hedge fund index and Long/Short Equity strategy, starting the middle of 2003, market exposure dramatically increased. For example, for the Combined Hedge fund index, the forecasted exposure in April 2003 was 0.07, seemingly market-neutral; however, exposure in March 2005 increased to 0.37, which is a significant positive market exposure. For the same time period, the exposure of the Long/Short Equity increased from 0.20 to 0.64, more than 3-fold.[9] It is interesting to note that in all these categories, the market beta is cyclical: it was increasing from 1994 through 1997, then it abruptly dropped and stayed low for 7 years, and started to increase in 2003. Similar behavior is also observed for Convertible Bond Arbitrage, Risk Arbitrage, Distressed, and Dedicated Shortseller (for this strategy, the exposure is increasing in the negative direction). This cyclical behavior in market beta can be largely attributed to the changes in market regimes over this time period.[10]

[9]Long/Short Equity strategy comprises majority of hedge funds represented in the Combined Hedge fund index.

[10]As stressed above, our analysis shows that in the first part of the sample, from July 1994 to December 1996, the S&P 500 returns are frequently characterized by the normal regime 1. The period from 1997

When volatility of the S&P 500 is high between 1997 and 2003, hedge funds in these strategies on average decrease their exposure to the market and increase when volatility of the market subsides (normal regime). Therefore, on average, when market volatility is high and changing, hedge funds reduce exposure.

On another hand, time-varying beta for the Emerging Markets category shows a different story. For the Emerging Markets category, from 1997 to 2003, the exposure fluctuates a lot, from 0.2 to 0.5. However, from the beginning of 2003 to the end of the data sample, the market exposure equilibrates at 0.41. The similar behavior is observed for Equity Market Neutral strategy and for the Event Driven Multi-Strategy.

In summary, hedge fund exposure depends on volatility regimes of the S&P 500. Moreover, the exposure to the S&P 500 index changes through time. Therefore, investors should take into account change in market volatility and how it affects hedge fund risk. Regulators should do stress testing with different market conditions and consider the implications for hedge fund behavior. This will contribute to the analysis of systemic risk.

This framework can be extended to calculating expected hedge fund exposures to different factors one month from now, 6 months from now, 1 year from now and so on. Our flexible approach allows us to calculate expected time-varying betas for $t + k$ periods by using specification 11.

Idiosyncratic risk presents different levels of volatility. Convertible Bond Arbitrage, Equity Market Neutral and Risk Arbitrage tend to have relatively low values of idiosyncratic volatility for both volatility regimes. The idiosyncratic volatility in the high volatility regime is always less than 2% for these strategies (Table 3). However, for the other five strategies, in both regimes, the idiosyncratic volatility is relatively high. The average idiosyncratic volatility for a high volatility regime for these strategies is about 4% at the monthly level. Moreover, high volatility regimes are persistent. This is more evident for Dedicated Shortseller, Emerging Markets, Equity Market Neutral and Long/Short Equity strategies. Controlling for idiosyncratic risk is important for investors in terms of portfolio risk and diversification, and for regulators in controlling spill-over effects that can propagate from the hedge fund idiosyncratic risk.

Nevertheless, other risk factors play a role as important as the S&P 500 in characterizing the time-varying hedge fund exposure. This aspect is investigated in the next section with a multifactor model.

---

through 2003 is characterized primarily by two other regimes: up-market and down-market. The last part of the sample from 2003 through 2005 is characterized by the normal regime.

3.2.3 Multifactor model

Multifactor model with non-linear exposure only to the S&P 500

As discussed above, other factors affect hedge fund index returns, and this calls for the use of a multifactor framework. We begin with a comprehensive set of risk factors that will be candidates for each of the risk models, covering stocks, bonds, currencies, commodities, emerging markets, momentum factor and volatility. These factors are presented in Table 4. They are also described by Chan et al. (2005) as relevant factors to be used for each hedge fund strategy. Given the limited dataset, we use a step-wise approach to limit the final list of factors for our analysis. Employing a combination of statistical methods and empirical judgement, we use these factors to estimate risk models for the 8 hedge fund indexes. In all our analyses, hedge fund returns, S&P 500, USD, Lehman Government Credit, Gold, MSCI Emerging Markets Bond Index, MSCI Emerging Markets Stocks Index and Momentum French factor are used in excess of LIBOR returns.

[INSERT Table (4) about here]

We first consider the model presented in equation (15) and the results for this model are contained in Table 5. Here, we are considering linear factors: Large-Small, Value-Growth, USD, Lehman Government Credit, Term Spread, change in VIX, Credit Spread, Gold, MSCI Emerging Markets Bond Index, MSCI Emergent Markets Stock Index, Momentum French factor and non-linear exposure to different states of the S&P 500.[11]

[INSERT Table (5) about here]

The number of factors F selected for each risk model varies from a minimum of 2 for Equity Market Neutral to a maximum of 8 for the Event Driven Multi-Strategy, not including the S&P 500 index. This pattern is plausible because the Event Driven Multi-Strategy by definition includes a broad set of strategies; hence a broad array of risk factors is needed to capture the variation in this category versus other categories.

The statistical significance of the factor loadings on the S&P 500 conditional on the different regimes is almost the same as the one obtained in the previous analysis with only the S&P 500 risk factor. The only main difference is the exposure of the Distressed strategy

[11] Large-Small and Value-Growth factors are constructed using Russell indexes.

in the up-market state to the S&P 500 and the exposure of the Emerging Markets strategy in the up-market and normal states to the S&P 500. This indicates that the analysis performed above is robust to the inclusion of other factors that may affect hedge index returns.

Regarding the Large Minus Small factor, we observe that this factor is relevant for almost all hedge fund strategies, the only exceptions are Equity Market Neutral and Emerging Markets strategies. The exposure to the Large Minus Small factor is negative for almost all hedge funds indexes (the only exception is the Dedicated Shortseller) suggesting that returns of these hedge indexes resemble those achieved by going long on small stocks and short on large stocks (as shown previously by Agarwal and Naik (2004) and Chan et al. (2005)). Another potential explanation is that this factor is capturing liquidity risk as highlighted by Amihud (2002) and Acharya et al. (2004). We consider this aspect later.

The hedge fund exposure to Value Minus Growth factor is positive for Convertible Bond Arbitrage, Dedicated Shortseller, Distressed, Event Driven Multi-Strategy and Risk Arbitrage.[12]

Credit spread is a common negative factor for five out of eight strategies. This is of great importance for regulators who are concerned about common risks among hedge funds. This is particulary relevant given the recent credit crisis and its effect on hedge funds (August 2007).

Change in VIX is only significant for 2 strategies. This is surprising given that hedge funds take bets on volatility. There could be two complementary reasons for this: (1) Switching in S&P 500 regimes based on mean and volatility already captures this exposure, and (2) Hedge funds take non-linear bets in volatility and thus the current linear change in VIX exposure does not capture the true underlying non-linear exposure. However, if the first reason were the only true reason, then change in VIX will be captured by OLS; however, it is not as will be shown in the robustness analysis. Therefore, later in the paper we introduce models with omitted factors to capture non-linearity in VIX exposure.

A detailed analysis of other factors is presented in Appendix 1 for each hedge fund strategy. The list of factors and hedge fund exposures to these factors is unique for each strategy; therefore, we are analyzing them one by one for each strategy.

Multifactor model with non-linear exposure to all factors

Finally, we estimate the multifactor model specified in equation (17) and the results are contained in Table 6. Here, we are considering non-linear exposure to factors: S&P 500,

[12] We also consider Fama and French "size" and "book-to-market" risk factors (Fama and French, 1993) and the results are similar. We prefer to use the Large-Small and Value-Growth Russell indexes because they are investable portfolios, following Chan et al. (2005).

Large-Small, Value-Growth, USD, Lehman Government Credit, Term Spread, change in VIX, Credit Spread, Gold, MSCI Emerging Markets Bond Index, MSCI Emerging Markets Stock Index and Momentum factor. The three coefficients that we estimate for each factor represent the non-linear factor exposure of hedge fund indexes to the three states of the S&P 500. Because of the limited dataset we only consider variables that are statistically significant in the previous multifactor linear exposure analysis. Clearly, the results may depend on this choice, thus later we relax this assumption and consider the possibility of a non-linear exposure to other risk factors as well (see section 4).

[INSERT Table (6) about here]

All strategies have exposure to the S&P 500 in at least one regime even after accounting for conditional exposure to other risk factors. Generally, we find that the model that accounts for different factors conditional on the state of the market is richer and captures more exposures compared to previous models. Moreover, the model shows that factor exposure is changing conditional on the state of the market. Finally, this model captures more of hedge fund return variation as is evidenced by a higher pseudo-R^2 for all hedge fund strategies compared to the one-factor model and the multifactor model with non-linear exposure only to the S&P 500.

For five out of eight strategies (Convertible Bond Arbitrage, Long/Short Equity, Distressed, Event-Driven Multi Strategy and Risk Arbitrage) our results suggests that hedge funds tend to hold illiquid or low-credit securities and thus are susceptible to liquidity crises.[13] We find that in all of these strategies, exposure to LS (Large-Small) is negative and highly significant during market downturn. In all these cases (except Long/Short Equity) the exposure is higher in absolute value compared to the exposure to LS during the normal market conditions.[14] Actually, for Convertible Bond Arbitrage, Event-Driven Multi-Strategy and Risk Arbitrage, the exposure to LS during normal market conditions is negligible. Overall, almost all hedge fund indexes have a significant exposure to the LS factor in at least two out of three states and especially during market downturn.

Furthermore, note that LS is the only common factor in the market downturn for six out of eight hedge funds strategies and for five out of eight it has the same sign. This

[13] For Dedicated Shortseller the exposure to LS is positive. The strategy makes money in the down-state of the market; therefore, the shock in the down-state will be beneficial for this strategy.

[14] The Long/Short Equity strategy is the only strategy compared, to the other four, which holds relatively liquid and higher-credit securities.

result suggests that this variable may potentially capture a common factor in the hedge fund industry. A potential explanation of this result is that liquidity risk is relevant for hedge funds and liquidity shocks are highly episodic and tend to be preceded by or associated with large and negative asset return shocks, whereby liquidity risk is rendered a particularly non-linear phenomenon. This result is in line with the potential interpretation of Acharya and Schaefer (2006) that the "illiquidity" prices in capital markets exhibit different regimes. In a normal regime, intermediaries, including hedge funds, are well capitalized and liquidity effects are minimal. In the "illiquidity" regime usually related to market downturns, intermediaries are close to their risk or collateral constraints and there is a "cash-in-the-market" pricing (Allen and Gale (1994, 1998)). In this framework, hedge funds, which often invest in derivatives and complex structured products, are more likely to be the marginal price setters and therefore more largely affected by the "illiquidity" regime.

Moreover, we find that another common risk factor for hedge funds is Credit Spread, especially the effect of the Credit Spread in the negative states of the market. For most of the strategies (Convertible Bond Arbitrage, Equity Market Neutral, Long/Short Equity, Distressed and Event-Driven Multi Strategy), the impact of the Credit Spread in the down-market regime on hedge fund index returns is negative.[15] The credit risk in the down-state of the market is the most important risk factor that should be controlled by regulators. Moreover, credit spread can also serve as a proxy for illiquidity risk. When credit spread increases, cost of capital increases and investors prefer to invest in more liquid and high-quality instruments. Therefore, low-credit illiquid investments suffer.

Furthermore, our analysis shows that many factor exposures are characterized by the phase-locking property. For example, the exposure to the S&P 500 is negligible during normal states of the market for the Convertible Bond Arbitrage, Equity Market Neutral, Event Driven Multi-Strategy and Risk Arbitrage, but changes to positive in up- and down-states of the market. Also, the exposure to Lehman Government Credit is negligible for Convertible Bond Arbitrage, Emerging Markets and Long/Short Equity indexes; however, it becomes highly positive and significant for up- and down-market states. The exposure to UMD is negligible in the normal state of the market for Emerging Markets, Long/Short Equity and Event Driven Multi-Strategy, but becomes highly positive and significant in the up- and down-states.

Nevertheless, the phase-locking phenomenon could be produced by dynamic strategies and/or a factor exposure of hedge fund asset portfolio that becomes statistically relevant only in certain states. With our approach we are not able to distinguish among the two

[15]The introduction of CS for the Equity Market Neutral strategy is in Section 4 and in Table 7 where we relax the assumption of factors chosen strictly by the step-wise linear analysis.

phenomena and simply capture the total exposure that arises from both dynamic strategies and asset portfolio non-linear exposures.

In Appendix 2 we consider each strategy separately and address time-varying risk exposures for various factors.

As a robustness check, we test whether statistically significant coefficients are also statistically different from each other. We investigate this aspect for different hedge fund indexes, and indeed for some coefficients we cannot reject the hypothesis that they are equal. Nevertheless, even if some of the estimated coefficients are similar, we are able to find that some of them are statistically equal only in two of the three states. This confirms that factor exposures change conditional on different states.

It is important to underline that our results may suffer due to data limitation. However, we still find convincing evidence that factor exposures are different for various factors conditional on the state of the market and for different hedge fund indexes. Moreover, the model shows that factor exposure is changing conditional on the volatility of the market risk factor. This confirms our initial hypothesis that the exposures to different risk factors are time-varying and conditional on the state of the market risk factor. Indeed, for many factors we observe that the risk exposure is zero during normal times, and suddenly becomes positive or of opposite sign during market downturns characterized by high volatility.

4 Omitted Factors

The step-wise linear approach was used to limit the final list of factors for the analysis in the multifactor models with linear and non-linear exposures (Tables 5 and 6). However, the step-wise linear analysis uses linear models and might miss several risk factors that can impact the return profile of hedge fund strategies.

Specifically, the step-wise linear analysis could miss exposures that are only present during market downturns, exposures related to liquidity events and low-probability events or exposures with different signs for different regimes. In this section we attempt to account for the omitted factors and perform several analyses of potential non-linear risk exposures not highlighted in previous sections. Specifically, we are considering factors that were originally eliminated by the step-wise linear procedure and are not considered in Tables 5 and 6.

Our analysis in Table 7 shows that the change in VIX is an omitted factor for most of the strategies. For these strategies VIX is important, as the return process of these strategies is related to market volatility. For example, convertible bonds contain imbedded equity call options that allow investors to convert the bonds into shares if the underlying share price rises.

[INSERT Table (7) about here]

Change in VIX is a variable that needs to be interpreted jointly with different regimes of the S&P 500. For the Convertible Bond Arbitrage strategy, the effect of Change in VIX is negative in crises markets (-0.08) and positive in up-markets (0.05).

The relationship between a convertible bond price and stock price is concave when stock price is low (down-market) and highly convex when the stock price is high (up-market). Therefore, in the up-market, we expect change in volatility to attribute to additional returns of the strategy, and in down-markets, the change in volatility negatively affects the returns of the strategy.

For Risk Arbitrage, the exposure to change in VIX is positive and significant, especially during normal periods (0.09), but negative during down-market periods (-0.12).

Risk Arbitrage strategy is concerned with the success of a merger, and increase in volatility in down-times often signals an increase in probability of failure. The same applies to Distressed strategies (-0.22 in down-state and 0.24 in the normal state).

Another example is the effect of change in VIX for the Dedicated Shortseller strategy. We find that the exposure to the change in VIX is highly positive only in the negative market state (0.27), but negative in all other states (-0.42 for up-state and -0.27 for normal state). In this case the exposure to the change in VIX is opposite to the other strategies, possibly due to the nature of the strategy that profits from negative volatility shocks to the market.

In all of these cases, exposures to the change in VIX have opposite signs and similar magnitudes for down and normal markets; and this is the main reason why linear factors are not able to capture this exposure.

Credit Spread and Term Spread were irrelevant factors for Equity Market Neutral strategy and were not considered in the models (Tables 5 and 6). In Table 7 we explicitly considered these factors. We find that in normal conditions, Credit Spread is irrelevant for Equity Market Neutral strategy. However, in downturns of the market, it is highly negative and significant (-1.75, t-stat: -2.39). This again confirms that credit risk is the common factor across different hedge fund strategies.

In the previous models, we found that neither LS nor change in VIX were relevant for the Emerging Markets strategy. However, after explicitly accounting for change in VIX for this strategy, we find that change in VIX is significant for the up-market and normal regime and exposure to the LS factor is negative and significant in normal and down-market periods.

In conclusion, we find that using linear models and a step-wise linear approach of narrowing down significant factors misses several factors for hedge fund analysis. On average, the effect of a factor can be negligible; however, this is due to lumping the effect of the factor instead of separately calculating exposures in up-market, down-market and normal states. We find that often exposures during normal and down-markets are of opposite signs, and often, the exposures during normal states are not significant from zero. Therefore, if we do not separate the factor effects into different market regimes, we underestimate the real hedge fund exposure to this factor.

We find that change in VIX is important for hedge fund strategies, and, specifically, the exposure of hedge fund strategies to the change in VIX is non-linear and depends on the state of the market. Moreover, we find that exposures to several factors, such as LS and Credit Spread, are highly negative for most of strategies in the down-market state. We argue that this exposure could be related to liquidity risk and credit risk, but a deep analysis of this issue is needed and is left to further investigation.

5 Idiosyncratic Risk Factor

In addition to the derivation of the expected market exposures, the switching regime beta model allows us to separate and show the evolution of the idiosyncratic risk of hedge funds. In particular, our estimation of the Markov chain for the idiosyncratic risk of hedge funds shows that the idiosyncratic risk is characterized by two different regimes with high and low volatility for 6 of the 8 strategies. Exceptions are Distressed and Dedicated Shortseller, which are always characterized by a large volatility regime (idiosyncratic volatility is 1.36% for Distressed and 2.31% for Dedicated Shortseller, Table 6). These monthly volatilities are in-line with high volatility regimes for other strategies. The volatility parameters in the two volatility regimes (high and low) are largely different, and the idiosyncratic risk factor of all 6 strategies shows that the volatility in the high regime is at least twice the volatility in the low volatility regime of the idiosyncratic risk (see in Table 6 for values of ϖ_0 and ϖ_1.)

The estimated probability of switching from one regime to another is on average about 10%, but the probability of remaining in the same regime is about 90%, meaning that volatility regimes are quite persistent.

The estimations of the coefficients and the evolution of the probability of being in the high volatility regime for the idiosyncratic risk factor are similar across three models described in equations 2, 13 and 17. This means that we are consistently estimating the idiosyncratic risk factor and it makes our results robust to different specifications. Therefore, we only depict results for the model described in equation 17.

Referring to the model estimation presented in Table 6, in Figures 4 and 5 we show the evolution of the probability of being in the high volatility regime for all 6 strategies.

[INSERT Figure(4) about here]

[INSERT Figure(5) about here]

Figures 4 and 5 plot monthly probabilities from January 1994 to March 2005 of hedge fund indexes facing a high volatility regime for the idiosyncratic risk factor, i.e., volatility of the hedge fund indexes not related to the volatility of the S&P 500 index and other risk factors. We see that the evolution of the volatility of different strategies is quite different. In particular, we observe that Long/Short Equity and Emerging Markets indexes present a low probability of being in the high volatility regime in the last part of the sample and a high probability in the middle of the sample that corresponds to the series of crises and rallies from 1997 till 2001. Therefore, the risk faced by the S&P 500 already captured by the switching beta is amplified in the middle of the sample for these strategies. This indicates not only that the link with the S&P 500 is changing, but also that the idiosyncratic risk of the hedge fund indexes may switch to the high-volatility regime at the same time when the market is characterized by turbulence. This can be explained by omitted or latent variables such as idiosyncratic liquidity risk or factors that affect mostly the hedge fund industry (as in the case of LTCM default). For example, Emerging Markets, Event Driven Multi-Strategy, Long/Short Equity and Risk Arbitrage are all related to different liquidity events more or less related to the LTCM crisis.

Event Driven Multi-Strategy is almost always characterized by the low volatility regime for its idiosyncratic risk factor; however, the probability of a high volatility regime greatly increases for periods characterized by high illiquidity events and other unexpected shocks not correlated with market returns. For example, in February 1994, the U.S. Federal Reserve started a tightening cycle that caught many hedge funds by surprise, causing significant dislocation in bond markets worldwide; the end of 1994 witnessed the start of the "Tequila Crisis" in Mexico; in August 1998, Russia defaulted on its government debt and LTCM collapsed leading to a liquidity crunch in worldwide financial markets; the first quarter of

2000 saw a crash of the Internet boom, and in the middle of 2002 there was a drying out of merger activities, a decrease in defaults and the release of news about WorldCom accounting problems. During all of these periods, the probability of a high volatility regime skyrocketed, reaching 1 for the LTCM and the Russian default crisis.

The most interesting indicator is the evolution of being in the high volatility regime by the Convertible Bond Arbitrage index that indicates that the strategy has moved to a large volatility regime from the end of 2003 and is still characterized by this regime at the end of the sample considered (March 2005). If we jointly consider the state of the market index (tranquil normal period in the last two years of the sample) and the state of the idiosyncratic risk factor for the Convertible Bond Arbitrage index, we see that the switching regime beta model is able to disentangle whether the source of risk is characterized by market conditions or by potential distress in the hedge fund index strategy. Not surprisingly, April 2005 (not in the sample period) saw extremely low returns and high liquidations in the Convertible Bond Arbitrage sector. Merely tracking market exposure will not lead to this predictive result.

We further explore the probability that all hedge fund strategies exhibit idiosyncratic risk in a high volatility regime. This could be interpreted as a proxy measure for contagion between different hedge fund strategies. Specifically, we calculate the joint filtered probability of being in a high volatility state for all hedge funds and plot them in Figure 6. We find that the joint filtered probability jumps from approximately 0% in May 1998 to 4% in June 1998 to 13% in July 1998 to 96% in August 1998, the month of the LTCM collapse. It started to subside in October 1998. The peak in the joint probability coincides with the liquidity crisis precipitated by the collapse of LTCM.[16] The results suggest that the LTCM crisis not only affected market risk factors, but also, after controlling for market and other factor exposures, affected idiosyncratic volatility of hedge funds. This provides evidence that even after accounting for market and other factor exposures, the LTCM crisis precipitated contagion across the hedge fund industry. In our data, we found that this was the only case where the joint probability of being in a high volatility state for all hedge funds spiked and approached one.

[INSERT Figure(6) about here]

[16]We check this result against a possibility that randomly we can have all eight strategies exhibiting high volatility regimes at the same time.

6 Robustness Analysis

6.1 Comparison with OLS Regression

In a multifactor setting, we consider the model presented in equation (15) and the results for this model are contained in Table 5.

The natural way to test the regime-switching model is to compare its results to those obtained using OLS regression. The results for the OLS regression are presented in Table 8. They are consistent, meaning, that factor loadings have the same sign in both models; however, the regime-switching model is clearly superior based on pseudo-R^2 metric.[17]

For each hedge fund index, pseudo-R^2 is larger for regime-switching models compared to OLS models. Moreover, several estimates that are significant in the regime-switching model are not significant for the OLS model. OLS is missing some factor exposure and does not take into account time-variability of risk factors based on market conditions.

[INSERT Table (8) about here]

6.2 Asymmetric Beta and Threshold Models

An alternative way to study time-varying non-linear hedge fund exposure to market factors is through an asymmetric beta model. In this model, the distribution of R_t is truncated either at the median or zero and betas for "up or down" markets are compared. This approach has been applied to hedge funds in Agarwal and Naik (2004), Mitchell and Pulvino (2001), Asness, Krail and Liew (2004) and Chan et al. (2005). The authors found significant differences between "up" and "down" betas. Specifically, they found Event-Driven types of strategies including Risk Arbitrage, Distressed and Event-Driven Multi-Strategy exhibit zero correlation with up-market conditions, but a large positive exposure during down-market conditions. Emerging Markets strategy shows a much higher down-market correlation compared to up-market. Moreover, authors find that the Equity-Market Neutral strategy has a

[17] It is important to note that a pseudo-R^2 only has meaning when compared to another pseudo-R^2 of the same type, on the same data, and predicting the same outcome. In this situation, a higher pseudo-R^2 indicates which model is preferable.

much higher up-market beta compared to the down-market beta. We replicate the analysis and find identical results in our analysis.[18]

We further extend the asymmetric beta model and develop a threshold model allowing for three states. Specifically, we look at asymmetric betas in hedge fund exposure by specifying different beta coefficients for down-markets, normal markets and up-markets. Specifically, consider the following regression:

$$R_{it} \; = \; \alpha_i \; + \; \beta_i^+ I_t^+ \; + \beta_i^0 I_t^0 \; + \; \beta_i^- I_t^- \; + \; \epsilon_{it} \tag{20}$$

where

$$I_t^+ = \begin{cases} I_t & \text{if } I_t > \mu + \sigma \\ 0 & \text{otherwise} \end{cases} \qquad I_t^0 = \begin{cases} I_t & \text{if } \mu - \sigma < I_t < \mu + \sigma \\ 0 & \text{otherwise} \end{cases} \qquad I_t^- = \begin{cases} I_t & \text{if } I_t \leq \mu + \sigma \\ 0 & \text{otherwise} \end{cases} \tag{21}$$

where I_t is the return on the index, μ is the mean and σ is its standard deviation.

Since $I_t = I_t^+ + I_t^0 + I_t^-$, the standard linear model in which fund i's market betas are identical in up and down-markets is a special case of the more general specification (20), the case where $\beta_i^+ = \beta_i^0 = \beta_i^-$. The specification (20) essentially tries to capture asymmetries in the index exposures.

Unlike the asymmetric model, a regime-switching model allows for endogenous definition of expected returns and volatilities defined from the data. The regime-switching model also does not switch as often as the asymmetric model. Moreover, the regime-switching model may include positive returns for the down-market state and negative returns for the up-market state.

Using the specification (20), we regress hedge fund returns on the S&P 500 index during up (I_t^+), normal (I_t^0) and down (I_t^-) conditions. The results are reported in Table 8. Beta asymmetries are quite pronounced especially, for Emerging Markets, Distressed, Event Driven Multi-Strategy and Risk Arbitrage. For example, the Distressed index has an up-market beta of 0.07 (not significant)—seemingly market neutral—however, its down-market beta is 0.38! The exposure of the Convertible Bond Arbitrage strategy to the S&P 500 is negligible for both up and down-markets; therefore, a more comprehensive model is needed to measure the exposure of this style.

[18] Results are not presented here but are available upon request.

[INSERT Table (8) about here]

The results using the threshold model are similar to the ones obtained using the regime-switching methodology presented in Table 3. However, there are several numerical differences. For example, the regime-switching methodology finds that the Market-Neutral strategy has market-neutral exposure in all states except an up-market state. However, the threshold methodology finds positive market exposure in up (I_t^+) and down (I_t^-) states. Regime-switching methodology also identifies a positive market exposure in the "up-market" state for the Emerging Markets strategy, whereas the threshold methodology misses this link.

Comparing (Table 9 and Table 5), we observe that regime-switching model fits data much better than the threshold or asymmetric beta models. For example, for all styles, pseudo-R^2 for regime-switching models exceeds pseudo-R^2 for threshold models, and in particular improves model fit for Convertible Bond Arbitrage, Equity Market Neutral and Event Driven Multi-Strategy. Therefore, the regime-switching models are able to capture linkages between hedge fund returns and the S&P 500 that are not possible to analyze by simply splitting past returns in different return quintiles. Moreover, asymmetric and threshold models have exogenous definitions of a state. On the other hand, regime-switching methodology allows for a flexible endogenous definition of a state and is able to categorize state distributions in terms of means and variances. This cannot been done with either asymmetric or threshold models. Based on this evidence, we conclude that regime-switching methodology is superior to threshold and asymmetric models for our analysis.

6.3 Data Smoothing and Illiquidity Effect

As shown by Getmansky et al. (2004), observed hedge fund returns are biased by performance smoothing and illiquidity, leading to autocorrelation of hedge fund returns on a monthly basis. Following the approach of Getmansky et al. (2004), we de-smooth returns using the following procedure:

Denote by R_t the true economic return of a hedge fund in period t, and let R_t satisfy the following single linear factor model:

$$R_t = \mu + \beta\Lambda_t + \epsilon_t \quad , \quad \mathrm{E}[\Lambda_t] = \mathrm{E}[\epsilon_t] = 0 \quad , \quad \epsilon_t \ , \ \Lambda_t \sim \text{IID} \tag{22a}$$

$$\mathrm{Var}[R_t] \equiv \sigma^2 \ . \tag{22b}$$

True returns represent the flow of information that would determine the equilibrium value of the fund's securities in a frictionless market. However, true economic returns are not observed. Instead, R_t^o denotes the reported or observed return in period t, and let

$$R_t^o = \theta_0 R_t + \theta_1 R_{t-1} + \cdots + \theta_k R_{t-k} \tag{23}$$

$$\theta_j \in [0,1] \ , \ j = 0, \ldots, k \tag{24}$$

$$1 = \theta_0 + \theta_1 + \cdots + \theta_k \tag{25}$$

which is a weighted average of the fund's true returns over the most recent $k+1$ periods, including the current period. Similar to the Getmansky et al. (2004) model, we estimate MA(2) model where k=2 using maximum likelihood method.

[INSERT Table (10) about here]

In line with this approach we determine R_t^o, i.e., "real returns" and estimate our models on the real returns. The results in Table 10 show that indeed there is evidence of data smoothing, but the estimated exposure to the different factors conditional on the states of the market are largely unaffected by the smoothing phenomenon.[19]

6.4 Single Hedge Funds Exposure

We investigate whether the exposures we observe on hedge fund indexes are in line with those we may find for single hedge funds in order to determine the degree of heterogeneity of hedge funds within each index and its effect on factor exposures. We randomly select different hedge funds for all categories and repeat all analyses described in the paper. Results show that exposures of single hedge funds to various factors are in line with index exposures.[20]

[19]We also estimate the following model for real returns and compare the estimates using the observed returns: $R_t = \alpha(Z_t) + \beta(S_t)I_t + \sum_{k=1}^{K} \theta_k F_{kt} + \omega(Z_t)u_t, I_t = \mu(S_t) + \sigma(S_t)\epsilon_t$. We also show that there is indeed evidence of data smoothing; however, the estimated exposure to different factors is largely not affected by smoothing. Results are available on request.

[20]Detailed results for all models and for all individual hedge funds in each category are available upon request.

6.5 Normality of Residuals Test

One of the reasons for introducing a regime-switching approach is to address non-normality in observed hedge fund index returns. If a regime-switching approach accurately describes the return process of hedge fund indexes, then we expect residuals in the regime-switching models to be normally distributed. Therefore, we implement Jarque-Bera test, which is a goodness-of-fit measure of departure from normality, based on the sample kurtosis and skewness.[21]

[INSERT Table (11) about here]

Table 11 presents results for the Jarque-Bera normality tests. In the original data, normality test was rejected for all strategies except the Market Neutral strategy.[22] We observe that for 4 of hedge fund indexes normality test is rejected for a linear model like OLS. Therefore, residuals in the OLS regression are normally distributed for four strategies.

We then consider the residuals obtained with the regime-switching methodology. We analyze the residuals of two models: a multifactor model with non-linear exposure only to the S&P 500 factor presented in equation (15) for which results are contained in Table 5, and a multifactor model with non-linear exposure to all factors presented in equation (17) for which results are presented in Table 6. There is an improvement using the regime-switching model based only on the S&P 500 factor loading (normality test is rejected for 3 out of 8 strategies). Moreover, even if we observe a rejection of normality, based on p-values, there is a strong improvement in the direction of normality, i.e., Jarque-Bera statistic is lower than for residuals obtained from the original data and the OLS model in all cases. We see a great improvement in normality of residuals for the more elaborate model which accounts for non-linearity in all factors (equation (17)). Normality is accepted for 6 out of 8 strategies. Therefore, based on the improvement in normality in our results, we show that regime-switching models are able to capture non-linear properties of original hedge fund index series. Nevertheless, there is still space for improvement, since for two hedge funds strategies normality test is still rejected.

[21] The Jarque-Bera (JB) test statistic is defined as $JB = \frac{n-k}{6}(S^2 + \frac{(K-3)^2}{4})$, where S is the skewness, K is the kurtosis, n is the number of observations, and k is the number of estimated coefficients used to create the series. The statistic has an asymptotic chi-squared distribution with two degrees of freedom and can be used to test the null hypothesis that the data are from a normal distribution.

[22] Market Neutral strategy is the oldest hedge fund strategy. This investment strategy aims to produce almost the same profit regardless of market circumstances, often by taking a combination of long and short positions. It is not designed to use options or other non-linear instruments.

7 Out-of-Sample Analysis of Hedge Fund Risk Exposure

In this section we conduct an out-of-sample analysis of hedge fund risk exposures.

Hedge fund risk exposures were estimated in-sample, and the validity of these risk exposures is analyzed in out-of-sample data of 2 years.

If risk exposures do not underlie the true return generating processes of hedge funds, then the out-of-sample analysis of hedge fund returns and risk using in-sample risk exposures will not conform with reality. However, if risk exposures estimated in-sample represent the true economic risks of various hedge fund strategies, then these risk exposures can indeed track the out-of-sample returns and risk of hedge fund strategies. Moreover, we calculate VaR for each hedge fund strategy and evaluate the ability of our multifactor regime-switching beta (MRSB) model to capture negative tail risks for these hedge fund strategies.

7.1 Out-of-sample Mimicking Performance

In order to access the validity of our risk model, we follow the approach introduced by Agarwal and Naik (2004). Specifically, we construct a replicating portfolio for each hedge fund index strategy using the factor loadings obtained from our multifactor regime-switching beta model (MRSB). We compute the difference between the monthly return on the hedge fund index and that of the replicating portfolio. Specifically, at each time t, factor loadings are estimated, and are combined with the value of the risk factors at $t+1$ to construct returns of the replicating portfolio.[23]

We use an out-of-sample of 24 observations (from November 2004 to October 2006) and therefore this procedure is repeated 24 times. We further conduct standard tests on the significance of the mean difference between the actual hedge fund index returns and replicated portfolios. Specifically, we calculate a model performance measure: Mean Absolute Error (MAE). We use this measure to compare the following models: OLS, Random Walk (RW), multifactor regime-switching beta (MRSB), and multifactor regime-switching beta estimated on "real" hedge fund index returns that are adjusted for autocorrelation (MRSB_AR). We report the results in Table 12 Panel A.

[INSERT Table (12) Panel A about here]

[23]The information set for the risk factors uses $t+1$ information in order not to introduce estimation errors in the value of risk factors. Thus, we estimate conditionally on risk factor data.

We find that for all the eight strategies considered either the MSRB or the MSRB-AR have smaller MAE compared to OLS and RW models. This provides evidence that the portfolio based on risk exposures estimated through regime-switching models does a better job in replicating hedge fund returns during the out-of-sample period compared to OLS and RW models. This suggests that regime-switching models are able to capture the dominant systematic risk exposures of hedge funds.

7.2 Negative tail risk exposure

A second out-of-sample analysis that we perform in this section highlights the ability of the regime-switching approach to account for negative tail risk and therefore downside risk. In line with the recommendation of the Basel Committee on Banking Supervision (1995, 2006) and current practice, we use the Value at Risk (VaR) to measure downside risk.

7.2.1 VaR definition

Value-at-Risk is a measure of market risk for a portfolio of financial assets. In its general formulation, VaR is the measure of the level of loss that a portfolio W could lose, with a given degree of confidence a, over a given time horizon h. Analytically it can be formulated as follows:

$$Pr[W_{t+h} - W_t < -VaR_W(h)] = a \tag{26}$$

where W_t is the portfolio value at time t, and $VaR_W(h)$ is the VaR value of the portfolio W with a time horizon of h. The confidence level $(1 - a)$ is typically chosen to be at least 95% and often as high as 99% and more (a equal to 5% or 1%, respectively). It is possible to express the VaR measure in terms of return of the portfolio instead of portfolio value. Analytically it can be formulated as follows:

$$Pr[R_{W_{t+h}} < -VaR_R(h)] = a \tag{27}$$

where $R_{W_{t+h}}$ is the portfolio return at time $t+h$ and $VaR_R(h)$ is the VaR value of portfolio return R_W with a time horizon of h. Statistically, VaR estimation corresponds to a specific quantile of a portfolio's potential loss distribution over a given holding period. Let us assume that $R_{W_t} \sim f_t$, where f_t is a general return distribution. For each model m (i.e., OLS and MSRB), the VaR for time $t+h$, conditional on the information available at time t

is estimated.[24] We denote this VaR estimate as $VaR_m(h,a)$, which corresponds to the point in $f_{m,t+h}$ return distribution at its lower a percent tail. That is, $VaR_m(h,a)$ is the solution to:

$$\int_{-\infty}^{VaR_m(h,a)} f_{m,t+h}(x)dx = a \tag{28}$$

In our framework, the key aspect we would like to highlight is the ability of regime-switching models to capture tail risk rather than measure the size of this risk. For this reason, if risk exposures estimated in-sample represent the true economic risks of various hedge fund strategies, then these risk exposures can indeed account for the out-of-sample losses (downside risk), i.e., the maximum loss the strategy can generate at a certain confidence level. As before, we concentrate the out-of-sample analysis on factor loadings and idiosyncratic risk and assume that factor values are known. We thus perform VaR analysis conditional on the information available at time t for factor loadings and distribution of idiosyncratic risk and on information at $t+1$ for the value of the factors. We follow Billio and Pelizzon (2000) to calculate VaR.[25] For OLS we use the factor loadings to determine the mean and standard errors of the residuals of the model to calculate standard deviation. For each month in the 24 months of out-of-sample data, VaR estimates are calculated. Table 12 presents the average of these VaR estimates.

[INSERT Table (12) about here]

We consider three confidence levels 95%, 99% and 99.5%. As the table shows, the VaR levels are quite different for various strategies and may differ quite a bit between Multifactor Regime-Switching Beta (MRSB) and OLS models. One key aspect that needs to be considered is that the numbers shown are averages and therefore are not capturing the dynamic risk evolution trough time. To account for time-varying property of VaR, we depict the evolution of VaR for one strategy: Emerging Markets for the two models (MRSB and OLS).

[INSERT Figure (7) about here]

[24] As in the construction of the replicating portfolios, the information set for the risk factors uses $t+1$ information. Therefore, we work conditionally on risk factor data.

[25] More precisely, we estimate the model with data till t and use the forecasting probability Prob $(S_{t+1}|\mathcal{R}_t)$ to obtain the factor loading and the distribution of the idiosyncratic risk.

As Figure 7 shows, the Multifactor Regime-Switching Beta (MRSB) model closely captures downside risk of the strategy compared to the OLS model.[26] Moreover, this model is able to take into account the impact of the idiosyncratic risk factor on the downside risk of the hedge fund strategy.[27]

Overall, out-of-sample forecasting tests confirm the economic importance of accounting for the presence of market regimes in determining hedge funds risk exposure.

8 Conclusion

In this paper we characterized the exposure of hedge fund indexes to risk factors using switching regime beta models. This approach allows us to analyze time-varying risk exposure and the phase-locking phenomenon for hedge funds. In particular, the changes in hedge fund exposure to various risk factors explicitly account for the change in volatility of the market risk factor.

We have three main results. First, hedge funds exhibit significant non-linear exposure not only to the market risk factor but also to Fama and French's (1993) size and value factors, bonds, currencies, commodities, volatility, credit and term spreads. In particular, we show that exposures can be strongly different in the down-market and up-market regimes compared to normal times, suggesting that risk exposures of hedge funds in the down-market regimes are quite different than those faced during normal regimes. Moreover, many risk factor exposures can only be captured with the switching regime analysis because for many factors the exposures exhibit a phase-locking characteristic where in the normal regime the exposure is zero and in market downturn it is statistically different than zero or there is a change in the sign of the exposure.

Second, we find that Credit Spread, Large-Small and change in VIX are common hedge fund factors in the down-state of the market, suggesting that these factors are important in accessing hedge fund risk especially in the down-state of the market. Specifically, in the market downturn regime six out of eight strategies are all negatively and significantly exposed to the Large-Small risk factor (this represents 84% of hedge funds in the sample). This feature is important in light of the results of Acharya and Petersen (2005) that the size risk factor is capturing liquidity risk. Moreover, considering that liquidity shocks are highly episodic and tend to be preceded by or associated with large and negative asset return shocks, our results indeed suggest that liquidity is a risk factor for hedge fund returns and

[26]Other strategies show qualitatively similar results.

[27]The determination of the minimum return with a certain confidence level determined by OLS is rather static and is primarily driven by the standard deviation of the standard errors.

needs further investigation.

Third, the extension of the regime switching model to allow for non-linearity in residuals suggests that switching regime models are able to capture and forecast the evolution of the idiosyncratic risk factor in terms of changes from a low volatility regime to a distressed state not directly related to market risk factors. In particular, our analysis shows that the Convertible Bond Arbitrage distress observed recently is not related to a particular regime of the market index or some other systemic risk factor, but to a switch in the volatility of the idiosyncratic risk factor for this category. Our sample does not include the period of distress in the Convertible Bond Arbitrage strategy; however, the model forecasted that in the beginning of 2004 this strategy would enter a challenging period, characterized by an increased volatility.

Moreover, we have allowed for a possibility and found evidence that all hedge fund strategies exhibit idiosyncratic risk in a high volatility regime during the sample considered. We find that for almost all of the sample the joint probability of high idiosyncratic volatility for all hedge funds is approximately zero, but there are three months among the 135 considered where we find that the joint probability that all hedge funds are in the high idiosyncratic volatility regime is close to 1: at the LTCM crash. This provides evidence that even after accounting for market and other factor exposures, the LTCM crisis precipitated contagion across the hedge fund industry. This is the only crisis event that generated this result, even though the market was characterized by other crises in the sample considered.

Finally, we find that the regime switching approach explains the data better than the asymmetric or the threshold beta approach largely used in the literature and it is robust even after controlling for the data smoothing and illiquidity effects.

The main goal of the paper is to analyze hedge fund risk. We provide a robust framework that can be used by investors and regulators to assess this risk. The framework can be used by investors for portfolio allocation and risk assessment, portfolio construction, risk management, and benchmark design. Regulators, on the other hand, can use this framework for stress testing and endogenously consider the effect of switching volatility of market factor and switching volatility of idiosyncratic risk on the overall risk hedge fund industry may face. Regulators are particularly interested in identifying common risk factors, especially in the down-state of the market. Our analysis suggests that they can use this framework to create “early warning indicators” for potential changes in risk exposure of hedge funds and increase in volatility of the hedge fund industry. This can help address regulators’ concern regarding the potential risk hedge funds may pose for stability of financial markets.

References

Acharya V. and S. Schaefer, 2006, "Liquidity Risk and Correlation Risk: Implications for Risk Management," London Business School Working Paper.

Acharya V. and H. Pedersen, 2005, "Asset Pricing with Liquidity Risk," *Journal of Financial Economics* 77, 2, 375–410.

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

Allen F. and D. Gale, 1994, "Liquidity Preference, Market Participation and Asset Price Volatility," *American Economic Review* 84, 933–955.

Allen F. and D. Gale, 1998, "Optimal Financial Crisis," *Journal of Finance* 53, 1245–1284.

Almazan, A. Brown, K., Carlson, M. and D. Chapman, 2004, "Why Constrain Your Mutual Fund Manager," *Journal of Financial Economics* 73, 289–321.

Amihud, Y., 2002, "Illiquidity and Stock Returns: Cross-section and Time-series Effects," *Journal of Financial Markets* 5, 31–56.

Ang, A. and G. Bekaert, 2002, "International Asset Allocation With Regime Shifts," *The Review of Financial Studies* 15, 4, 1137–1187.

Asness, C., Krail, R. and J. Liew, 2001, "Do Hedge Funds Hedge?," *The Journal of Portfolio Management* 28, 6–19.

Basel Committee on Banking Supervision, 1995, "An Internal Model-Based Approach to Market Risk Capital Requirements," Basel.

Basel Committee on Banking Supervision, 2006, "International Convergence of Capital Measurements and Capital Standards: A Revised Framework," Basel.

Bali, T., Gokcan, S. and B. Liang, 2007, "Value at Risk and the Cross-Section of Hedge Fund Returns," *Journal of Banking and Finance* 30, 4, 1135-1166.

Bekaert, G. and C. Harvey, 1995, "Time-Varying World Market Integration," *The Journal of Finance* 50, 2, 403–444.

Billio, M. and L. Pelizzon, 2000, "Value-at-Risk: A Multivariate Switching Regime Approach," *Journal of Empirical Finance* 7, 531–554.

Billio, M. and L. Pelizzon, 2003, "Volatility and Shocks Spillover Before and After EMU in European Stock Markets," *Journal of Multinational Financial Management* 13, 323–340.

Bollen, N. and R. Whaley, 2007, "Hedge Fund Risk Dynamics: Implications for Performance Appraisal," Vanderbilt University Working Paper.

Boyson, N., Stahel, C. and R. Stulz, 2006, "Is There Hedge Fund Contagion?," Northeastern University Working Paper.

Brealey, R. and E. Kaplanis, 2001, "Hedge Funds and Financial Stability: An Analysis of Their Factor Exposures," *Journal of International Finance* 4, 2, 161–187.

Brooks, C. and G. Persand, 2001, "The Trading Profitability of Forecasts of the Gilt-Equity Yield Ratio," *Journal of International Forecasting* 17, 11–29.

Chan, N., Getmansky, M., Haas, S. and A. Lo., 2005, "Systemic Risk and Hedge Funds," *NBER Book On Risks of Financial Institutions, Topic: Systemic Risk.*

Dueker, M. and C.J. Neely, 2004, "Can Markov Switching Models Predict Excess Foreign Exchange Returns?" Federal Reserve Bank of St. Louis Working Paper 2001-021B.

Edwards, F. and M. Caglayan, 2001, "Hedge Fund Performance and Manager Skill," *Journal of Futures Markets* 21, 1003-1028.

Fama, E. and K. French, 1993, "Common Risk Factors in the Returns on Stocks and Bonds," *Journal of Financial Economics* 33, 1 3–56.

Fung, W. and D. Hsieh, 1997, "Empirical Characteristics of Dynamic Trading Strategies: The Case of Hedge Funds," *Review of Financial Studies* 10, 275–302.

Fung, W. and D. Hsieh, 2000, "Performance Characteristics of Hedge Funds and Commodity Funds: Natural versus Spurious Biases," *Journal of Financial and Quantitative Analysis* 35, 291–307.

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

Getmansky, M., Lo, A. and I. Makarov, 2004, "An Econometric Analysis of Serial Correlation and Illiquidity in Hedge-Fund Returns," *Journal of Financial Economics* 74, 3, 529–610.

Goetzmann, W., Ingresoll, J., Spiegel, M. and I. Welch, 2007, "Portfolio Performance Manipulation and Manipulation-Proof Performance Measures," *Review of Financial Studies* Forthcoming.

Guidolin, M. and A., Timmermann, 2006, "International Asset Allocation under Regime Switching, Skew and Kurtosis Preferences," mimeo, Federal Reserve Bank of St. Louis Working Paper 2005-018A.

Gupta, A. and B. Liang, 2005, "Do Hedge Funds Have Enough Capital? A Value at Risk Approach," *Journal of Financial Economics* 77, 219–253.

Hamilton, J., 1989, "A New Approach to the Economic Analysis of Nonstationary Time Series and the Business Cycle," *Econometrica* 57, 357–384.

Hamilton, J., 1990, "Analysis of Time Series Subject to Changes in Regime," *Journal of Econometrics* 45, 39–70.

Hamilton, J., 1994, Time Series Analysis, New Jersey: Princeton University Press.

Huber, P. J., 1981, Robust Statistics, New York: Wiley.

Hwang, S. and S. Satchell, 2007, "The Disappearance of Style in U.S. Equity Market," *Applied Financial Economics* 17, 8, 597–613.

Koski, J. L. and J. Pontiff, 1999, "How Are Derivatives Used? Evidence from the Mutual Fund Industry," *Journal of Finance*, 54, 2, 791–816.

Lettau, M., Ludvigson, S. and J. Wachter, 2007, "The Declining Equity Premium: What Role Does Macroeconomic Risk Play?," *Review of Financial Studies* Forthcoming.

McFadden, P., 1974, "The Measure of Urban Travel Demand," *Journal of Public Economics* 303–328.

Mitchell,M. and T. Pulvino, 2001, "Characteristics of Risk and Return in Risk Arbitrage," *The Journal of Finance* 56, 6, 2135-2175.

Schneeweis, T., Karavas, V. and G. Georgiev, 2002, "Alternative Investments in the Institutional Portfolio," University of Massachusetts, Amherst Working Paper.

Sharpe, W. F., 1992, "Asset Allocation: Management Style and Performance Measurement," *Journal of Portfolio Management* 18, 2, 7–19.

White, H., 1982, "Maximum Likelihood Estimation of Misspecified Models," *Econometrica* 50, 1–25.

Table 1: **Summary Statistics**

This table presents summary statistics for monthly CSFT/Tremont hedge-fund index returns as well as for the S&P 500 returns from January 1994 to March 2005. All returns are in excess of a risk-free rate. N is the number of observations, $\beta_{S\&P500}$ is contemporaneous market beta, Ann. Mean is annualized mean return, Ann. SD is annualized standard deviation. Min, Med and Max are annualized minimum, median and maximum returns. Skew measures skewness and Kurt measures kurtosis. JB Stat. is the Jarque-Bera statistics with a corresponding p-value.

Strategy	N	$\beta_{S\&P500}$	Ann. Mean	Ann. SD	Min	Med	Max	Skew	Kurt	JB Stat.	p-value
Conv. Bond Arb	135	0.04	3.24	4.71	-5.29	0.59	3.04	-1.43	6.63	119.96	0.00
Dedicated Shortseller	135	-0.89	-6.48	17.63	-9.29	-0.95	22.06	0.83	4.84	34.58	0.00
Emerging Markets	135	0.54	3.12	16.97	-23.68	0.83	15.92	-0.65	7.13	105.21	0.00
Equity Mkt Neutral	135	0.07	4.08	2.94	-1.68	0.33	2.68	0.14	3.32	1.02	0.60
Long/Short Equity	135	0.41	6.12	10.50	-12.08	0.43	12.5	0.19	6.7	77.64	0.00
Distressed	135	0.24	7.32	6.69	-13.1	0.79	3.58	-2.88	20.67	1942.12	0.00
Event Driven MS	135	0.19	4.68	6.17	-12.17	0.45	4.15	-2.72	20.51	1891.51	0.00
Risk Arb	135	0.12	2.16	4.26	-6.8	0.19	3.19	-1.4	9.95	315.67	0.00
S&P 500	135	1.00	5.52	15.10	-15.09	0.97	9.25	-0.59	3.47	9.05	0.01

Figure 1: **Unconditional and Conditional Distributions of the S&P 500 in 3 Regimes**

The first panel describes unconditional distribution of the S&P 500 as a mixture of the down-market, up-market and normal regimes. The second panel describes the distribution of the S&P 500 conditional on the down-market regime. There are 3 states of the market: regime 0 is an up-market regime, regime 1 is a normal regime and regime 2 is a down-market regime.

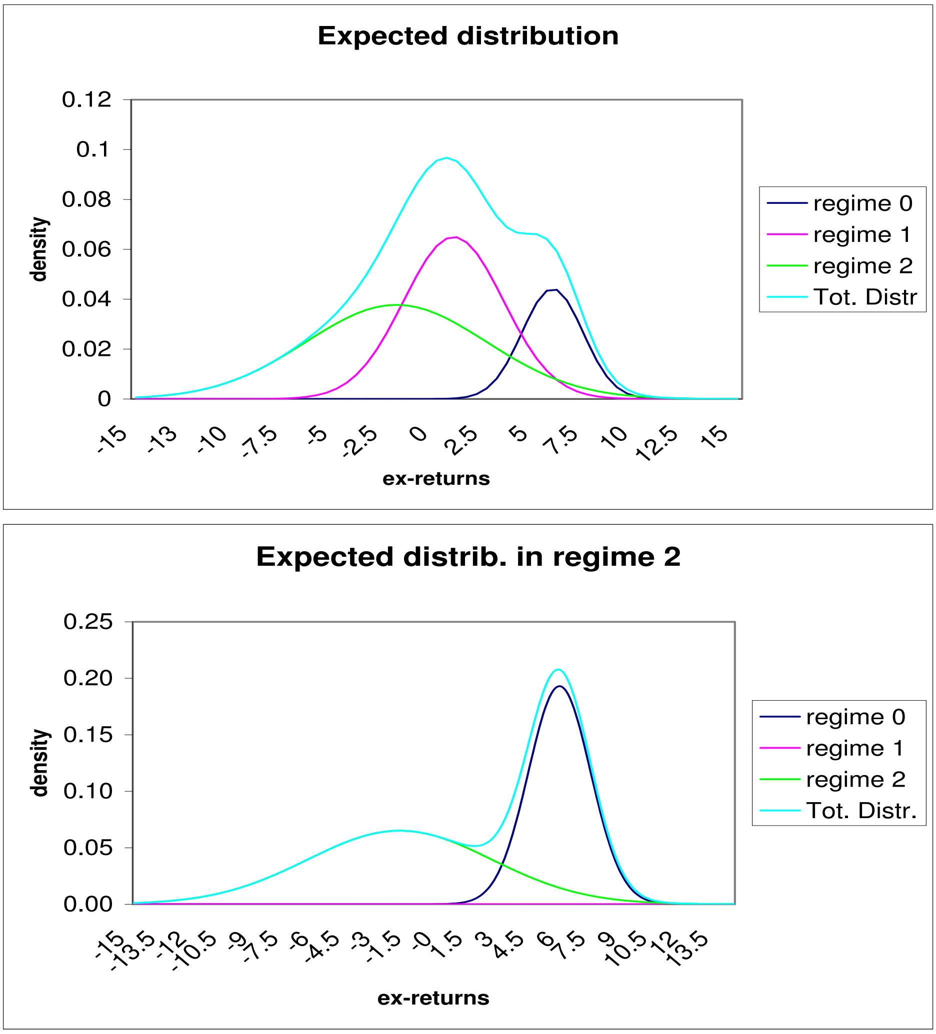
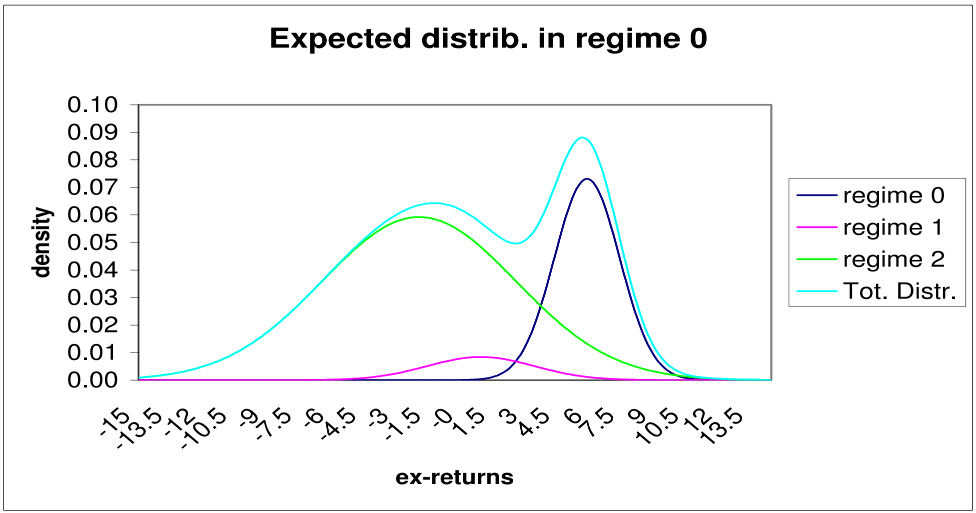


Figure 2: **Conditional Distributions of the S&P 500 in 3 Regimes**

The first panel describes the distribution of the S&P 500 conditional on the up-market regime. The second panel describes the distribution of the S&P 500 conditional on the normal regime. There are 3 states of the market: regime 0 is an up-market regime, regime 1 is a normal regime and regime 2 is a down-market regime.



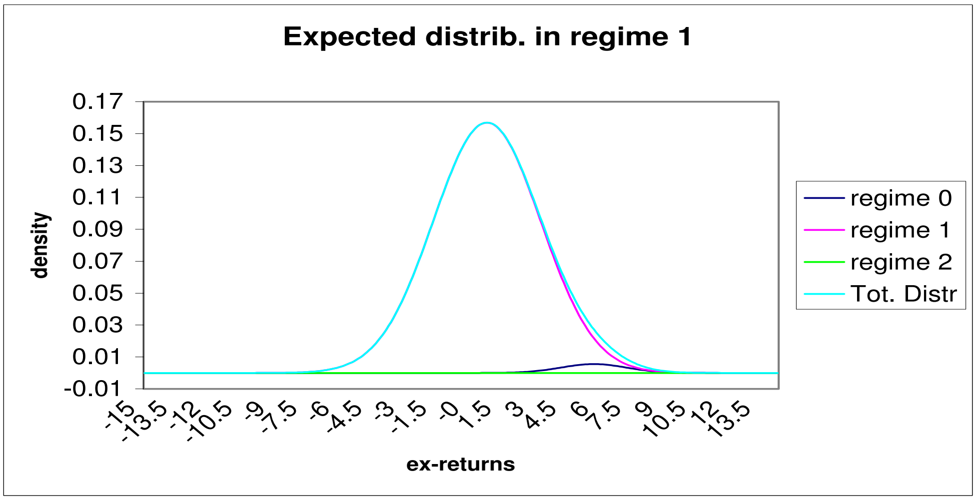


Figure 3: **Evolution of Market Betas**

The figures present the evolution of market betas for Hedge fund index, Long/Short Equity and Emerging Markets strategies from January 1994 to March 2005. Market is defined as the S&P 500.

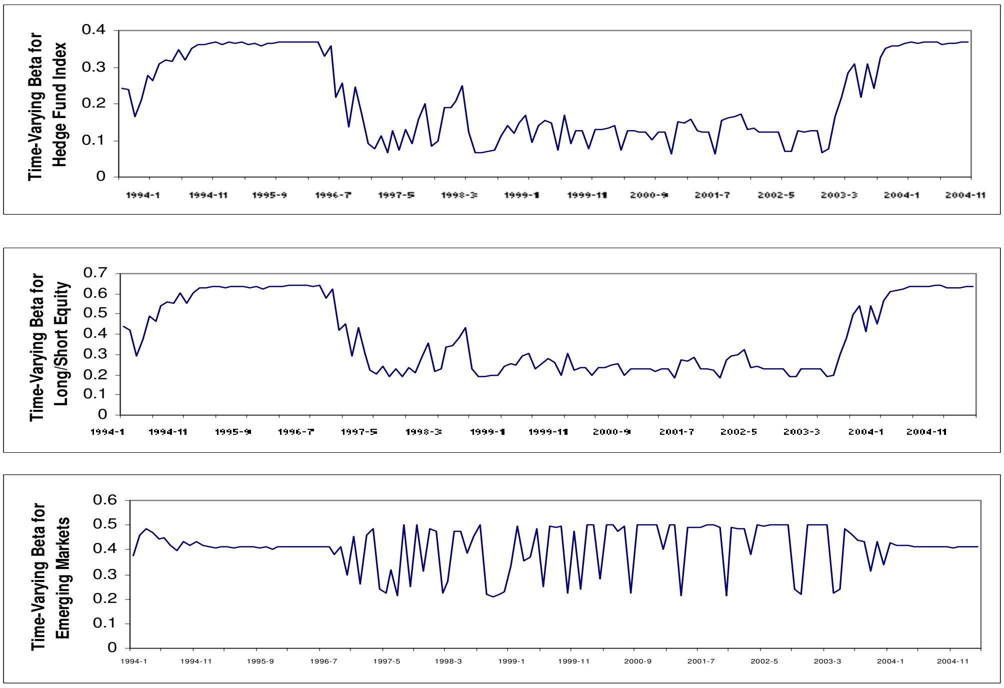


Table 2: **Regime-Switching Model for the Market Risk Factor, S&P 500**

This table presents the results for the regime-switching model for the market risk factor, S&P 500. The following model is estimated: I_t=$\mu(S_t)$+$\sigma(S_t)\epsilon_t$, where μ_i and σ_i are mean and standard deviation of regime i, respectively. There are three regimes that are estimated: regime 0 (up-market), regime 1 (normal) and regime 2 (down-market). The frequency of S&P 500 regimes from 1994 to 2005 is calculated. The 3X3 matrix of transition probabilities is estimated (P_{ij} is the transition probability of moving from regime i to regime j). Parameters that are significant at the 10% level are shown in bold type.

Mean (%)

Regime 0 (μ_0)		Regime 1 (μ_1)		Regime 2 (μ_2)	
Estimate	t-stat	Estimate	t-stat	Estimate	t-stat
5.79	**15.22**	**0.85**	**2.53**	**-2.02**	**-2.25**

Standard Deviation (%)

Regime 0 (σ_0)		Regime 1 (σ_1)		Regime 2 (σ_2)	
Estimate	t-stat	Estimate	t-stat	Estimate	t-stat
1.52	**12.80**	**2.49**	**25.74**	**4.51**	**29.46**

Frequency of S&P500 regimes from 1994-2005 (%)

Regime 0	Regime 1	Regime 2
18%	**40%**	**42%**

Transition Probabilities

	Regime 0	Regime 1	Regime 2
Regime 0	**0.28**	0.05	**0.67**
Regime 1	0.02	**0.98**	0.00
Regime 2	**0.26**	0.00	**0.74**

Table 3: **One-Factor Model**

This table presents the exposure of the CSFB/Tremont hedge-fund index strategies to different S&P 500 regimes. The following model is estimated: $R_t{=}\alpha(Z_t){+}\beta(S_t)I_t{+}\omega(Z_t)u_t$. I_t is the market factor, S&P 500. S_t is the Markov Chain for the S&P 500. I_t is characterized by 3 states (regime 0: up-market, regime 1: normal and regime 2: down-market). Each state of the market index I has its own mean and variance: $I_t{=}\mu(S_t){+}\sigma(S_t)\ \epsilon_t$. u_t is IID, ω is volatility of the idiosyncratic risk factor, which is characterized by the Markov Chain Z_t. The Z_t Markov Chain has two states (state 0: low volatility and state 1: high volatility of idiosyncratic risk factor). p^z_{00} and p^z_{11} are transition probabilities of staying in state 0 (1) given state 0 (1) of the idiosyncratic risk factor. Parameters that are significant at the 10% level are shown in bold type.

Variable/ Strategy	Convertible Bond Arb		Dedicated Shortseller		Emerging Markets		Equity Market Neutral	
	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat
α_0	**0.75**	**7.28**	**0.32**	**11.95**	**1.12**	**4.78**	**0.31**	**4.37**
α_1	**-0.57**	**-2.79**	-0.13	-0.48	-0.09	-0.16	0.16	1.10
β_0 (SP)	0.02	0.84	**-0.67**	**-43.38**	0.16	1.56	**0.11**	**3.42**
β_1 (SP)	0.06	1.48	**-1.26**	**-61.16**	**0.41**	**2.80**	0.07	1.62
β_2 (SP)	-0.02	-0.92	**-0.78**	**-238.32**	**0.50**	**8.57**	0.03	1.50
ω_0	**0.51**	**9.17**	**0.04**	**5.77**	**1.63**	**10.50**	**0.58**	**19.90**
ω_1	**1.75**	**8.93**	**3.37**	**16.60**	**5.27**	**15.21**	**0.97**	**14.82**
p^Z_{00}	**0.88**		**0.37**		**0.98**		**0.99**	
p^Z_{11}	**0.83**		**0.97**		**1.00**		**1.00**	
PseudoR^2	0.10		0.12		0.09		0.07	

Variable/ Strategy	Long/Short Equity		Distressed		Event Driven Multi-Strategy		Risk Arb	
	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat
α_0	-0.10	-0.88	**0.68**	**6.73**	**0.52**	**6.27**	**0.21**	**2.58**
α_1	**1.09**	**2.29**	**-3.84**	**-81.92**	-3.99	-1.43	-0.25	-0.64
β_0 (SP)	**0.18**	**2.30**	**0.09**	**1.76**	**0.14**	**2.35**	**0.09**	**2.48**
β_1 (SP)	**0.64**	**12.71**	**0.37**	**9.26**	**0.14**	**2.71**	**0.14**	**3.39**
β_2 (SP)	**0.23**	**4.49**	**0.13**	**3.22**	**0.17**	**3.99**	**0.06**	**1.67**
ω_0	**1.24**	**13.71**	**1.18**	**22.59**	**1.13**	**26.56**	**0.68**	**12.30**
ω_1	**3.88**	**8.74**	**3.78**	**2.73**	**3.44**	**2.32**	**1.85**	**4.63**
p^Z_{00}	**0.99**		**0.98**		**0.99**		**0.89**	
p^Z_{11}	**0.97**		**0.51**		**0.77**		**0.66**	
PseudoR^2	0.13		0.12		0.12		0.08	

Table 4: **Variable Definitions**

This table presents definitions of market and other risk factors used in multifactor models. All variables except Change in VIX and Momentum Factor are obtained using Datastream. Change in VIX is obtained from the CBOE. Momentum Factor is obtained from Ken French's website.

Variable	Abbreviation	Definition
S&P500	SP	Monthly return of the S&P 500 index including dividends
Large-Small	LS	Monthly return difference between Russell 1000 and Russell 2000 indexes
Value-Growth	VG	Monthly return difference between Russell 1000 Value and Growth indexes
USD	USD	Monthly return on Bank of England Trade Weighted Index
Lehman Government Credit	L.GC	Monthly return of the Lehman U.S. Aggregated Government/Credit index
Term Spread	TS	10-year T Bond minus 6-month LIBOR
Change in VIX	dVIX	Monthly change in implied volatility based on the CBOE's OEX options.
Credit Spread	CS	The difference between BAA and AAA indexes provide by Moody's
Gold	Gold	Monthly return using gold bullion $/Troy Oz. Price
MSCI Emerging Bond	MSCIEmD	Monthly return of the MSCI Emerging Markets Bond Index
MSCI Emerging Stock	MSCIEMS	Monthly return of the MSCI Emerging Markets Stock Index
Momentum Factor	UMD	Momentum factor

Table 5: **Multifactor Model with Non-Linear Exposure Only to S&P 500**

This table presents the exposure of the CSFB/Tremont hedge-fund index strategies to the S&P 500 (SP) in different S&P 500 regimes and other risk factors: Large-Small (LS), Value-Growth (VG), USD, Lehman Government Credit (L.GC), Term Spread (TS), Change in VIX (dVIX), Credit Spread (CS), Gold, MSCI Emerging Bond (MSCIEMD), MSCI Emerging Stock (MSCIEMS) and Momentum Factor (UMD). The following model is estimated: $R_t{=}\alpha(Z_t){+}\beta(S_t)I_t{+}\sum_{k=1}^{K}\theta_k F_{kt}{+}\omega(Z_t)u_t$. I_t is the market factor, S&P 500 and F_{kt} are other risk factors. S_t is the Markov Chain for the S&P 500. I_t is characterized by 3 states (regime 0: up-market, regime 1: normal and regime 2: down-market). Each state of the market index I has its own mean and variance: $I_t{=}\mu(S_t){+}\sigma(S_t)\ \epsilon_t$. u_t is IID, ω is volatility of the idiosyncratic risk factor, which is characterized by the Markov Chain Z_t. The Z_t Markov Chain has two states (state 0: low volatility and state 1: high volatility of idiosyncratic risk factor). p^z_{00} and p^z_{11} are transition probabilities of staying in state 0 (1) given state 0 (1) of the idiosyncratic risk factor. Hedge fund returns, S&P 500, USD, Lehman Government Credit and Gold are used in excess of LIBOR returns. Panel A presents results for the Convertible Bond Arbitrage, Dedicated Shortseller, Emerging Markets and Equity Market Neutral strategies. Panel B presents results for the Long/Short Equity, Distressed, Event Driven Multi-Strategy and Risk Arbitrage strategies. Parameters that are significant at the 10% level are shown in bold type.

Panel A

Variable/ Strategy	Convertible Bond Arb		Dedicated Shortseller		Emerging Markets		Equity Market Neutral	
	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat
α_0	**0.79**	**11.39**	0.11	0.69	**0.45**	**2.79**	**0.27**	**2.32**
α_1	**-0.38**	**-2.06**			0.52	1.51	0.22	1.21
β_0 (SP)	**0.04**	**1.89**	**-0.87**	**-7.98**	0.04	0.37	**0.09**	**2.81**
β_1 (SP)	0.01	0.38	**-1.09**	**-10.44**	-0.14	-1.42	0.03	0.59
β_2 (SP)	0.01	0.64	**-0.77**	**-7.39**	0.10	1.16	0.00	0.16
θ_1 (LS)	**-0.05**	**-4.11**	**0.47**	**7.35**				
θ_2 (VG)	**0.05**	**4.66**	**0.24**	**5.33**				
θ_3 (USD)			**0.33**	**3.62**	**0.26**	**2.78**		
θ_4 (L.GC)	**0.13**	**4.16**			**0.49**	**3.06**	**0.08**	**1.95**
θ_5 (TS)					**0.64**	**3.62**		
θ_6 (dVIX)								
θ_7 (CS)	**-1.79**	**-4.43**	**-0.73**	**-211.82**				
θ_8 (Gold)								
θ_9 (MSCIEMD)			**0.25**	**2.49**				
θ_{10} (MSCIEMS)					**0.44**	**8.42**	**0.03**	**2.08**
θ_{11} (UMD)					**0.12**	**1.90**		
ω_0	**0.34**	**8.52**	**2.47**	**22.09**	**1.07**	**5.03**	**0.56**	**15.13**
ω_1	**1.66**	**10.79**			**3.57**	**12.42**	**0.96**	**9.55**
p^Z_{00}	**0.85**				**0.98**		**0.99**	
p^Z_{11}	**0.85**				**1.00**		**1.00**	
PseudoR^2	0.13		0.18		0.20		0.08	

Panel B

Variable/ Strategy	Long/Short Equity		Distressed		Event Driven Multi-Strategy		Risk Arb	
	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat
α_0	**-0.16**	**-1.86**	**0.73**	**5.73**	**0.58**	**6.87**	0.05	0.72
α_1	0.63	1.24			-3.04	-1.64	**0.48**	**2.48**
β_0 (SP)	**0.59**	**10.10**	0.08	1.52	**0.19**	**4.72**	**0.09**	**2.79**
β_1 (SP)	**0.51**	**11.24**	**0.30**	**4.89**	**0.11**	**2.05**	**0.15**	**3.11**
β_2 (SP)	**0.48**	**11.51**	**0.39**	**3.20**	**0.16**	**3.52**	**0.17**	**4.58**
θ_1 (LS)	**-0.35**	**-9.81**	**-0.18**	**-4.72**	**-0.11**	**-4.98**	**-0.14**	**-6.96**
θ_2 (VG)			**0.11**	**2.36**			**0.07**	**3.90**
θ_3 (USD)					**0.24**	**3.54**		
θ_4 (L.GC)	**0.23**	**3.53**	**0.23**	**2.95**				
θ_5 (TS)	**-0.31**	**-2.71**						
θ_6 (dVIX)	**0.12**	**3.49**			**0.09**	**4.35**		
θ_7 (CS)	**-2.25**	**-2.55**	**-2.69**	**-2.14**	**-1.24**	**-17.81**		
θ_8 (Gold)								
θ_9 (MSCIEMD)			**-0.13**	**-1.75**	**0.12**	**1.72**		
θ_{10} (MSCIEMS)					**0.09**	**5.51**		
θ_{11} (UMD)	**0.17**	**8.18**			**0.04**	**3.26**		
ω_0	**1.03**	**23.51**	**1.37**	**12.09**	**0.86**	**16.91**	**0.74**	**17.01**
ω_1	**2.57**	**6.21**			**2.99**	**4.15**	**1.29**	**5.78**
p^Z_{00}	**0.99**				**0.98**		**0.99**	
p^Z_{11}	**0.94**				**0.64**		**0.96**	
PseudoR^2	0.25		0.11		0.20		0.13	

Table 6: **Multifactor Model with Non-Linear Exposure to All Factors**

This table presents the non-linear exposure of the CSFB/Tremont hedge-fund index strategies to the S&P 500 (SP), Large-Small (LS), Value-Growth (VG), USD, Lehman Government Credit (L.GC), Term Spread (TS), Change in VIX (dVIX), Credit Spread (CS), Gold, MSCI Emerging Bond (MSCIEMD), MSCI Emerging Stock (MSCIEMS) and Momentum Factor (UMD) for different S&P 500 regimes. The following model is estimated: $R_t = \alpha(Z_t) + \beta(S_t)I_t + \sum_{k=1}^{K}\theta_k(S_t)F_{kt} + \omega(Z_t)u_t$. I_t is the market factor, S&P 500 and F_{kt} are other risk factors. Regime 0: up-market, regime 1: normal and regime 2: down-market. Parameters that are significant at the 10% level are shown in bold type.

Panel A

Variable/ Strategy	Convertible Bond Arb		Dedicated Shortseller		Emerging Markets		Equity Market Neutral	
	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat
α_0	**0.75**	**12.44**	-0.23	-1.13	0.31	1.60	**0.29**	**4.86**
α_1	**-0.35**	**-1.74**			**0.66**	**2.12**	0.16	1.46
β_0 (SP)	**0.05**	**2.18**	**-0.88**	**-8.54**	0.01	0.04	**0.10**	**2.30**
β_1 (SP)	0.05	0.85	**-0.88**	**-8.85**	**-0.31**	**-2.79**	0.06	1.08
β_2 (SP)	0.01	0.73	**-0.80**	**-5.97**	**0.17**	**2.28**	-0.01	-0.56
θ_{1_0} (LS)	-0.03	-1.08	0.24	1.62				
θ_{1_1} (LS)	0.00	0.01	**0.86**	**8.72**				
θ_{1_2} (LS)	**-0.09**	**-4.78**	**0.45**	**4.90**				
θ_{2_0} (VG)	**0.07**	**2.26**	-0.03	-0.23				
θ_{2_1} (VG)	0.04	0.61	**0.70**	**4.11**				
θ_{2_2} (VG)	**0.06**	**5.49**	**0.23**	**2.71**				
θ_{3_0} (USD)			0.54	1.64	**0.69**	**2.45**		
θ_{3_1} (USD)			-0.19	-0.95	-0.06	-0.42		
θ_{3_2} (USD)			0.21	1.57	**0.37**	**5.72**		
θ_{4_0} (L.GC)	**0.17**	**2.74**			**1.57**	**4.96**	0.19	1.47
θ_{4_1} (L.GC)	0.03	0.26			0.12	0.56	0.11	1.34
θ_{4_2} (L.GC)	**0.14**	**2.70**			**0.48**	**1.75**	0.02	0.31
θ_{5_0} (TS)					**2.01**	**7.91**		
θ_{5_1} (TS)					**0.59**	**1.94**		
θ_{5_2} (TS)					0.52	1.44		
θ_{6_0} (dVIX)								
θ_{6_1} (dVIX)								
θ_{6_2} (dVIX)								
θ_{7_0} (CS)	**-2.01**	**-112.86**	**1.75**	**5.09**				
θ_{7_1} (CS)	**1.12**	**73.38**	**-5.98**	**-18.30**				
θ_{7_2} (CS)	**-2.72**	**-50.07**	3.50	1.16				
θ_{8_0} (Gold)								
θ_{8_1} (Gold)								
θ_{8_2} (Gold)								
θ_{9_0} (MSCIEMD)			**-0.44**	**-1.78**				
θ_{9_1} (MSCIEMD)			-0.09	-0.72				
θ_{9_2} (MSCIEMD)			0.12	0.96				
θ_{10_0} (MSCIEMS)					**0.66**	**4.41**	0.03	0.83
θ_{10_1} (MSCIEMS)					**0.58**	**4.76**	0.01	0.16
θ_{10_2} (MSCIEMS)					**0.38**	**7.18**	**0.04**	**2.46**
θ_{11_0} (UMD)					**0.17**	**2.25**		
θ_{11_1} (UMD)					-0.08	-1.31		
θ_{11_2} (UMD)					**0.16**	**4.34**		
ω_0	**0.31**	**6.20**	**2.31**	**14.91**	**0.96**	**5.35**	**0.57**	**21.38**
ω_1	**1.70**	**9.37**			**3.41**	**12.04**	**0.97**	**14.17**
p^Z_{00}	**0.85**				**0.98**		**0.99**	
p^Z_{11}	**0.85**				**1.00**		**1.00**	
PseudoR^2	0.18		0.23		0.23		0.10	

Panel B

Variable/ Strategy	Long/Short Equity		Distressed		Event Driven Multi-Strategy		Risk Arb	
	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat
α_0	**-0.15**	**-2.59**	**0.69**	**14.35**	**0.50**	**6.44**	-0.03	-0.16
α_1	**0.68**	**16.13**			**-2.95**	**-10.35**	**0.21**	**1.92**
β_0 (SP)	**0.73**	**8.96**	**0.12**	**2.12**	**0.28**	**5.21**	**0.14**	**3.24**
β_1 (SP)	**0.58**	**13.04**	**0.26**	**4.27**	0.08	1.40	0.12	1.33
β_2 (SP)	**0.38**	**9.67**	**0.39**	**3.26**	**0.11**	**2.04**	**0.21**	**3.41**
θ_{1_0} (LS)	**-0.61**	**-7.62**	**-0.21**	**-5.86**	**-0.13**	**-3.77**	-0.12	-1.59
θ_{1_1} (LS)	**-0.40**	**-5.63**	**-0.13**	**-2.73**	0.01	0.20	**-0.10**	**-1.91**
θ_{1_2} (LS)	**-0.27**	**-5.60**	**-0.18**	**-2.34**	**-0.12**	**-3.92**	**-0.20**	**-3.83**
θ_{2_0} (VG)			**0.14**	**1.81**			**0.18**	**3.01**
θ_{2_1} (VG)			0.01	0.19			-0.13	-1.17
θ_{2_2} (VG)			0.12	1.61			**0.11**	**2.23**
θ_{3_0} (USD)					**0.11**	**1.71**		
θ_{3_1} (USD)					**0.22**	**3.25**		
θ_{3_2} (USD)					0.05	0.66		
θ_{4_0} (L.GC)	**0.12**	**2.32**	**0.52**	**4.29**				
θ_{4_1} (L.GC)	0.11	1.11	**0.13**	**2.43**				
θ_{4_2} (L.GC)	**0.35**	**3.61**	**0.23**	**1.83**				
θ_{5_0} (TS)	**-0.62**	**-1.72**						
θ_{5_1} (TS)	**-0.48**	**-2.94**						
θ_{5_2} (TS)	0.01	0.05						
θ_{6_0} (dVIX)	**0.28**	**4.28**			**0.25**	**7.76**		
θ_{6_1} (dVIX)	**0.13**	**2.61**			0.07	1.31		
θ_{6_2} (dVIX)	-0.02	-0.51			0.03	0.73		
θ_{7_0} (CS)	**3.52**	**167.44**	**-5.35**	**-262.94**	**-0.34**	**-15.77**		
θ_{7_1} (CS)	**-0.86**	**-80.03**	**-6.42**	**-1727.59**	**-3.50**	**-69.20**		
θ_{7_2} (CS)	**-3.30**	**-457.00**	**-1.17**	**-552.60**	**-0.76**	**-5.58**		
θ_{8_0} (Gold)								
θ_{8_1} (Gold)								
θ_{8_2} (Gold)								
θ_{9_0} (MSCIEMD)			**-0.46**	**-4.54**				
θ_{9_1} (MSCIEMD)			0.07	0.86				
θ_{9_2} (MSCIEMD)			**-0.13**	**-1.77**				
θ_{10_0} (MSCIEMS)					**0.08**	**1.93**		
θ_{10_1} (MSCIEMS)					**0.09**	**2.83**		
θ_{10_2} (MSCIEMS)					**0.08**	**3.07**		
θ_{11_0} (UMD)	**0.24**	**4.75**			**0.04**	**1.84**		
θ_{11_1} (UMD)	-0.07	-1.41			0.05	1.15		
θ_{11_2} (UMD)	**0.16**	**4.78**			0.02	1.35		
ω_0	**0.91**	**25.44**	**1.36**	**7.93**	**0.79**	**18.65**	**0.42**	**6.58**
ω_1	**2.45**	**7.72**			**2.74**	**4.85**	**0.96**	**16.00**
p^Z_{00}	**0.99**				**0.98**		**0.95**	
p^Z_{11}	**0.94**				**0.66**		**1.00**	
PseudoR^2	0.31		0.15		0.25		0.17	

Table 7: **Multifactor Model with Omitted Factors**

This table adds omitted factors to the results in Table 6, where the non-linear exposure of the CSFB/Tremont hedge-fund index strategies to S&P 500 (SP), Large-Small (LS), Value-Growth (VG), USD, Lehman Government Credit (L.GC), Term Spread (TS), Change in VIX (dVIX), Credit Spread (CS), Gold, MSCI Emerging Bond (MSCIEMD), MSCI Emerging Stock (MSCIEMS) and Momentum Factor (UMD) for different S&P 500 regimes is analyzed. The following model is estimated: $R_t = \alpha(Z_t) + \beta(S_t)I_t + \sum_{k=1}^{K} \theta_k(S_t)F_{kt} + \omega(Z_t)u_t$. I_t is the market factor, S&P 500 and F_{kt} are other risk factors. Regime 0: up-market, regime 1: normal and regime 2: down-market. Parameters that are significant at the 10% level are shown in bold type.

Panel A

Variable/ Strategy	Convertible Bond Arb		Dedicated Shortseller		Emerging Markets		Equity Market Neutral	
	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat
α_0	**0.77**	**11.25**	-0.16	-0.75	0.09	0.83	**0.32**	**6.06**
α_1	**-0.38**	**-2.05**			**0.54**	**1.72**	-0.07	-0.36
β_0 (SP)	**0.07**	**2.21**	**-1.02**	**-8.01**	0.34	1.58	**0.14**	**2.25**
β_1 (SP)	0.05	0.87	**-1.01**	**-9.47**	**-0.28**	**-4.65**	0.07	1.64
β_2 (SP)	-0.03	-1.12	**-0.57**	**-4.83**	-0.02	-0.19	-0.01	-0.49
θ_{1_0} (LS)	-0.02	-0.94	**0.27**	**1.75**	0.14	0.88	0.04	0.66
θ_{1_1} (LS)	0.01	0.32	**0.99**	**9.78**	**-0.08**	**-2.02**	-0.02	-0.69
θ_{1_2} (LS)	**-0.08**	**-4.65**	**0.37**	**5.05**	**-0.17**	**-2.47**	0.01	0.33
θ_{2_0} (VG)	**0.07**	**2.18**	**-0.25**	**-2.07**				
θ_{2_1} (VG)	0.06	0.89	**0.73**	**4.08**				
θ_{2_2} (VG)	**0.07**	**4.49**	**0.27**	**4.04**				
θ_{3_0} (USD)			**1.42**	**2.44**	**0.89**	**2.90**		
θ_{3_1} (USD)			-0.36	-1.42	0.03	0.46		
θ_{3_2} (USD)			0.12	0.29	-0.01	-0.03		
θ_{4_0} (L.GC)	**0.14**	**1.71**						
θ_{4_1} (L.GC)	0.00	-0.05						
θ_{4_2} (L.GC)	**0.13**	**2.81**						
θ_{5_0} (TS)							-0.29	-1.29
θ_{5_1} (TS)							**0.22**	**1.68**
θ_{5_2} (TS)							0.18	1.52
θ_{6_0} (dVIX)	**0.05**	**1.79**	**-0.42**	**-2.69**	**0.58**	**3.82**	0.08	1.40
θ_{6_1} (dVIX)	-0.04	-1.20	**-0.27**	**-2.22**	**0.17**	**2.52**	**0.09**	**2.39**
θ_{6_2} (dVIX)	**-0.08**	**-2.98**	**0.27**	**2.15**	-0.03	-0.20	**-0.06**	**-1.69**
θ_{7_0} (CS)	**-2.02**	**-12.07**	-1.97	-0.26	-7.56	-0.81	-0.41	-0.18
θ_{7_1} (CS)	**0.40**	**4.59**	**-4.96**	**-8.54**	-1.99	-1.25	-1.85	-1.34
θ_{7_2} (CS)	**-2.57**	**-7.06**	3.29	0.92	-3.66	-0.85	**-1.75**	**-2.39**
θ_{8_0} (Gold)								
θ_{8_1} (Gold)								
θ_{8_2} (Gold)								
θ_{9_0} (MSCIEMD)			**1.10**	**1.75**				
θ_{9_1} (MSCIEMD)			-0.42	-1.53				
θ_{9_2} (MSCIEMD)			0.19	0.55				
θ_{10_0} (MSCIEMS)					**0.55**	**3.16**		
θ_{10_1} (MSCIEMS)					**0.50**	**14.08**		
θ_{10_2} (MSCIEMS)					**0.57**	**7.06**		
θ_{11_0} (UMD)								
θ_{11_1} (UMD)								
θ_{11_2} (UMD)								
ω_0	**0.31**	**5.72**	**2.22**	**21.14**	**0.70**	**11.84**	**0.54**	**14.01**
ω_1	**1.61**	**10.80**			**3.01**	**16.47**	**1.15**	**7.72**
p^Z_{00}	**0.85**				**0.99**		**0.98**	
p^Z_{11}	**0.86**				**0.99**		**0.96**	
PseudoR^2	0.19		0.24		0.28		0.14	

Panel B

Variable/ Strategy	Long/Short Equity		Distressed		Event Driven Multi-Strategy		Risk Arb	
	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat
α_0	**-0.15**	**-2.59**	**0.63**	**6.20**	**0.50**	**6.44**	**-0.18**	**-2.10**
α_1	**0.68**	**16.13**			**-2.95**	**-10.35**	**0.26**	**2.08**
β_0 (SP)	**0.73**	**8.96**	**0.18**	**2.73**	**0.28**	**5.21**	**0.14**	**2.55**
β_1 (SP)	**0.58**	**13.04**	**0.36**	**9.94**	0.08	1.40	**0.16**	**3.75**
β_2 (SP)	**0.38**	**9.67**	**0.22**	**3.60**	**0.11**	**2.04**	**0.08**	**2.03**
θ_{1_0} (LS)	**-0.61**	**-7.62**	**-0.23**	**-5.13**	**-0.13**	**-3.77**	**-0.15**	**-2.43**
θ_{1_1} (LS)	**-0.40**	**-5.63**	**-0.19**	**-3.91**	0.01	0.20	**-0.12**	**-4.67**
θ_{1_2} (LS)	**-0.27**	**-5.60**	**-0.13**	**-1.81**	**-0.12**	**-3.92**	**-0.17**	**-7.05**
θ_{2_0} (VG)			**0.17**	**4.71**			**0.16**	**3.16**
θ_{2_1} (VG)			**0.05**	**1.95**			0.05	0.81
θ_{2_2} (VG)			0.09	1.37			**0.07**	**2.56**
θ_{3_0} (USD)					**0.11**	**1.71**		
θ_{3_1} (USD)					**0.22**	**3.25**		
θ_{3_2} (USD)					0.05	0.66		
θ_{4_0} (L.GC)	**0.12**	**2.32**	**0.48**	**3.12**				
θ_{4_1} (L.GC)	0.11	1.11	**0.22**	**2.44**				
θ_{4_2} (L.GC)	**0.35**	**3.61**	**0.23**	**2.13**				
θ_{5_0} (TS)	**-0.62**	**-1.72**						
θ_{5_1} (TS)	**-0.48**	**-2.94**						
θ_{5_2} (TS)	0.01	0.05						
θ_{6_0} (dVIX)	**0.28**	**4.28**	0.04	0.73	**0.25**	**7.76**	0.01	0.14
θ_{6_1} (dVIX)	**0.13**	**2.61**	**0.24**	**4.93**	0.07	1.31	**0.09**	**1.90**
θ_{6_2} (dVIX)	-0.02	-0.51	**-0.22**	**-1.97**	0.03	0.73	**-0.12**	**-1.92**
θ_{7_0} (CS)	**3.52**	**167.44**	**-5.22**	**-1975.22**	**-0.34**	**-15.77**	**4.45**	**1.73**
θ_{7_1} (CS)	**-0.86**	**-80.03**	**-5.71**	**-2457.87**	**-3.50**	**-69.20**	-0.85	-0.85
θ_{7_2} (CS)	**-3.30**	**-457.00**	**-1.07**	**-450.18**	**-0.76**	**-5.58**	-0.25	-0.33
θ_{8_0} (Gold)								
θ_{8_1} (Gold)								
θ_{8_2} (Gold)								
θ_{9_0} (MSCIEMD)			**-0.48**	**-7.10**				
θ_{9_1} (MSCIEMD)			-0.07	-1.11				
θ_{9_2} (MSCIEMD)			-0.09	-0.92				
θ_{10_0} (MSCIEMS)					**0.08**	**1.93**		
θ_{10_1} (MSCIEMS)					**0.09**	**2.83**		
θ_{10_2} (MSCIEMS)					**0.08**	**3.07**		
θ_{11_0} (UMD)	**0.24**	**4.75**			**0.04**	**1.84**		
θ_{11_1} (UMD)	-0.07	-1.41			0.05	1.15		
θ_{11_2} (UMD)	**0.16**	**4.78**			0.02	1.35		
ω_0	**0.91**	**25.44**	**0.07**	**10.74**	**0.79**	**18.65**	**0.50**	**11.65**
ω_1	**2.45**	**7.72**			**2.74**	**4.85**	**0.98**	**12.62**
p^Z_{00}	**0.99**				**0.98**		**0.99**	
p^Z_{11}	**0.94**				**0.66**		**0.99**	
$PseudoR^2$	0.31		0.16		0.25		0.18	

Figure 4: **Probability of Being in a High-Volatility State of the Idiosyncratic Risk Factor for CA, EM, and EM Strategies**

These figures depict the probability of being in a high-volatility state of the idiosyncratic risk factor for Convertible Bond Arbitrage, Emerging Markets and Equity Market Neutral strategies from January 1994 to March 2005.

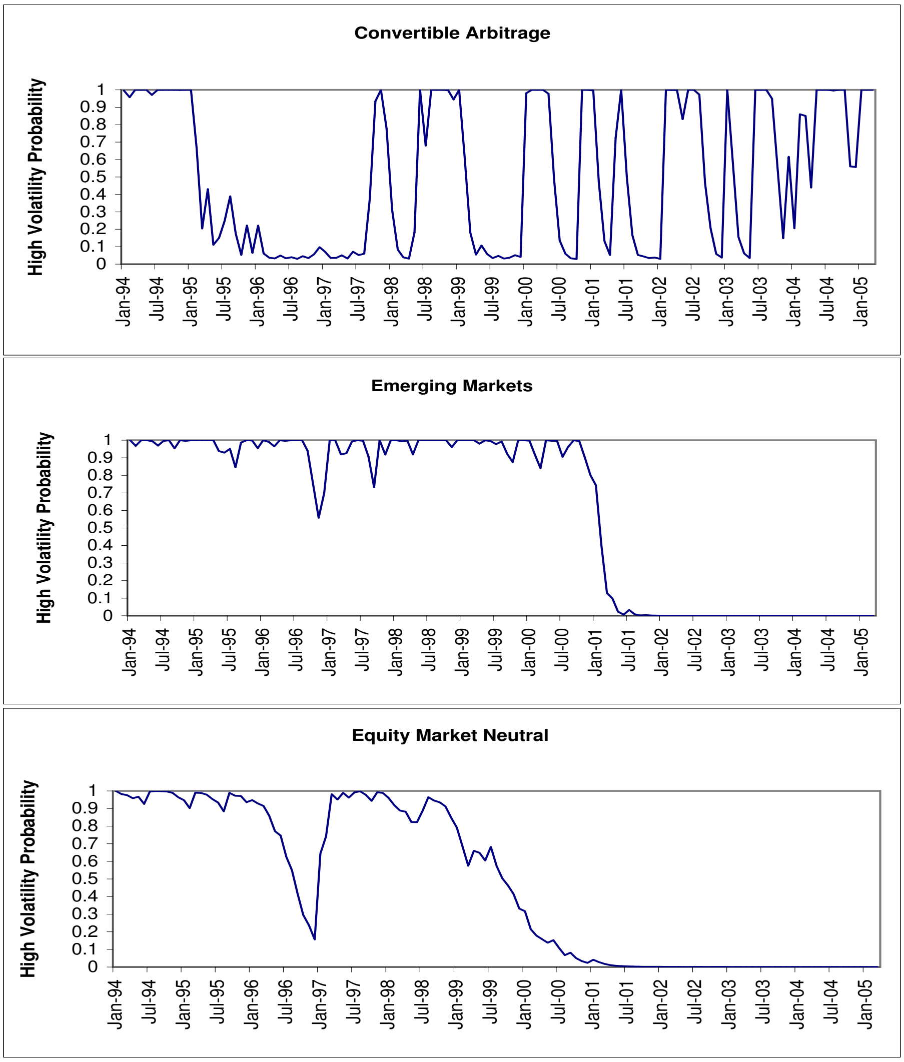


Figure 5: **Probability of Being in a High-Volatility State of the Idiosyncratic Risk Factor for LS, ED and RA Strategies**

These figures depict the probability of being in a high-volatility state of the idiosyncratic risk factor for Long/Short Equity, Event Driven Multi-Strategy and Risk Arbitrage strategies from January 1994 to March 2005.

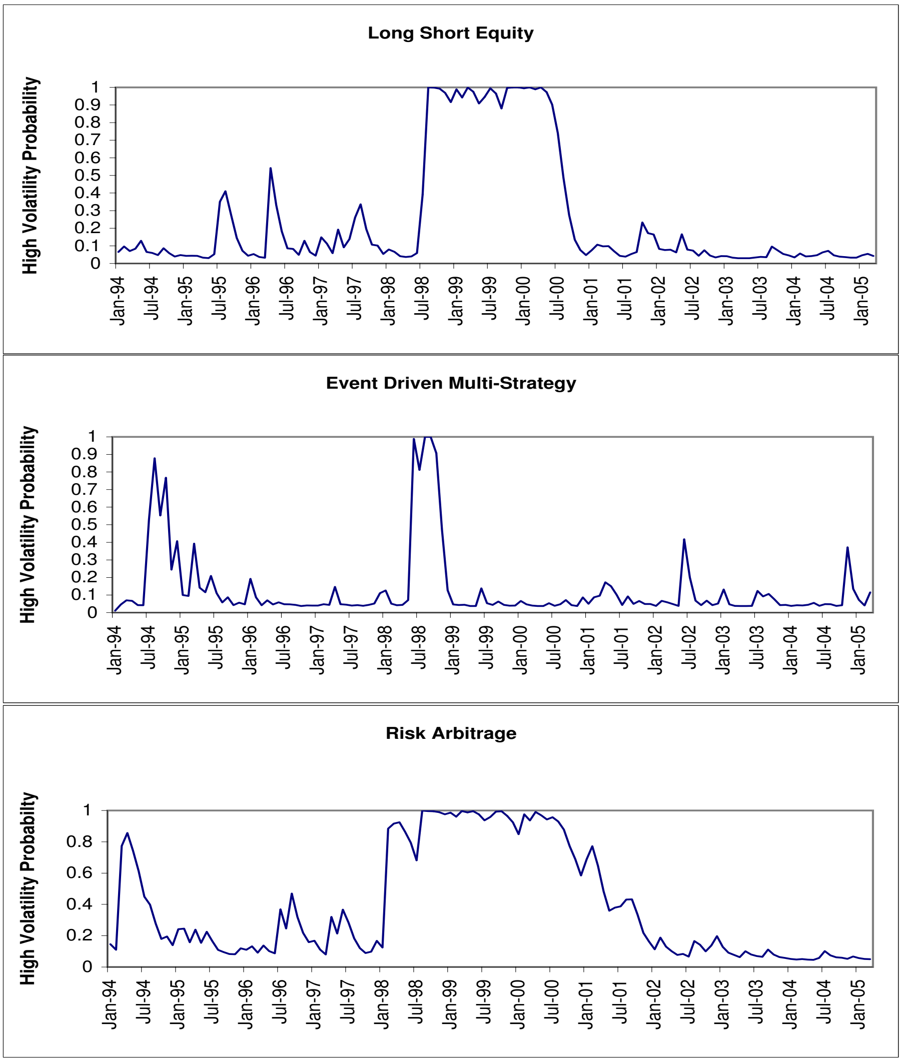
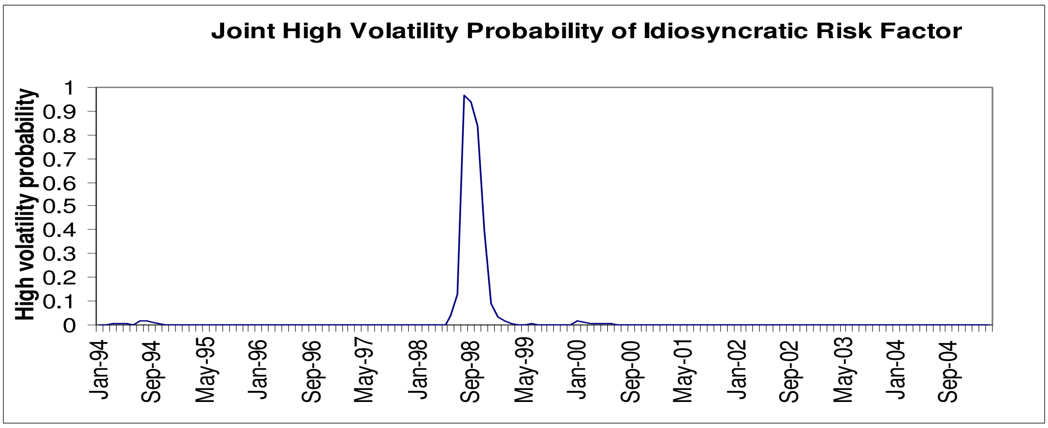


Figure 6: **The Joint Probability of High-Volatility State of the Idiosyncratic Risk Factor for All Hedge Fund Strategies**

Panel A presents the joint filtered probability of high-volatility state of the idiosyncratic risk factor for all CSFB/Tremont hedge-fund index strategies from January 1994 to March 2005. Panel B concentrates on the joint filtered probability of high-volatility state of the idiosyncratic risk factor in 1998, around the time of the Long-Term Capital Management (LTCM) crisis.

Panel A



Panel B

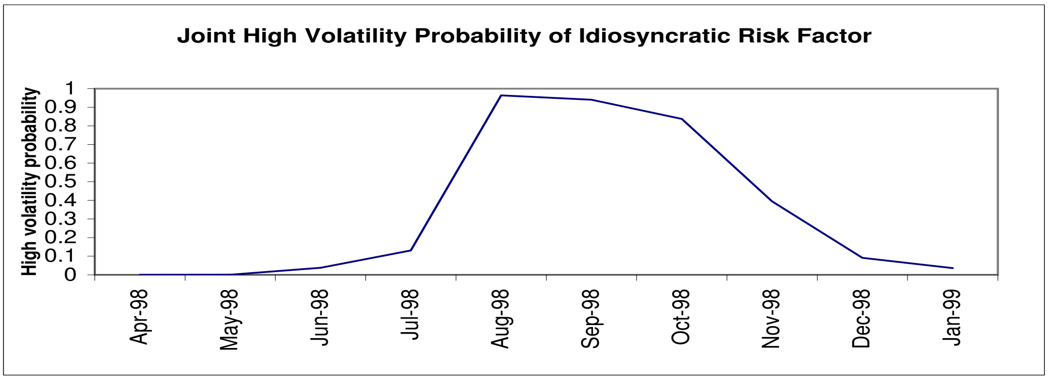


Table 8: **Multifactor OLS Model**

This table presents the results for the OLS regression of the CSFB/Tremont hedge-fund index strategies on S&P 500 (SP), Large-Small (LS), Value-Growth (VG), USD, Lehman Government Credit (L.GC), Term Spread (TS), Change in VIX (dVIX), Credit Spread (CS), Gold, MSCI Emerging Bond (MSCIEMD), MSCI Emerging Stock (MSCIEMS) and Momentum Factor (UMD). Hedge fund returns, S&P 500, USD, Lehman Government Credit and Gold are used in excess of LIBOR returns. Parameters that are significant at the 10% level are shown in bold type.

Variable/ Strategy	Convertible Bond Arb		Dedicated Shortseller		Emerging Markets		Equity Market Neutral	
	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat
α_0	**0.33**	**3.39**	-0.24	-1.25	0.23	1.45	**0.31**	**4.99**
β_0 (SP)	0.05	1.43	**-0.87**	**-12.74**	0.09	1.33	**0.07**	**4.72**
β_1 (LS)	**-0.08**	**-1.95**	**0.47**	**5.61**				
β_2 (VG)			**0.23**	**4.36**				
β_3 (USD)	**0.17**	**2.35**						
β_4 (L.GC)	**0.20**	**2.70**			**0.68**	**3.82**		
β_5 (TS)					**0.91**	**3.88**		
β_6 (dVIX)					**0.20**	**2.94**		
β_7 (CS)	**-0.95**	**-428.94**			**-3.90**	**-299.92**		
β_8 (Gold)			**-0.11**	**-2.23**				
β_9 (MSCIEMD)					**-0.62**	**-5.49**		
β_{10} (MSCIEMS)					**0.62**	**14.79**		
β_{11} (UMD)					**0.19**	**7.55**		
ω_0	**1.27**	**11.31**	**2.48**	**16.48**	**2.54**	**19.96**	**0.78**	**16.48**
Adj. R^2	0.04		0.75		0.51		0.14	
Pseudo R^2	0.02		0.18		0.10		0.04	

Variable/ Strategy	Long/Short Equity		Distressed		Event Driven Multi-Strategy		Risk Arb	
	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat
α_0	0.01	0.12	**0.46**	**3.56**	**0.36**	**3.26**	0.09	1.02
β_0 (SP)	**0.57**	**12.34**	**0.29**	**4.14**	**0.16**	**3.19**	**0.17**	**5.03**
β_1 (LS)	**-0.39**	**-10.07**	**-0.19**	**-4.22**	**-0.13**	**-3.86**	**-0.16**	**-5.83**
β_2 (VG)			**0.11**	**2.27**	**0.09**	**2.17**	**0.08**	**3.02**
β_3 (USD)					**0.19**	**2.43**		
β_4 (L.GC)	**0.14**	**1.70**	**0.24**	**4.36**				
β_5 (TS)	**-0.23**	**-1.85**						
β_6 (dVIX)	**0.09**	**1.81**						
β_7 (CS)	**-4.20**	**-2.91**	**-3.37**	**-2.61**	**-3.23**	**-1513.27**		
β_8 (Gold)								
β_9 (MSCIEMD)			**-0.15**	**-2.22**				
β_{10} (MSCIEMS)					**0.10**	**2.87**		
β_{11} (UMD)	**0.23**	**7.83**			**0.06**	**2.53**		
ω_0	**1.36**	**19.94**	**1.42**	**10.38**	**1.27**	**8.47**	**0.93**	**13.91**
Adj. R^2	0.79		0.43		0.46		0.41	
Pseudo R^2	0.23		0.10		0.11		0.11	

Table 9: **Asymmetric Beta and Threshold Models**

This table presents the results for regressions of monthly CSFB/Tremont hedge-fund index returns on three threshold periods of the S&P 500 index return, from January 1994 to March 2005. $R_{it} = \alpha_i + \beta_i^+ I_t^+ + \beta_i^0 I_t^0 + \beta_i^- I_t^- + \epsilon_{it}$, where $I_t^+ = \mu + \sigma, I_t^0 = \mu - \sigma < I_t < \mu + \sigma, I_t^- = \mu + \sigma$. I_t is the return on the market index, S&P 500. I_t^+, I_t^0, and I_t^- represent the returns of the S&P 500 that are, respectively, larger than the mean plus one standard deviation, between the mean plus and minus one standard deviation, and below the mean minus one standard deviation. μ is the mean and σ is the standard deviation of the S&P 500. Parameters that are significant at the 10% level are shown in bold type.

Variable/ Strategy	Convertible Bond Arb		Dedicated Shortseller		Emerging Markets		Equity Market Neutral	
	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat
α	**0.31**	**2.40**	-0.29	-0.81	0.45	1.15	**0.25**	**3.37**
β+	0.03	0.39	**-0.81**	**-8.84**	**0.34**	**3.03**	**0.13**	**4.45**
β0	0.00	-0.02	**-0.87**	**-5.78**	**0.47**	**2.50**	0.02	0.60
β–	0.06	0.81	**-0.97**	**-6.94**	**0.73**	**3.73**	**0.05**	**2.15**
Adj.R^2	0.00		0.58		0.23		0.17	
PseudoR^2	0.00		0.11		0.04		0.05	

Variable/ Strategy	Long/Short Equity		Distressed		Event Driven Multi-Strategy		Risk Arb	
	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat
α	**0.36**	**1.65**	**0.84**	**5.71**	**0.55**	**3.79**	**0.24**	**2.08**
β+	**0.35**	**3.06**	0.07	1.46	0.08	1.45	**0.06**	**1.62**
β0	**0.49**	**4.72**	**0.22**	**4.33**	**0.15**	**2.63**	**0.13**	**2.29**
β–	**0.42**	**4.69**	**0.38**	**2.82**	**0.30**	**2.18**	**0.17**	**2.21**
Adj.R^2	0.33		0.35		0.25		0.22	
PseudoR^2	0.06		0.08		0.05		0.05	

Table 10: **Multifactor Model: Observed vs. Real Hedge Fund Returns**

This table presents the comparison of non-linear exposure of the CSFB/Tremont hedge-fund index strategies to S&P 500 (SP), Large-Small (LS), Value-Growth (VG), USD, Lehman Government Credit (L.GC), Term Spread (TS), Change in VIX (dVIX), Credit Spread (CS), Gold, MSCI Emerging Bond (MSCIEMD), MSCI Emerging Stock (MSCIEMS) and Momentum Factor (UMD) for different S&P 500 regimes for "observed" (provided by the data) versus "real" hedge fund index returns. "Real" returns are obtained by using MA(2) estimation via maximum likelihood. Parameters that are significant at the 10% level are shown in bold type.

Panel A

Variable/ Strategy	Convertible Bond Arb		Dedicated Shortseller		Emerging Markets		Equity Market Neutral	
	Observed	Real	Observed	Real	Observed	Real	Observed	Real
α_0	**0.75**	**0.27**	-0.23	0.24	0.31	0.05	**0.29**	0.01
α_1	**-0.35**	-0.07			**0.66**		0.16	-0.05
β_0 (SP)	**0.05**	**0.07**	**-0.88**	**-0.82**	0.01	0.29	**0.10**	**0.10**
β_1 (SP)	0.05	0.02	**-0.88**	**-0.93**	**-0.31**	0.05	0.06	0.06
β_2 (SP)	0.01	0.02	**-0.80**	**-0.79**	**0.17**	**-0.21**	-0.01	0.00
θ_{1_0} (LS)	-0.03	**-0.07**	0.24	**0.22**		**0.22**		
θ_{1_1} (LS)	0.00	0.07	**0.86**	**0.89**				
θ_{1_2} (LS)	**-0.09**	**-0.12**	**0.45**	**0.43**				
θ_{2_0} (VG)	**0.07**	**0.10**	-0.03	-0.03				
θ_{2_1} (VG)	0.04	-0.01	**0.70**	**0.74**				
θ_{2_2} (VG)	**0.06**	**0.06**	**0.23**	**0.24**				
θ_{3_0} (USD)			0.54	0.41	**0.69**	**0.48**		
θ_{3_1} (USD)			-0.19	-0.18	-0.06	0.10		
θ_{3_2} (USD)			0.21	0.14	**0.37**	**0.38**		
θ_{4_0} (L.GC)	**0.17**	0.13			**1.57**	**1.00**	0.19	**0.21**
θ_{4_1} (L.GC)	0.03	-0.03			0.12	**0.27**	0.11	0.09
θ_{4_2} (L.GC)	**0.14**	0.11			**0.48**	**0.71**	0.02	0.05
θ_{5_0} (TS)					**2.01**	**0.70**		
θ_{5_1} (TS)					**0.59**	0.46		
θ_{5_2} (TS)					0.52	0.63		
θ_{6_0} (dVIX)								
θ_{6_1} (dVIX)								
θ_{6_2} (dVIX)								
θ_{7_0} (CS)	**-2.01**	**-0.42**	**1.75**	**0.57**				
θ_{7_1} (CS)	**1.12**	**-3.07**	**-5.98**	**-7.06**				
θ_{7_2} (CS)	**-2.72**	**-2.01**	3.50	**3.32**				
θ_{8_0} (Gold)								
θ_{8_1} (Gold)								
θ_{8_2} (Gold)								
θ_{9_0} (MSCIEMD)			**-0.44**	-0.08				
θ_{9_1} (MSCIEMD)			-0.09	-0.35				
θ_{9_2} (MSCIEMD)			0.12	0.18				
θ_{10_0} (MSCIEMS)					**0.66**	**0.61**	0.03	0.03
θ_{10_1} (MSCIEMS)					**0.58**	**0.50**	0.01	0.00
θ_{10_2} (MSCIEMS)					**0.38**	**0.36**	**0.04**	**0.04**
θ_{11_0} (UMD)					**0.17**	**0.16**		
θ_{11_1} (UMD)					-0.08	-0.02		
θ_{11_2} (UMD)					**0.16**	**0.18**		
ω_0	**0.31**	**0.26**	**2.31**	**2.26**	**0.96**	**1.14**	**0.57**	**0.53**
ω_1	**1.70**	**1.33**			**3.41**	**2.95**	**0.97**	**0.92**
p^Z_{00}	**0.85**	**0.80**			**0.98**	**0.98**	**0.99**	**0.99**
p^Z_{11}	**0.85**	**0.86**			**1.00**	**1.00**	**1.00**	**1.00**
PseudoR^2	0.14	0.17	0.20	0.19	0.17	0.16	0.09	0.11

Panel B

Variable/ Strategy	Long/Short Equity		Distressed		Event Driven Multi-Strategy		Risk Arb	
	Observed	Real	Observed	Real	Observed	Real	Observed	Real
α_0	**-0.15**	**-0.51**	**0.69**	**0.30**	**0.50**	**0.20**	-0.03	-0.05
α_1	**0.68**	0.11			**-2.95**	-0.68	**0.21**	0.07
β_0 (SP)	**0.73**	**0.70**	**0.12**	**0.10**	**0.28**	**0.26**	**0.14**	**0.14**
β_1 (SP)	**0.58**	**0.54**	**0.26**	**0.22**	0.08	**0.11**	0.12	**0.15**
β_2 (SP)	**0.38**	**0.36**	**0.39**	**0.40**	**0.11**	**0.09**	**0.21**	0.17
θ_{1_0} (LS)	**-0.61**	**-0.63**	**-0.21**	**-0.19**	**-0.13**	**-0.18**	-0.12	-0.13
θ_{1_1} (LS)	**-0.40**	**-0.36**	**-0.13**	**-0.12**	0.01	-0.03	**-0.10**	**-0.10**
θ_{1_2} (LS)	**-0.27**	**-0.26**	**-0.18**	**-0.16**	**-0.12**	**-0.10**	**-0.20**	**-0.15**
θ_{2_0} (VG)			**0.14**	0.05			**0.18**	**0.14**
θ_{2_1} (VG)			0.01	0.01			-0.13	**-0.14**
θ_{2_2} (VG)			0.12	0.10			**0.11**	0.08
θ_{3_0} (USD)					**0.11**	**0.20**		
θ_{3_1} (USD)					**0.22**	0.05		
θ_{3_2} (USD)					0.05	0.06		
θ_{4_0} (L.GC)	**0.12**	0.15	**0.52**	**0.62**				
θ_{4_1} (L.GC)	0.11	0.10	**0.13**	0.10				
θ_{4_2} (L.GC)	**0.35**	**0.44**	**0.23**	**0.34**				
θ_{5_0} (TS)	**-0.62**	**-0.67**						
θ_{5_1} (TS)	**-0.48**	**-0.43**						
θ_{5_2} (TS)	0.01	0.21						
θ_{6_0} (dVIX)	**0.28**	**0.19**			**0.25**	**0.17**		
θ_{6_1} (dVIX)	**0.13**	0.07			0.07	-0.02		
θ_{6_2} (dVIX)	-0.02	-0.07			0.03	0.02		
θ_{7_0} (CS)	**3.52**	**1.50**	**-5.35**	**-3.20**	**-0.34**	**1.15**		
θ_{7_1} (CS)	**-0.86**	**-1.55**	**-6.42**	**-2.94**	**-3.50**	**-1.00**		
θ_{7_2} (CS)	**-3.30**	**-2.99**	**-1.17**	**-1.47**	**-0.76**	**-1.27**		
θ_{8_0} (Gold)								
θ_{8_1} (Gold)								
θ_{8_2} (Gold)								
θ_{9_0} (MSCIEMD)			**-0.46**	**-0.17**				
θ_{9_1} (MSCIEMD)			0.07	0.07				
θ_{9_2} (MSCIEMD)			**-0.13**	**-0.14**				
θ_{10_0} (MSCIEMS)					**0.08**	0.06		
θ_{10_1} (MSCIEMS)					**0.09**	0.08		
θ_{10_2} (MSCIEMS)					**0.08**	**0.10**		
θ_{11_0} (UMD)	**0.24**	**0.27**			**0.04**	0.02		
θ_{11_1} (UMD)	-0.07	-0.06			0.05	0.00		
θ_{11_2} (UMD)	**0.16**	**0.17**			0.02	**0.03**		
ω_0	**0.91**	**0.86**	**1.36**	**1.24**	**0.79**	**0.75**	**0.42**	0.40
ω_1	**2.45**	**2.08**			**2.74**	**2.23**	**0.96**	**1.14**
p^Z_{00}	**0.99**	**0.99**			**0.98**	**0.98**	**0.95**	**0.74**
p^Z_{11}	**0.94**	**0.94**			**0.66**	**0.84**	**1.00**	**0.79**
PseudoR^2	0.28	0.27	0.12	0.15	0.21	0.21	0.17	0.16

Table 11: **Normality Test**

This table presents Jarque-Bera statistics and corresponding p-values for Original Data, OLS, Multifactor Model with Non-Linear Exposure Only to S&P 500, and Multifactor Model with Non-Linear Exposure to All Factors for all CSFB/Tremont hedge-fund index strategies. Multifactor Model with Non-Linear Exposure Only to S&P 500: $R_t=\alpha(Z_t)+\beta(S_t)I_t+\sum_{k=1}^{K}\theta_k F_{kt}+\omega(Z_t)u_t$. Multifactor Model with Non-Linear Exposure to All Factors: $R_t=\alpha(Z_t)+\beta(S_t)I_t+\sum_{k=1}^{K}\theta_k(S_t)F_{kt}+\omega(Z_t)u_t$. I_t is the market factor, S&P 500 and F_{kt} are other risk factors. S_t is the Markov Chain for the S&P 500. I_t is characterized by 3 states (regime 0: up-market, regime 1: normal and regime 2: down-market). Each state of the market index I has its own mean and variance: $I_t=\mu(S_t)+\sigma(S_t)\ \epsilon_t$. u_t is IID, ω is volatility of the idiosyncratic risk factor, which is characterized by the Markov Chain Z_t. The Z_t Markov Chain has two states (state 0: low volatility and state 1: high volatility of idiosyncratic risk factor). Jarque-Bera test statistics that lead to rejection of normality of residuals are shown in bold. Parameters that are significant at the 5% level are shown in bold type.

Strategy/Model	Original Data		OLS		Table 5		Table 6	
	JB statistic	p-value	JB statistic	p-value	JB statistic	p-value	JB statistic	p-value
Convertible Bond Arb.	**119.97**	**0.00**	**63.28**	**0.00**	**46.37**	**0.00**	**43.50**	**0.00**
Dedicated Shortseller	**34.58**	**0.00**	2.96	0.23	3.56	0.17	5.68	0.06
Emerging Markets	**105.21**	**0.00**	4.53	0.10	0.37	0.83	1.05	0.59
Equity Market Neutral	1.02	0.60	0.24	0.89	0.89	0.64	1.34	0.51
Long/Short Equity	**77.64**	**0.00**	0.16	0.92	2.11	0.35	2.40	0.30
Distressed	**1942.12**	**0.00**	**330.90**	**0.00**	**126.04**	**0.00**	**133.80**	**0.00**
Event Driven M.S.	**1891.51**	**0.00**	**355.15**	**0.00**	4.59	0.10	4.20	0.12
Risk Arbitrage	**315.67**	**0.00**	**12.52**	**0.00**	**9.31**	**0.01**	4.61	0.10

Figure 7: **Out-of-Sample Dynamics: Emerging Markets Strategy**

This figure presents out-of-sample dynamics for the Emerging Markets strategy. The first panel shows the VaR calculated using the Multifactor Regime-Switching Beta Model (MRSB) versus actual observations of the strategy. The second panel shows the VaR calculated using OLS Model versus actual observations. Both return and VaR estimates are in percentages. Three confidence levels are considered: 95%, 99%, and 99.5%.

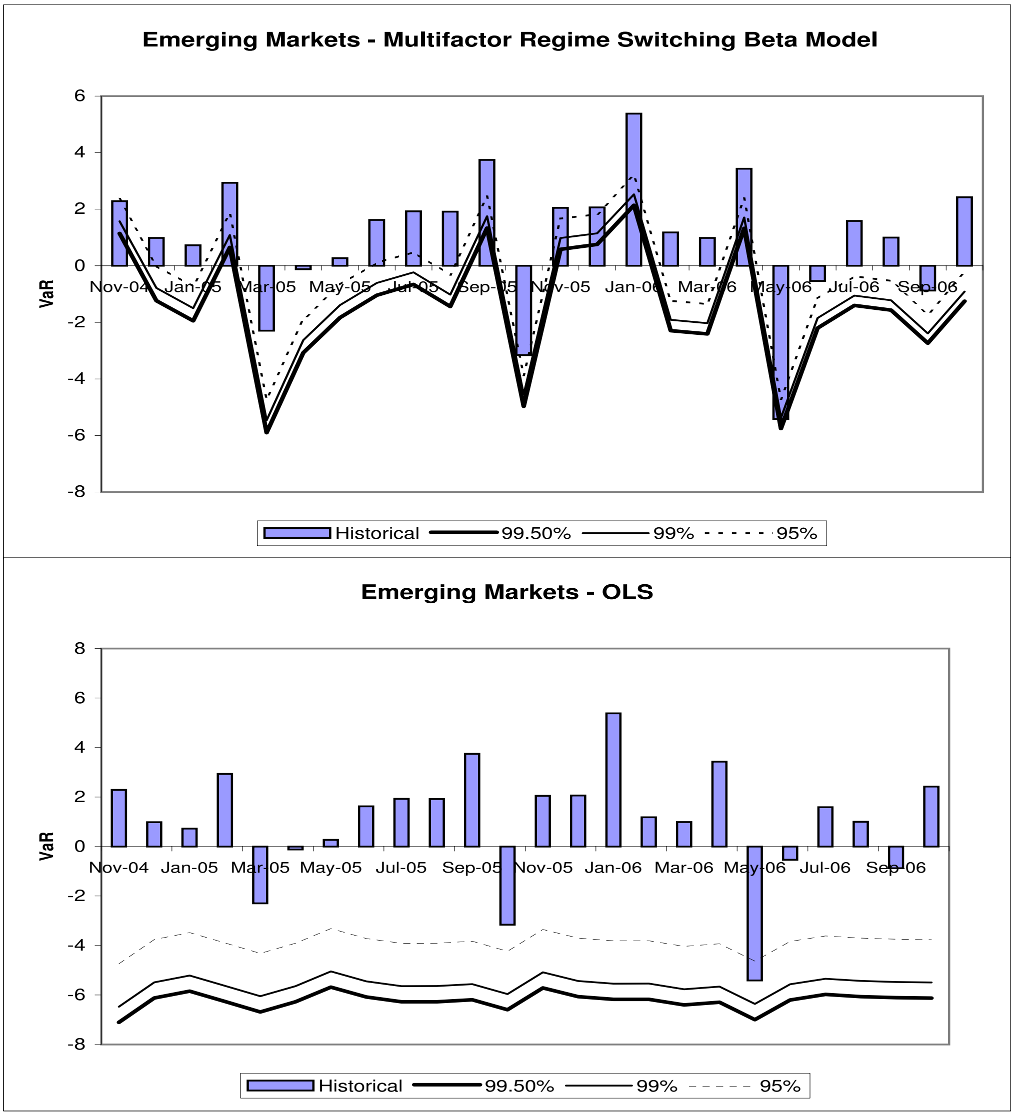


Table 12: **Out-of-Sample Tests**

Panel A presents results for mimicking performance. Results for Mean Absolute Error (MAE) tests for OLS, Random Walk (RW), Multifactor Regime-Switching Beta (MRSB) and Multifactor Regime-Switching Beta Adjusted for Autocorrelation MRSB_AR models are presented. Panel B presents results for negative tail risk exposure for each hedge fund strategy. For each month in the 24 months of out-of-sample data, VaR estimates are calculated. This panel presents the average of these VaR estimates. These estimates are in percentages. Three confidence levels are considered: 95%, 99%, and 99.5%. VaR levels are calculated for Multifactor Regime-Switching Beta (MRSB) and OLS models.

Panel A

Strategy/Test	MAE			
	OLS	RW	MRSB	MRSB_AR
Conv. Bond Arb.	0.94	0.91	0.86	0.80
Dedicated Shortseller	1.86	3.38	1.85	1.85
Emerging Markets	1.82	2.47	0.70	1.01
Equity Mkt Neutral	0.53	0.54	0.49	0.47
Long/Short Equity	0.86	2.06	0.89	0.89
Distressed	0.58	0.94	0.47	0.63
Event Driven MS	2.18	1.66	1.03	0.83
Risk Arb	0.40	0.60	0.41	0.38

Panel B

Strategy/Model	OLS			MSRB		
	99.50%	99%	95%	99.50%	99%	95%
Conv. Bond Arb.	-3.00	-2.68	-1.82	-3.49	-2.94	-1.16
Dedicated Shortseller	-7.25	-6.63	-4.93	-6.29	-5.72	-4.16
Emerging Markets	-2.96	-2.61	-1.64	-2.54	-2.21	-1.31
Equity Mkt Neutral	-6.24	-5.60	-3.87	-1.41	-1.01	-0.30
Long/Short Equity	-1.64	-1.44	-0.92	-1.29	-1.13	-0.71
Distressed	-2.27	-1.95	-1.08	-7.69	-7.01	-5.16
Event Driven MS	-2.96	-2.62	-1.70	-2.11	-1.80	-1.10
Risk Arb	-2.14	-1.90	-1.27	-1.13	-0.99	-0.66

9 Appendix

9.1 Category Analysis for Multifactor Model with Non-Linear Exposure Only to the S&P 500

Convertible Bond Arbitrage

This strategy is characterized by investing in a company bond while shorting the common stock of the same company. Positions are designed to protect the principal from market moves. As was shown before in a one-factor setting, the convertible bond arbitrage strategy is not correlated with S&P 500 moves in all regimes (Table 3). However, in the multifactor setting, we find a slight positive exposure of 0.04 to the S&P 500 in the up-market. There are two potential explanations for this effect. First, as the market moves up, hedge fund managers do not have adequate time to hedge the stock exposure by shorting more stock. Second, the arbitrageurs would like to capitalize on the up-market move, and will not hedge perfectly in order to make more money. The strategy does better when returns on small and value stocks are high. Clearly, because the strategy is designed to profit from upward fixed income moves, the strategy is positively related to the Lehman Government Credit bond index returns. The most significant coefficient in the regression is -1.79 effect of Credit Spread. Clearly, when credit spread increases, liquidity decreases and there is a low demand for low-credit securities. Convertible Bond Arbitrage funds primarily hold low-credit securities. At the time of high credit spreads, brokers request a higher hair-cut fee to obtain more leverage. Cost of funding goes up; therefore, the return on the strategy decreases.

Dedicated Shortseller

This strategy is geared to maintain net short position at all times. The highest net negative market exposure is during the normal regime of the market (-1.09). Dedicated Shortseller strategy does well when large and value indexes are performing well. The strategy also has a positive exposure to the US Dollar and MSCI Emerging Bond returns. Similar to the Convertible Bond Arbitrage strategy, this strategy has a negative exposure (-0.73) to the Credit Spread. However, the exposure is about twice as small: -0.73 compared to -1.77. It makes sense that as credit spread increases, the cost of shorting a stock increases, thus, decreasing the returns of the strategy.

Emerging Markets

This strategy involves both equity and fixed income investing around the world. The net market exposure is insignificant in all states of the market. The effect of the US Dollar is positive and significant (0.27). A stronger US Dollar increases demand for foreign goods, thus boosting emerging markets economy. Since many emerging markets funds invest in fixed income, it makes sense that the relationship between the Lehman Government Credit index returns and the strategy returns is positive and significant (0.49). The strategy does well when the yield curve is sloping up (the exposure to Term-Spread is 0.64). The Emerging Markets strategy has a big and significant (estimate is 1.07 and t-stat is 5.03) exposure to the MSCI Emerging Stock, which makes sense as this strategy trades directly in this market. Finally, there is a slight positive exposure to the Momentum Factor.

Equity Market Neutral

The strategy is designed to be market beta neutral, which is confirmed for normal market conditions (0.03 and not significant). However, the strategy is not neutral during up-market times. Managers are not able to timely put market hedges in place, thus, the strategy is slightly positively exposed to upward market movements (0.09). The strategy seems to be marginally exposed to Lehman Government Credit index and MSCIEMS.

Long/Short Equity

The strategy takes both long and short market positions. During the normal times of the market factor, the exposure is 0.51 and remains almost the same in both down-market and up-market periods. The strategy does well when small stocks do well. The strategy does well during the low interest rate environment (the exposure to the Lehman Government Credit index returns is positive = 0.23). Generally, the strategy is doing well when the yield curve is flat. So, if long or short-term rates are changing, then the return of the Long/Short Equity strategy decreases as can be seen by a negative coefficient on the term spread (-0.31). The exposure to the Credit Spread is -2.25 and very significant, which is consistent with the general preference for small illiquid stocks and increase in stock lending rate in increased credit spread environments. The strategy also benefits from increase in volatility and momentum factor.

Distressed

The Distressed strategy primarily concentrates on investing in the debt, equity or trade claims of companies in financial distress and generally bankruptcy. There is a modest market exposure during normal times (0.30) and the exposure increases during down-market times. The strategy does well when small stocks are outperforming their large counterparts and when value stocks perform better than growth stocks. Because the strategy is also investing in fixed income, it is highly positively correlated with the Lehman Government Credit index returns (0.23). Similar to Convertible Bond Arbitrage, the strategy suffers from an increase in credit spreads, as the strategy primarily invests in Distressed, or low-quality and highly illiquid securities. These distressed securities will greatly suffer in liquidity crises. Therefore, compared to all other strategies, the coefficient (-2.69) on Credit Spread for the Distressed strategy is the largest. There is also a slight negative exposure to the MSCI Emerging Bond index.

Event Driven Multi-Strategy

This subset refers to hedge funds that draw upon multiple themes, including risk arbitrage, distressed securities, and occasionally others such as investments in micro and small capitalization public companies that are raising money in private capital markets. Fund managers often shift assets between strategies in response to market opportunities. Therefore, the market exposure is positive in all market states. The strategy does well when small stocks are outperforming large ones. Event Driven Multi-Strategy managers are opportunistic and therefore when US Dollar is stronger, they have more investing power and can take advantage of more investment opportunities. Therefore, the relationship between the US Dollar and strategy returns is 0.24. There is a positive, but small exposure to change in VIX (0.09). The most significant coefficient in the regression is -1.24 effect of Credit Spread. Clearly, when credit spread increases, liquidity decreases and there is a low demand for low-credit securities. Event Driven Multi-Strategy funds mostly hold low-credit securities. At the time of high credit spreads, brokers request a higher hair-cut fee to obtain more leverage. Cost of funding goes up, therefore, the return on the strategy decreases. The strategy also has a positive exposure to MSCI Emerging Bond and Stock indexes as well as to the Momentum Factor.

Risk Arbitrage

Risk (or sometimes called Merger) arbitrageurs are typically long the stock of the company being acquired and short the stock of the acquiring company. Market exposure is positive especially in crises periods (0.17), indicating that managers in this strategy take a lot of risk. The strategy is correlated with the performance of small versus large stocks (-0.14). There is a small premium to value stocks (0.07).

9.2 Category Analysis for Multifactor Model with Non-Linear Exposure to All Factors

Convertible Bond Arbitrage

Compared to previous results, the Convertible Bond Arbitrage strategy has a significant positive exposure to the S&P 500 during up-market times. During normal times and down-market, there is no exposure because managers typically perfectly hedge market fluctuations.

Therefore, during market up-turns, the strategy is positively related to the market. The strategy has a positive exposure to credit spread when the market is in the normal regime (1.12). The spread reflects investor perception relating to how likely it is that the issuing company will be able to make timely interest payments and pay off the principal at maturity. The larger, or wider, the spread, the more concern investors have regarding the issuing company's ability to make timely interest payments. During normal times of the market, investors are less worried about the increase in credit spread. However, during crises times, this worry is more sound and the strategy is negatively compensated for having a high credit spread (-2.72). During up-market times, the coefficient on the credit spread is -2.01. We observe this negative sign because convertible bond funds tend to short stock.

Dedicated Shortseller

Unlike other strategies, this strategy has a positive (0.45) exposure to LS during down-markets. Moreover, it has insignificant exposure to CS in down-markets, negative exposure during normal markets (-5.98) and positive during up-markets (1.75).

Emerging Markets

This strategy involves both equity and fixed income investing around the world. The net market exposure is positive for the down-state of the market, negative for the normal state and zero in the up-state. Due to inability to short sell or the lack of put or other hedging instruments, the exposure to the market is highly significant in the down-state as expected. Therefore, the exposure result is similar to writing a put option on the S&P index. Interestingly, the exposure to the MSCI Emerging Stock is greatly reduced in the down-market periods. The exposure to the Lehman Government Credit is negligible during normal periods but positive during up and down-markets.

Equity Market Neutral

In the previous analysis on multifactor model with linear factors, Equity Market Neutral index appears to be linked only to the Lehman Government Credit and MSCI Emerging stock risk factors. Allowing for non-linearities, we find that the exposure to the MSCI Emerging stock risk factor is positive in the down-market and not significant for other regimes. The exposure to the S&P 500 is positive and significant for the up-market and not significant for the normal and down-markets.

Long/Short Equity

The exposure to credit spread in a down-market period is (-3.30) and in a normal period is (-0.86), whereas in an up-market period it is (3.52). It can be interpreted that generally

Long/Short Equity managers tend to buy low liquidity, low credit rated instruments; however, in the up-market, they quickly adjust their exposure to buying high credit securities. This might make sense because managers tend to take concentrated trades in specific sectors or markets. The change in VIX is positively related to the strategy return in up and normal states of the S&P 500.

Distressed

The exposure to credit spread is negative and significant during all regimes of the credit spread, meaning that distressed funds always hold illiquid and low quality securities. This strategy is usually categorized by taking positions in companies that will do better in the future through restructuring and other means. Therefore, an increase in credit spread sends a signal that these companies might have an inability to make timely interest payments. Therefore, the relationship between credit spread and Distressed returns is negative in all states of the market factor.

Distressed funds also hold bonds; therefore, the exposure to Lehman Government Credit bonds is positive in all states in the world, the highest being in the up-market (0.52).

Event Driven Multi-Strategy

Similar to previous results, the exposure to the change in VIX is positive and significant, especially during up-market periods (0.25). The strategy has a high negative exposure to credit spread in all states of the market. Generally, event driven types of strategies do well when credit risk premium is moderate and is declining. However, unlike Distressed strategy managers, managers in this strategy might bet on a merger or engage in other strategies during market upturns. The exposure to MSCIEMS is positive and significant in all market environments.

Risk Arbitrage

As for Equity Market Neutral, the linear exposure of risk factor of this strategy is limited. Similar to Event Driven Multi-Strategy, Equity Market Neutral and Convertible Bond Arbitrage, the exposure to the S&P 500 during normal market regimes is zero, but positive in up and especially down-states. During the normal state, the exposure to LS is zero, but is negative during the down-state of the market, suggesting a liquidity premium. Also, the exposure to VG is zero in the normal regime, but is positive and significant in both up and down regimes.