Crises and Hedge Fund Risk*

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Abstract

We study the effect of financial crises on hedge fund risk. Using a regime-switching beta model, we separate systematic and idiosyncratic components of hedge fund exposure. The systematic exposure to various risk factors is conditional on market volatility conditions. We find that in the high-volatility regime (when the market is rolling-down and is likely to be in a crisis state) most 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 a high volatility regime of the idiosyncratic risk, which could be attributed to contagion among hedge fund strategies. In our sample this event happened only during the Long-Term Capital Management (LTCM) crisis of 1998. Other crises including the recent subprime mortgage crisis affected hedge funds only through systematic risk factors, and did not cause contagion among hedge funds.

Keywords: Hedge Funds; Risk Management; Regime-Switching Models;

JEL Classification: G12, G29, C51

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1 Introduction

The aim of this paper is to study the effect of financial crises on hedge fund risk. We narrow down common risk factors across different hedge fund strategies, especially, in the down-state of the market, which is often associated with financial crises, and pin down contagion events that affect the whole hedge fund industry not directly driven by systematic state-dependent exposure to risk factors.

Specifically, we analyze the exposure of hedge fund indexes with a factor model based on regime-switching volatility, where nonlinearity in the exposure is captured by factor loadings that are state-dependent (based on market mean and volatility changes). Our approach is consistent with the time-varying market integration perspective proposed by Bekaert and Harvey (1995) and the work of Bollen and Whaley (2007) who show that allowing for switching in risk exposure is essential when analyzing hedge fund performance. Moreover,we build on the work by Fung and Hsieh (2001,1997) and Agarwal and Naik (2004) and extend their analysis of dynamic risk exposure in hedge funds by 1) investigating dynamic risk exposure in hedge funds conditional on the market risk factor states, and 2) accounting for the change in volatility of the idiosyncratic risk factor for different hedge fund strategies.

The regime-switching model allows us to measure hedge fund risk exposure in different market states: up-state, normal, and down-state, which is often associated with market crises. Moreover, this model allows us to capture the change in volatility of the idiosyncratic risk factor in different hedge fund strategies and investigate if this change could be associated with a specific financial crisis. To our knowledge, this is the first paper that analyzes the evolution of volatility of the idiosyncratic risk factor for different hedge fund strategies. The importance of investigating the evolution of idiosyncratic risk in hedge funds is introduced by Adrian (2007) and Brown and Spitzer (2006).

This investigation is relevant for many reasons. First, capturing the evolution of volatility of the idiosyncratic risk factor for various hedge fund strategies is essential in (i) evaluating the possibility of eliminating the idiosyncratic risk through diversification and (ii) detecting the presence of diversification implosion.[1] Second, an increase in volatility of the idiosyncratic risk factor contributes to potential margin calls for hedge fund investors.

Third, and most importantly for our work, the switch in volatility of the idiosyncratic risk factor allows us to investigate the presence of contagion among hedge funds strategies. In our framework we define contagion among hedge funds strategies when we observe a significant

[1]This term was coined by Fung, Hsieh, and Tsatsaronis (2000), where authors underlie the possibility of the convergence of opinion among different hedge funds.

change in the joint probability that all hedge funds are in the high volatility state for the idiosyncratic risk factor.

Our definition of contagion is related to the one proposed by Boyson, Stahel, and Stulz (2007) for hedge funds, who define contagion as the joint occurrence of large events (i.e., the probability of one hedge fund having extremely poor performance increases when other hedge funds also experience extreme poor performance.)[2] Specifically, in our framework contagion is a joint occurrence of the high volatility of the idiosyncratic risk factor across hedge fund indices. Our approach allows us to identify whether the switch to the high volatility regime coincides with a specific financial crisis. This means that financial crises may affect the hedge fund industry not only through the dynamic exposure to market risk factors, but also through contagion among hedge fund strategies.

Our analysis confirms that hedge funds change their exposure based on different market conditions. We find that in all cases hedge fund exposure to the S&P 500 in the down-state of the S&P 500 is smaller than in the normal or up-state of the market. This suggests that hedge fund managers are able to timely hedge market exposures, especially during financial crises. This is consistent with the finding by Brunnermeier and Nagel (2004) who showed that hedge funds captured the upturn, but reduced their positions in technology stocks that were about to decline, avoiding much of the downturn during the technology bubble of 2000.

Moreover, our framework can capture the phase-locking property of hedge funds introduced by Chan, Getmansky, Haas, and Lo (2005).[3] For example, we observe 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 results suggest that the common exposures of different hedge fund indices 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 an increase of the systematic risk exposure among the hedge fund family during market downturns. The systematic risk is attributed to liquidity and credit risks, two typically nonlinear phenomena, and is more relevant during market downturns that are usually characterized by large volatility. The recent subprime mortgage crisis of August 2007 emphasized the importance of credit and liquidity for hedge fund returns. Our findings are consistent with Khandani and Lo (2007) who find an increased correlation between hedge fund styles in this period and

[2]This definition was originally proposed by Bae, Karolyi, and Stulz (2003).

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

conjecture that this can be due to the increase in systematic linkages with market factors, liquidity, and credit proxies.

Finally, 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 occurrence of contagion among hedge funds in our sample. 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.

We also considered other financial crises: February 1994 (the U.S. Federal Reserve started a tightening cycle that caught many hedge funds by surprise), the end of 1994 (Tequila Crisis in Mexico), 1997 (Asian down-market), the first quarter of 2000 (a crash of the Internet boom), March 2001 (Japanese down-market), September 11, 2001, the middle of 2002 (drying out of merger activities, increase in defaults, and WorldCom accounting problems), and the recent August 2007 subprime mortgage crisis. However, none of these crises coincided with all hedge fund strategies being in a high volatility regime of the idiosyncratic risk factor. By extending the analysis to the recent subprime mortgage crisis, we find that the crisis affected the hedge fund industry through the exposure to systematic risk factors and influenced the idiosyncratic volatility of several strategies. However, for Emerging Markets and Long Short Equity strategies, idiosyncratic volatility has not been affected. Therefore, we did not find any evidence of contagion among all hedge fund strategies. However, we found contagion among the selected strategies: Convertible Bond Arbitrage, Equity Market Neutral, Event Driven Multi-Strategy, and Risk Arbitrage, i.e., we observed a sharp increase in the joint probability that all of these strategies exhibit a high volatility regime of the idiosyncratic risk factor during August 2007.

We further test our results that are generated using the regime-switching framework. We provide a series of robustness checks by comparing our model to 1) a linear factor model; 2) a linear factor model with a dummy variable for financial crises; 3) an option-based factor model (Fung and Hsieh (2004,2002) and Agarwal and Naik (2004)); 4) a linear factor model that accounts for a switch in volatility of the idiosyncratic risk factor; and 5) an option-

based factor model that accounts for a switch in volatility of the idiosyncratic risk factor. Our results are robust to these tests and out-of-sample analyses.

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 (Bali, Gokcan and Liang (2007), Gupta and Liang (2005), Agarwal and Naik (2004), Schneeweis, Karavas, and Georgiev (2002), Brealey and Kaplanis (2001), Edwards and Caglayan (2001), and Fung and Hsieh (1997)), liquidity and systemic risk (Khandani and Lo (2007), Chan, Getmansky, Haas, and Lo (2005), and Getmansky, Lo, and Makarov (2004)), the role of hedge funds in financial crises (Brunnermeier and Nagel (2004), Fung, Hsieh, and Tsatsoronis (2000), Brown, Goetzmann, and Park (2000), and Eichengreen, Mathieson, Chadha, Jansen, Kodres, and Sharma (1998)), and hedge fund liquidation and failures (Liang and Park (2007) and Getmansky, Lo, and Mei (2004)).

Our work is mostly related to the Boyson, Stahel, and Stulz (2007) paper that investigates the presence of contagion among hedge funds and channels through which contagion occurs.[4] The authors find evidence of contagion among hedge funds, but do not identify when these events happen. In this paper we identify when the contagion events happen and tie them to the presence of specific financial crises. In our sample, we find that contagion among all hedge fund strategies happened only during the LTCM crisis.

The second related paper is by Adrian (2007) who investigates hedge fund risk and comovement. He analyzes the evolution of the correlation and variance of hedge fund returns through time, but does not distinguish between variance generated by the exposure to market risk factors and the variance generated by the idiosyncratic risk factors. Adrian (2007) and Khandani and Lo (2007) also show that a hedge fund risk profile during the LTCM crisis was drastically different from other financial crises. Our work provides a potential explanation for this. In fact we show that the LTCM crisis is the only crisis where we observe contagion among hedge funds strategies.

The rest of the paper is organized as follows. In Section 2 we develop a theoretical framework for multi-factor regime-switching models that can be used to analyze different hedge fund style indices. Section 3 describes data and presents results. Section 4 provides robustness checks. Section 5 concludes.

[4]The authors also concentrate on contagion between markets and hedge funds.

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 multi-factor model applied to hedge fund index returns could be represented as:

$$R_t = \alpha + \beta I_t + \sum_{k=1}^{K} \theta_k F_{k,t} + \omega u_t \tag{1}$$

where R_t is the return of a hedge-fund index in period t, I_t is a market factor, for example, the S&P 500 in period t, $F_{k,t}$ are k other risk factors, ω is the volatility of the idiosyncratic risk factor, and u_t is IID.

In this model, we can identify the exposure of hedge fund returns to risk factors I and F_k. 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 and whose exposures may change during financial crises. 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.[5] The change in a regime should not be regarded as predictable but rather as a random event. Unlike an exogenous definition of crises (as in the case of crises dummies), this methodology allows for an endogenous definition of financial distress.[6]

[5] 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.

[6] 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

More formally, the model could be represented as:

$$R_t = \alpha(Z_t) + \beta(S_t)I_t + \sum_{k=1}^{K} \theta_k(S_t)F_{k,t} + \omega(Z_t)u_t \quad (2)$$

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

where S_t and Z_t are Markov chains with n_s and n_z states respectively and transition probability matrices $\mathbf{P}_s$ and $\mathbf{P}_z$ respectively. The state of the market index I is described by the Markov chain S_t. Each state of the market index I has its own mean and variance. The Markov chain Z_t characterizes the change in volatility of the idiosyncratic risk as well as extra returns captured by $\alpha(Z_t)$. Hedge fund mean returns are related to the states of the market index I and the states of the idiosyncratic risk volatility. Hedge fund volatilities are also related to the states of the market index I and are defined by the factor loadings on the conditional volatility of the factors plus the volatility of the idiosyncratic risk factor $\omega(Z_t)$. In both cases β and θ_k could be different conditional on a state of the risk factor I.

Let us provide an illustration for a three state Markov chain: if $n_s = 3$ (state labels are denoted as 0, 1 or 2), β depends on the state variable S_t:

$$\beta(S_t) = \begin{cases} \beta_0 & \text{if } S_t = 0 \\ \beta_1 & \text{if } S_t = 1 \\ \beta_2 & \text{if } S_t = 2 \end{cases} \quad (4)$$

and the Markov chain S_t (the regime-switching process) is described by the following transition probability matrix $\mathbf{P}_s$:[7]

$$\mathbf{P}_s = \begin{bmatrix} p_{00} & p_{01} & p_{02} \\ p_{10} & p_{11} & p_{12} \\ p_{20} & p_{21} & p_{22} \end{bmatrix} \quad (5)$$

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

to infer time-varying risk exposures of hedge funds, make forecasts, calculate transition probabilities from one state to another, and calculate conditional expectations.

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

for a change in variance of returns only in response to occasional, discrete events. Despite the fact that the states S_t and Z_t are unobservable, they can be statistically estimated (see for example Hamilton (1990, 1989)). 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 S_t is given by $\mathbf{P}_s^k$, 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 regimes is 2 (regime 0 and 1):

$$\begin{aligned} \text{Prob}\left(S_{t+k}=0|\mathcal{R}_t\right) &= \pi_1 \ + (p_{00}-(1-p_{11}))^k\Big[\text{Prob}\left(S_t=0|\mathcal{R}_t\right)-\pi_1\Big] && (6)\\ \pi_1 &\equiv \frac{(1-p_{11})}{(2-p_{00}-p_{11})} && (7) \end{aligned}$$

where $\text{Prob}\left(S_t=0|\mathcal{R}_t\right)$ 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:

$$\begin{aligned} \text{Prob}\left(S_{t+k}=0|\mathcal{R}_t\right) &= \mathbf{P}_s^{k\prime}\mathbf{a}_t && (8)\\ \mathbf{a}_t &= \Big[\ \text{Prob}\left(S_t=0|\mathcal{R}_t\right)\ \ \text{Prob}\left(S_t=1|\mathcal{R}_t\right)\ \ ..\text{Prob}\left(S_t=n|\mathcal{R}_t\right)\Big]' && (9) \end{aligned}$$

Using similar recursions of the Markov chain, the conditional probability of the Markov chain Z_{t+k}, that characterizes the change in volatility of the idiosyncratic risk, given date-t data for strategy i.

$$\begin{aligned} \text{Prob}\left(Z_{i,t+k}=0|\mathcal{R}_{i,t}\right) &= \mathbf{P}_{n_z}^{k}{}'\mathbf{b}_{i,t} && (10)\\ \mathbf{b}_t = \Big[\ \text{Prob}\left(Z_{i,t}\right. &= \left.0|\mathcal{R}_{i,t}\right)\ \ \text{Prob}\left(Z_{i,t}=1|\mathcal{R}_{i,t}\right)\ \ ..\text{Prob}\left(Z_{i,t}=n_s|\mathcal{R}_{i,t}\right)\Big]' && (11) \end{aligned}$$

Our test of contagion is based on the determination of the joint probability that all m hedge fund strategies are in a high volatility regime for the idiosyncratic risk factor:

$$J_p = \prod_{i=1}^{m} \text{Prob}\left(Z_{i,t} = 1 | R_{i,t}\right) \tag{12}$$

In our framework we define contagion among hedge funds strategies when we observe a significant change in the joint probability that all hedge funds are in the high volatility state for the idiosyncratic risk factor, i.e., a large change in J_p.

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, Guidolin and Timmermann's (2006) and Ang and Bekaert's (2002) regime-switching asset allocation models, Lettau, Ludvigson, and Wachter's (Forthcoming) regime-switching equity premia model, and Billio and Pelizzon's (2003, 2000) analysis of VaR 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 indices 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, we use a regime-switching *beta* model that can distinguish whether the distress in the hedge fund industry is generated from the dynamic exposure to systematic risk factors that are affected by financial crises, from contagion in the hedge fund industry, or both.

As noted earlier, we use the regime-switching approach for the majority of our analyses. In addition, we use the linear factor model with a dummy crisis variable, Fung and Hsieh (2004, 2002) model with option-based factors, an asymmetric beta model, a threshold model, a linear factor model and the Fung and Hsieh model with the switch in volatility of the idiosyncratic risk factor, and the Getmansky et al. (2004) approach for accounting for the smoothing effect as robustness tests.

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 July 2007.[8] We also extend the data till January 2008 to study the recent Subprime mortgage crisis.

The CSFB/Tremont indices are asset-weighted indices 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-indices based on investment style are also computed using a similar method. Indices 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 one-month 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 excess 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 indices to the market index, the S&P 500; therefore, we concentrate only on hedge fund styles that either directly or indirectly have the S&P 500 exposure.[9] 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

[8] Fung and Hsieh option-based factors used in the out-of-sample analysis are downloaded from David Hsieh's website and are available up to July 2007.

[9] The model is flexible and can be applied to any market index. For example, for Fixed Income Arbitrage Funds, fitting regimes of Lehman Brothers Bond Index is going to be more appropriate.

as Event Driven Multi-Strategy, Risk Arbitrage and Convertible Bond Arbitrage all have negative skewness and high excess kurtosis. The exception is the Equity Market Neutral strategy, which has a low positive skewness and excess kurtosis. Directional strategies such as Dedicated Shortseller, Long/Short Equity have positive skewness and small excess kurtosis. Emerging Markets strategy has a slight negative skewness of -0.65 and a small excess kurtosis. The market factor, the S&P 500, 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.

As discussed above, other factors besides the S&P 500 affect hedge fund index returns. 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 3. 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 indices. 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 one-month LIBOR returns.

[INSERT Table (3) about here]

3.2 S&P 500 regimes

In this section we estimate S&P 500 regimes in order to endogenously identify potential market downturns that could be associated with financial distress. Conditional on this result, in the next Section 3.3 we estimate a multi-factor model.

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.[10] Moreover, the use of the three regimes is in line with our objective — disentangling the effect of financial crises on the hedge fund industry.

The results of the estimation are shown in Table 2.[11] S&P 500 returns are in excess of one-month LIBOR.

[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 regime, 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, regime 2, which is often associated with financial crises, 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%.[12]

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's 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 downturns 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

[10] Goetzmann, Ingersoll, Spiegel, and Welch (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.

[11] All switching regime models have been estimated by maximum likelihood using the Hamilton's filter and the econometric software GAUSS.

[12] 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. For the switching-regime models the standard deviations obtained with the usual covariance matrix estimator and the robust covariance matrix estimator are similar.

1 (100%). It is important to note that the three-regime approach does not imply simply 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.[13]

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, 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.

The possibility of characterizing the distribution of the S&P500 during market downturns allows us to analyze the exposure of the hedge fund industry to the market and other systematic risk factors when the market is in financial distress.

[INSERT Figure (2) about here]

Our analysis also allows us to analyze the distribution of the S&P500 and derive hedge funds risk exposures in the other two regimes.

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,

[13]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 4. 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.

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.

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 and other systematic risk factors in all these regimes (i.e., different market conditions).

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 during market financial distress.

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 and other risk factors. The use of a switching regime beta model allows us to distinguish between dynamic exposure to systematic risk factors and idiosyncratic risk factors in different volatility regimes. We separately analyze these two components in the following Sections 3.3 and 3.4.

3.3 Dynamic Risk Exposure to Systematic Risk Factors

In this section, for each hedge fund strategy we estimate the multi-factor model specified in equation (2) and the results are contained in Table 4.[14] Here, we are considering nonlinear exposure to systematic risk factors: S&P 500, 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.[15] For each factor, we estimate three exposures: $\theta_{i,0}$ is a hedge fund exposure for a factor i when the $S\&P500$ is in the up-state; $\theta_{i,1}$ is a hedge fund exposure for a factor i when the $S\&P500$ is in the normal state; and $\theta_{i,2}$ is a hedge fund exposure for a factor i when the $S\&P500$ is in the down-state.

[INSERT Table (4) about here]

[14] All switching regime models have been estimated by maximum likelihood using the Hamilton's filter and the econometric software GAUSS.

[15] Because of the limited dataset, the step-wise linear approach was used to limit the final list of factors for the analysis.

Figure 3 presents the synthesis of the results, where the number of strategies with significant risk exposures to various risk factors conditional on the market states is depicted.

[INSERT Figure (3) 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. Moreover, the model shows that factor exposure is changing conditional on the state of the market.

We find that in all cases hedge fund exposure to the S&P 500 in the down-state of the S&P 500 is smaller than in the normal or up-state of the market. This suggests that hedge fund managers are able to timely hedge market exposures, especially during financial crises. We further study if hedge fund managers are able to reduce hedge fund exposure to other risk factors during financial market distress.

Our analysis of the dynamic exposures on other risk factors shows that Credit Spread, Large-Small, and change in VIX are common factors for many hedge fund strategies in the down-state of the market, as Figure 3 well highlights, suggesting that these factors are important in accessing systematic hedge fund risk, especially in the down-state of the market, which is often associated with financial crises.

In particular, we find that LS is a common factor in the market downturn for seven out of eight hedge funds strategies and for six out of eight it has the same sign. This 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 nonlinear 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 (1998, 1994)). 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. However, a deep analysis of this issue is needed and is left to further investigation.

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. 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.

Also change in VIX is a common risk factor for the hedge fund industry. 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 all other strategies, possibly due to the nature of the strategy that profits from negative volatility shocks to the market.

In many 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 usually not able to capture this exposure.[16]

3.4 Idiosyncratic Risk Factor

In addition to the analysis of expected market exposures, the regime-switching beta model allows us to obtain the evolution of the idiosyncratic risk for separate hedge fund strategies. To our knowledge, this is the first paper that captures the evolution of the volatility of the idiosyncratic risk factors for different hedge fund strategies.

In particular, our estimation of the Markov chain for the idiosyncratic risk of hedge funds

[16] 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 indices, 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.

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 4). 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 4 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.

Using the model specification described in equation 2 and presented in Table 4, 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 indices facing a high volatility regime for the idiosyncratic risk factor, i.e., volatility of the hedge fund indices 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 indices 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 exposure to the S&P 500 is changing, but also that the idiosyncratic risk of the hedge fund indices may switch to the high-volatility regime at the same time when the market is characterized by turbulence. This can be explained by contagion among hedge fund strategies.

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 result 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.[17] The results suggest that the LTCM crisis not only affected market risk factors, but also, after controlling for market and other systematic 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.

[INSERT Figure(6) about here]

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

3.5 Subprime Mortgage Crisis

In the sample considered, we found that the LTCM crisis was the only case where the joint probability of being in a high volatility state for all hedge fund strategies spiked and approached one. Given the recent subprime mortgage crisis of August 2007 and speculations that hedge funds might be affected by this crisis, we performed a similar analysis for this period.

Khandani and Lo (2007) find an increased correlation between hedge fund styles in this period. The authors suggest that this can be due to the increase in systematic linkages with market factors, liquidity, and credit proxies. In our framework, we test whether the increase in correlations is due to the increase in the systematic linkages or due to contagion. Specifically, we re-estimate our model till January 2008 and find that the coefficients to Large-Small (liquidity proxy) and Credit Spread (credit proxy) increased when the subprime mortgage crisis period is taken into account, confirming Khandani and Lo (2007)'s conjecture.

Furthermore, we explored whether contagion among hedge funds occurred during the subprime mortgage crisis. Specifically, we obtained individual estimates for probability of high-volatility state of the idiosyncratic risk factor for the same six hedge fund strategies: Event Driven Multi-Strategy, Long Short Equity, Risk Arbitrage, Convertible Bond Arbitrage, Emerging Markets, and Equity Market Neutral strategies.[18]

The obtained evolutions of the idiosyncratic risk factor are plotted in Panels A and B of Figure 7 from January 2005 through January 2008. The probability of being in a high-volatility state of the idiosyncratic risk factor for Event Driven Multi-Strategy, Risk Arbitrage, Convertible Bond Arbitrage, and Equity Market Neutral greatly increased during the subprime mortgage crisis of August 2007. Therefore, these strategies were affected by the crisis, even after taking into account systematic risk exposure. Long Short Equity experienced only a slight increase at the end of 2007. However, Emerging Markets category had a zero probability of being in a high-volatility state of the idiosyncratic risk factor during the whole time period. As a result, the joint probability of a high volatility state for all strategies is zero during the subprime mortgage crisis (Figure 8, Panel A).[19] Even though the subprime mortgage crisis affected separate hedge fund categories (Panels A and B of Figure 7), it did not affect the hedge fund industry as a whole and did not lead to contagion among all hedge fund categories.

[18] Dedicated Shortseller and Distressed still present only one volatility regime, therefore, are omitted from the analysis.

[19] The result is robust even when Emerging Markets are taken out from the estimation.

[INSERT Figure(7) about here]

We further concentrate our analysis on the four strategies that were affected by the crisis: Event Driven Multi-Strategy, Risk Arbitrage, Convertible Bond Arbitrage, and Equity Market Neutral and calculate the joint probability of the high volatility state of the idiosyncratic risk factor. As expected, we find some evidence of contagion among these four strategies, i.e., evidence of a significant increase in the co-movement of the volatility of the idiosyncratic risk factor for these strategies, as shown in Figure 8, Panel B. In this case, the joint probability of high volatility in August 2007 (subprime mortgage crisis) is below 50%. If we compare this result with the one obtained during the LTCM crisis that reaches a joint probability higher than 95%, we can conclude that the LTCM was the only crisis where the whole hedge fund industry was affected.

[INSERT Figure(8) about here]

4 Robustness Analysis

After documenting the existence of common factor exposures among hedge fund strategies during market downturns and finding that the LTCM was the only crisis in our sample that precipitated contagion among hedge funds, we investigate the robustness of our results.

First, we would like to compare our model to other models available in the literature in the ability of capturing hedge fund risk exposures. Specifically, in this section we compare our multi-factor regime-switching model for analysis of hedge fund style indices to a linear factor model, an asymmetric beta model, a threshold model, a linear factor model with a dummy variable for the presence of financial crises, and Fung and Hsieh (2004, 2002) option-based model. We also adjust for potential illiquidity and smoothing in the data, check that the regime-switching approach is applicable to individual hedge funds as well as indices, and perform an out-of-sample analysis.

Second, it is possible that our finding of contagion among hedge funds during the LTCM crisis is driven by the way we model systematic risk factor exposures. This finding can be attributed to (i) nonlinearities generated using our regime-switching model, or (ii) nonlinearities in hedge fund returns that could be easily captured using option-like factors, but are not captured with the regime-switching model. In order to address these concerns we extend the linear factor model and the Fung and Hsieh (2004,2002) option-based factor model to

include the change in volatility of the idiosyncratic risk factor. The analysis of the joint probability of the high volatility of the idiosyncratic risk factor for these models provides a robustness test for our result.

4.1 Comparison with a Linear Factor Model

In this section we compare our multi-factor regime-switching model with a linear factor model (LFM). Unlike LFM, our model is able to capture hedge fund factor exposures during different market conditions, especially, during market crises.

The results for the LFM are presented in Table 5. The comparison with the LFM regression shows that LFM is missing some factor exposures and does not take into account time-variability of risk factors based on market conditions.

[INSERT Table (5) about here]

In fact, 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, and Event Driven Multi-Strategy, but changes to positive in up- or down-states of the market. Also, the exposure to Lehman Government Credit is negligible for Convertible Bond Arbitrage and Long/Short Equity indices; 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 Long/Short Equity and Event Driven Multi-Strategy, but becomes highly positive and significant in the up- or 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 during financial distress. With our approach we are not able to distinguish among the two phenomena and simply capture the total exposure that arises from both dynamic strategies and asset portfolio nonlinear exposures.

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 up- 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 nonlinear 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 strategies in the down-market state.

In terms of goodness-of-fit for nonlinear models we use the pseudo R^2 approach proposed by McFadden (1974). This measure has also been used by Boyson, Stahel and Stulz (2007) to compare different hedge fund risk models. The results show that the regime-switching model is clearly superior to the LFM model based on the pseudo R^2 metric.

4.2 Comparison with Nonlinear Factor Models

An alternative way to investigate how our results are different from other models that account for nonlinear exposures to market risk factors is to analyze risk exposures highlighted with (i) an asymmetric beta model, (ii) a threshold model, and (iii) an option-based factor model.

Asymmetric Beta and Threshold Models

In the asymmetric beta 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 Chan et al. (2005), Agarwal and Naik (2004), Mitchell and Pulvino (2001), and Asness, Krail, and Liew (2001). 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, we consider the following regression:

$$R_{it} \;=\; \alpha_i \;+\; \beta_i^{+}\, I_t^{+} \;+\beta_i^{0}\, I_t^{0} \;+\; \beta_i^{-}\, I_t^{-} \;+\; \epsilon_{it} \tag{13}$$

where

$$I_t^{+} = \begin{cases} I_t & \text{if } I_t > \mu + \sigma \\ 0 & \text{otherwise} \end{cases} \qquad I_t^{0} = \begin{cases} I_t & \text{if } \mu - \sigma < I_t < \mu + \sigma \\ 0 & \text{otherwise} \end{cases} \qquad I_t^{-} = \begin{cases} I_t & \text{if } I_t \leq \mu + \sigma \\ 0 & \text{otherwise} \end{cases} \tag{14}$$

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 (13), the

case where $\beta_i^+ = \beta_i^0 = \beta_i^-$. The specification (13) essentially tries to capture asymmetries in the index exposures.

Using the specification (13), we regress hedge fund returns on the S&P 500 index during up (I_t^+), normal (I_t^0), and down (I_t^-) conditions.[20] Beta asymmetries are quite pronounced especially, for Emerging Markets, Distressed, Event Driven Multi-Strategy, and Equity Market Neutral. For example, the Equity Market Neutral index has zero normal and down-market betas — seemingly market neutral — however, its up-market beta is 0.14. The exposure of the Convertible Bond Arbitrage strategy to the S&P 500 is negligible for both normal and down-markets, and is slightly positive (0.07) for the up-market.

The results using the threshold model are similar to the ones obtained using the regime-switching methodology. 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 Event Driven Multi-Strategy, whereas the threshold methodology misses this link.

Comparing the two models, 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. The 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.

Option-Based Factor Model

An option-based factor model was originally proposed by Fung and Hsieh (2004, 2002) to explain hedge fund returns. We compare our multi-factor regime-switching model (MRSM) to the Fung and Hsieh's model (FHM), and results are presented in Table 6. The option-based factor model also shows evidence of the presence of a common exposure to the LS (liquidity) factor and a slightly common exposure to the credit spread (CS).

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

Moreover, we observe that the MRSM fits the data better than the FHM. In fact for all styles, pseudo R^2 for the MRSM is larger than the one for the FHM. Therefore, the MRSM model comparably well captures systematic risk exposure of hedge funds.

[INSERT Table (6) about here]

Given that the focus of the option-based model is to explain hedge fund returns rather than investigate hedge fund risk exposure during financial crises, this model is unable to highlight if hedge fund strategies present a common risk exposure during market downturns.

Linear Factor Model with a Crisis Dummy

The objective of our paper is to investigate the impact of financial crises on hedge fund risk exposures. With the regime-switching model we have endogenously identified a down-market (crisis) state. Our analysis shows that hedge fund exposures during market downturns are different from normal and up-market conditions. We investigate whether this change in the exposures can also be captured with a simple dummy variable for the presence of financial crises. We have created a dummy variable that is equal to one when we observe the Mexican, Asian, Russian and LTCM, Brazilian, Argentinean, and Internet crises (the crises periods are identified by Rigobon (2003), Table 2).[21]

As Table 7 shows, the crisis dummy variable is often significant for different risk factors. This confirms that during crisis periods risk exposures of hedge funds change and not always lead to the reduction of those risk exposures. The increases of risk exposures during crises are mixed and partially fit with those we found with the MRSM. However, the linear factor model with a crisis dummy is rather simple and may not capture all nonlinear exposures hedge funds may present.

Adjusted R^2 for the model that accounts for the crisis dummy is higher than for the model that does not account for the crisis dummy, confirming that risk exposures of hedge funds change during crisis periods. Moreover, Pseudo R^2 is higher for this model compared to the option-based FHM model. However, Pseudo R^2 is lower than that for the multi-factor regime-switching MRSM model, indicating that it is important to control for crisis periods when evaluating risk exposure for hedge funds.

[INSERT Table (7) about here]

[21] The list of factors is consistent with the main analysis, where due to the limited dataset the step-wise linear approach was used to limit the final list of factors.

4.3 Data Smoothing and Illiquidity Effect

As shown by Getmansky, Lo, and Makarov (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:

$$R_t = \mu + \beta\Lambda_t + \epsilon_t \ , \ \mathrm{E}[\Lambda_t] = \mathrm{E}[\epsilon_t] = 0 \ , \ \epsilon_t \ , \ \Lambda_t \sim \mathrm{IID} \tag{15a}$$

$$\mathrm{Var}[R_t] \equiv \sigma^2 \ . \tag{15b}$$

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

$$R_t^o = \theta_0 R_t + \theta_1 R_{t-1} + \cdots + \theta_k R_{t-k} \tag{16}$$

$$\theta_j \in [0,1] \ , \ j = 0, \ldots, k \tag{17}$$

$$1 = \theta_0 + \theta_1 + \cdots + \theta_k \tag{18}$$

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.

In line with this approach we determine R_t^o, i.e., "real returns" and estimate our models on the real returns.[22] The results 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.[23]

Moreover, the dynamics of the volatility of the idiosyncratic risk factor are not affected by data smoothing or illiquidity; and the result about the joint probability that switches from zero to more than 95% during LTCM crisis is confirmed.

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

[23] 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.

4.4 Single Hedge Funds Exposure

We investigate whether the exposures we observe on hedge fund indices 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.[24]

4.5 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 indices, 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.[25]

In the original data, normality test was rejected for all strategies except the Market Neutral strategy.[26]

When a multi-factor model (MRSM) is considered, normality is accepted for 6 out of 8 strategies. Therefore, based on the improvement in normality in our results, we conclude that regime-switching models are able to capture nonlinear 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.

4.6 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 are estimated in-sample, and the validity of these risk exposures is analyzed in out-of-sample data.

If risk exposures do not underlie the true return generating processes of hedge funds, then

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

[25]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.

[26]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 nonlinear instruments.

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.

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 multi-factor regime-switching beta model (MRSM). 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 risk factors at $t+1$ to construct returns of the replicating portfolio.[27]

We use an out-of-sample of 33 observations (from November 2004 to July 2007) and therefore this procedure is repeated 33 times.[28] We further conduct standard tests on the significance of the mean difference between the actual hedge fund index returns and returns of replicating portfolios. Specifically, we calculate a model performance measure: Mean Absolute Error (MAE). We use this measure to compare the following models: Linear factor model (LFM), Random Walk (RW), Fung and Hsieh option-based model (FHM), and multi-factor regime-switching beta (MRSM). We report the results in Table 8.

[INSERT Table (8) about here]

We find that for six out of the eight strategies considered the MSRM model always has a smaller MAE compared to LFM, RW, and FHM models. For other two strategies, the MAE is close to the minimum. Therefore, we conclude that a portfolio based on risk exposures estimated through the multi-factor regime-switching model is at least as good as that based on LFM and FHM models in replicating hedge fund returns during the out-of-sample period. This suggests that regime-switching models are able to capture at least some dominant systematic risk exposures of hedge funds.

4.7 Analysis of Idiosyncratic Risk Using LFM and FHM Models

As discussed above, for most of the sample we find the joint probability of high idiosyncratic volatility for all hedge funds, our proxy for contagion, is approximately zero, but there are

[27] 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.

[28] We stop in July 2007 because option-based factors from David Hsieh's website are available through July 2007.

three months among the 157 considered where we find that the joint probability that all hedge funds are in the high idiosyncratic volatility regime is close to 1 — during the LTCM crash of August 1998. It is possible that our finding of contagion among hedge funds during the LTCM crisis is driven by the way we model systematic risk factor exposures. For this reason we extend the linear factor (LFM) and Fung and Hsieh option-based (FHM) models by directly modeling a change in volatility of the idiosyncratic risk factor.

Formally, for the Linear Factor Idiosyncratic Switching Volatility model (LFIM) we estimate the following:

$$R_t = \alpha(Z_t) + \lambda_k L_{k,t} + \omega(Z_t) \tag{19}$$

where R_t is the return of a hedge-fund index in period t, $L_{k,t}$ are k linear factors, and ω is the volatility of the idiosyncratic risk factor. The Markov chain Z_t characterizes the change in volatility of the idiosyncratic risk factor.

Moreover, for the Fung and Hsieh Idiosyncratic Switching Volatility model (FHIM) we estimate the following:

$$R_t = \alpha(Z_t) + \lambda_k H_{k,t} + \omega(Z_t) \tag{20}$$

where R_t is the return of a hedge-fund index in period t, $H_{k,t}$ are k Fung and Hsieh option-based factors, and ω is the volatility of the idiosyncratic risk factor.

The joint high volatility probabilities of idiosyncratic risk factor for both models are reported in Figure 9.

[INSERT Figure(9) about here]

Figure 9 is qualitatively similar to the result obtained before. For both models, the joint probability that all the hedge fund strategies switch to a high volatility regime is almost zero during the sample considered. The only exception is during the LTCM crisis. The probability for the LFIM changes from zero to 60%. It is possible that some element of noise is present and the model is not able to disentangle this effect from the evolution of the idiosyncratic volatility. However, when FHIM is considered, the joint probability is almost identical to

the one estimated with the multi-factor regime-switching model. This confirms that the LTCM crisis is the only case which precipitated contagion among hedge funds strategies, even though the market was characterized by other crises in the sample considered.

5 Conclusion

In this paper we study the effect of financial crises on hedge fund risk. We analyze state-dependent risk exposures for various hedge fund strategies, identify common risk factors across different hedge fund strategies, especially, in the down-state of the market, and isolate a crisis event where all different hedge fund strategies move to a high volatility state due to non-market related shocks.

We characterize the exposure of hedge fund indices 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, 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, which are often associated with financial crises, are quite different than those faced during normal regimes. We find that in most cases hedge fund exposure to the S&P 500 in the down-state of the S&P 500 is smaller than in the normal or up-state of the market. This suggests that hedge fund managers are able to timely hedge market exposures, especially during financial crises.

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, when financial crises are more prevalent. 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. In summary, our results suggest that liquidity and credit are important risk factors for hedge fund returns especially when the markets are in a crisis state.

Third, we have allowed for a possibility and found evidence that all hedge fund strategies exhibit a high volatility regime of the idiosyncratic risk 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 157 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. In fact, our analysis shows that other crises including the recent subprime mortgage crisis affected hedge funds only through systematic risk factors, and did not cause contagion among hedge funds.

Understanding hedge fund risk exposure and contagion is important for investors, risk managers, and regulators. Contagion among hedge funds eliminates the benefits of portfolio diversication and may lead to diversification implosion.[29] Moreover, it can lead to potential margin calls for hedge fund investors. Furthermore, both contagion and potential increase in systematic exposure during financial crises can lead to systemic risk. Identifying common risk factors, especially in the down-state of the market and sources of contagion among hedge funds can help address regulators' concern regarding the potential risk hedge funds may pose for stability of financial markets.

[29]For examples of diversification implosion in hedge funds, see Fung, Hsieh and Tsatsoronis (2000).

References

Acharya Viral and Stephen M. Schaefer, 2006, "Liquidity Risk and Correlation Risk: Implications for Risk Management," London Business School Working Paper.

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

Adrian, Tobias, 2007, "Measuring Risk in the Hedge Fund Sector," *Current Issues in Economics and Finance* 13, 3, 1–7.

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

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

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

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

Asness, Cliff, Krail, Robert and John Liew, 2001, "Do Hedge Funds Hedge?," *The Journal of Portfolio Management* 28, 6–19.

Bae, Kee-Hong, Karolyi, G. Andrew, and Rene M. Stulz, 2003, "A New Approach to Measuring Financial Contagion," *The Review of Financial Studies* 16, 3, 717–763.

Bali, Turan G., Gokcan, Suleyman and Bing Liang, 2007, "Value at Risk and the Cross-Section of Hedge Fund Returns," *Journal of Banking and Finance* 30, 4, 1135–1166.

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

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

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

Bollen, Nicolas P.B. and Robert E. Whaley, 2007, "Hedge Fund Risk Dynamics: Implications for Performance Appraisal," Vanderbilt University Working Paper.

Boyson, Nicole M., Stahel, Christof W. and Rene M. Stulz, 2007, "Is There Hedge Fund Contagion?," Northeastern University Working Paper.

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

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

Brown, Stephen J., William N. Goetzmann, and James M. Park, 2000, "Hedge Funds and the Asian Currency Crisis of 1997," *Journal of Portfolio Management* 26, 4, 95–101.

Brown, Stephen J. and Jonathan F. Spitzer, 2006, "Caught by the Tail: Tail Risk Neutrality and Hedge Fund Returns," NYU Stern School of Business Working Paper.

Brunnermeier, Markus and Stefan Nagel, 2004, "Hedge Funds and the Technology Bubble," *Journal of Finance* 59, 5, 2013–2040.

Chan, Nicholas T., Getmansky, Mila, Haas, Shane M. and Andrew W. Lo., 2005, "Systemic Risk and Hedge Funds," *NBER Book On Risks of Financial Institutions, Topic: Systemic Risk.*

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

Edwards, Franklin R. and Mustafa O. Caglayan, 2001, "Hedge Fund Performance and Manager Skill," *Journal of Futures Markets* 21, 1003–1028.

Eichengreen, Barry, Mathieson, Donald, Chadha, Bankim, Jansen, Anne, Kodres, Laura, and Sunil Sharma, 1998, "Hedge Fund and Financial Market Dynamics," Occasional Paper 166. Washington: International Monetary Fund (May 15).

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

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

Fung, William, David A. Hsieh, and Konstantinos Tsatsoronis, 2000, "Do Hedge Funds Disrupt Emerging Markets?," *Brookings-Wharton Papers on Financial Services* 377–421.

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

Fung, William and David A. Hsieh, 2002, "Asset-Based Style Factors for Hedge Funds," *Financial Analysts Journal* 58, 16–27.

Fung, William and David A. Hsieh, 2004, "Hedge Fund Benchmarks: A Risk-Based Approach," *Financial Analysts Journal* 60, 5, 65–80.

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

Getmansky, Mila, Lo, Andrew W. and Shauna Mei, 2004, "Sifting Through the Wreckage: Lessons from Recent Hedge-Fund Liquidations," *Journal of Investment Management* 2, 4, Fourth Quarter 6–38.

Goetzmann, William, Ingersoll, Jonathan, Spiegel, Matthew and Ivo Welch, 2007,"Portfolio Performance Manipulation and Manipulation-Proof Performance Measures," *Review of Financial Studies* 20, 5, 1503–1546.

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

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

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

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

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

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

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

Khandani, Amir and Andrew W. Lo, 2007, "What Happened To The Quants in August 2007?," *Journal of Investment Management* 5, 4, Fourth Quarter.

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

Liang, Bing and Hyuna Park, 2007, "Share Restrictions, Liquidity Premium and Offshore Hedge Funds," University of Massachusetts, Amherst Working Paper.

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

Mitchell, Mark and Todd Pulvino, 2001, "Characteristics of Risk and Return in Risk Arbitrage," *The Journal of Finance* 56, 6, 2135–2175.

Rigobon, Roberto, 2003, "Identification Through Heteroskedasticity," *Review of Economics and Statistics* 85, 4, 777–792.

Schneeweis, Thomas, Karavas, Vassilios and Georgi Georgiev, 2002, "Alternative Investments in the Institutional Portfolio," University of Massachusetts, Amherst Working Paper.

White, Halbert, 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 one-month LIBOR. 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 excess 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. S&P 500 returns are in excess of one-month LIBOR. 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.

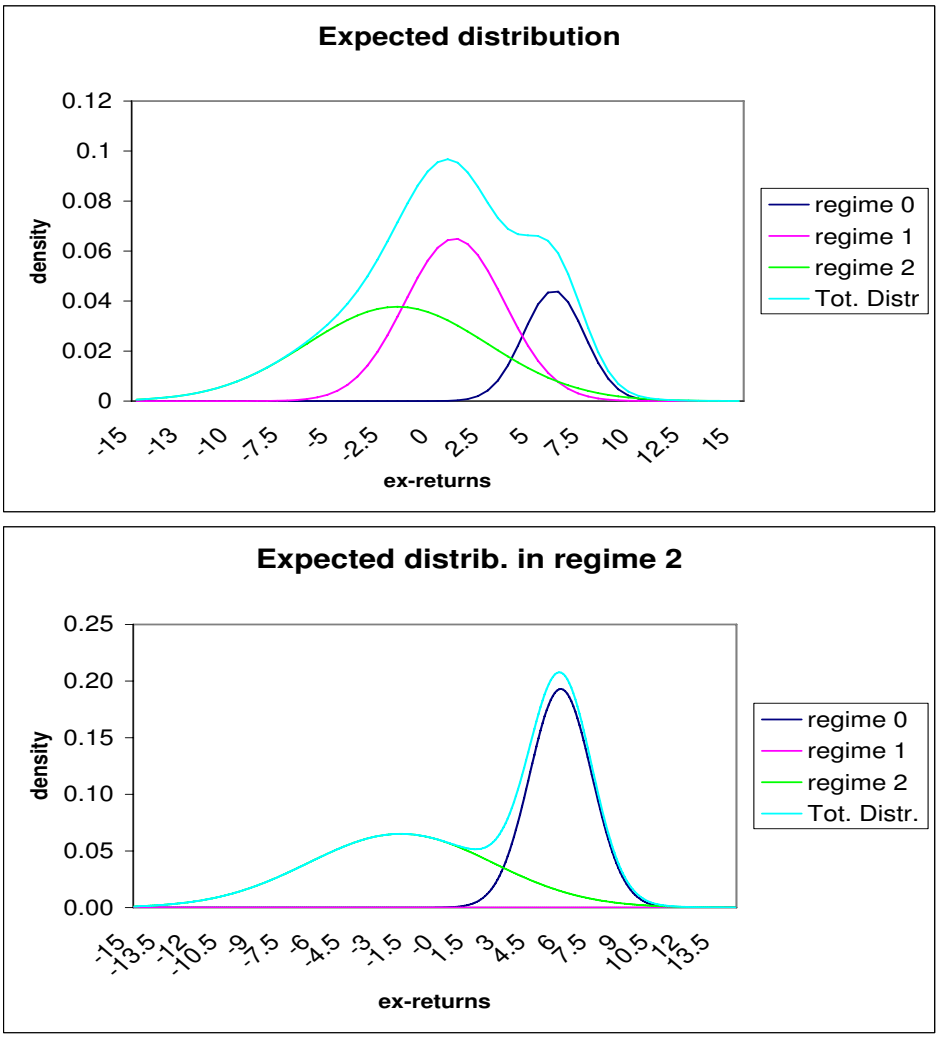
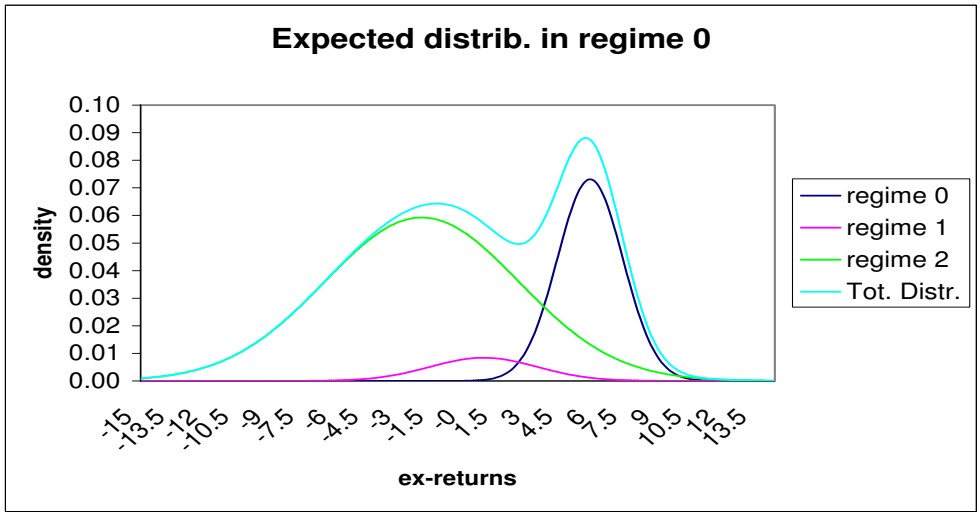


Figure 2: **Conditional Distributions of the S&P 500 in 3 Regimes**

The first panel describes the distribution of the S&P 500 conditional on the up-market regime. S&P 500 returns are in excess of one-month LIBOR. 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.



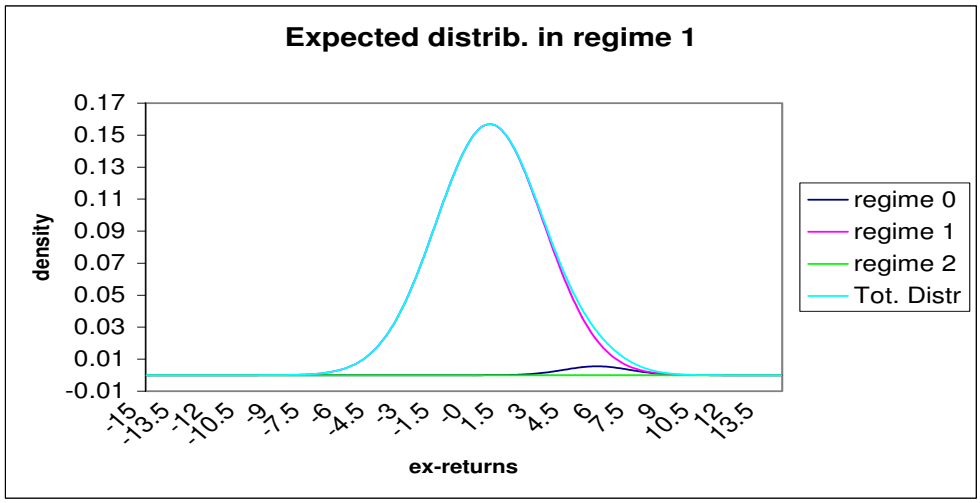


Table 2: **Regime-Switching Model for the Market Risk Factor, S&P 500**

This table presents the results for the regime-switching model for the market risk factor, S&P 500. S&P 500 returns are in excess of one-month LIBOR. 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 January 1994 to March 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: **Variable Definitions**

This table presents definitions of market and other risk factors used in multi-factor 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 4: **Multi-factor Model**

This table presents the nonlinear 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, F_{kt} are other risk factors, and $\omega(Z_t)$ is the volatility of the idiosyncratic risk factor. 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**	
Pseudo R^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	**-0.07**	**-0.94**	**0.64**	**4.75**	**0.50**	**6.44**	**-0.17**	**-1.60**
α_1	**0.43**	**0.96**			**-2.95**	**-10.35**	**0.23**	**2.33**
β_0 (SP)	**0.73**	**8.69**	**0.17**	**1.64**	**0.28**	**5.21**	**0.14**	**3.33**
β_1 (SP)	**0.53**	**14.16**	**0.34**	**4.00**	0.08	1.40	**0.20**	**3.69**
β_2 (SP)	**0.38**	**9.42**	**0.20**	**2.58**	**0.11**	**2.04**	**0.07**	**1.51**
θ_{1_0} (LS)	**-0.62**	**-6.21**	**-0.17**	**-1.80**	**-0.13**	**-3.77**	**-0.16**	**-2.39**
θ_{1_1} (LS)	**-0.29**	**-6.14**	**-0.19**	**-2.50**	0.01	0.20	**-0.14**	**-3.44**
θ_{1_2} (LS)	**-0.28**	**-6.12**	**-0.12**	**-2.32**	**-0.12**	**-3.92**	**-0.17**	**-6.51**
θ_{2_0} (VG)			**0.10**	**0.88**			**0.16**	**3.35**
θ_{2_1} (VG)			**0.04**	**0.37**			-0.03	-0.46
θ_{2_2} (VG)			0.09	1.87			**0.07**	**2.59**
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)	**0.13**	**0.65**	**0.14**	**0.43**				
θ_{4_1} (L.GC)	0.05	0.78	**0.20**	**1.65**				
θ_{4_2} (L.GC)	**0.29**	**2.38**	**0.12**	**0.75**				
θ_{5_0} (TS)	**-0.62**	**-1.72**						
θ_{5_1} (TS)	**-0.57**	**-5.67**						
θ_{5_2} (TS)	0.14	0.65						
θ_{6_0} (dVIX)	**0.28**	**3.89**	0.11	1.02	**0.25**	**7.76**	0.01	0.24
θ_{6_1} (dVIX)	**0.11**	**2.90**	**0.20**	**2.48**	0.07	1.31	**0.15**	**3.24**
θ_{6_2} (dVIX)	-0.02	-0.44	**-0.25**	**-3.47**	0.03	0.73	**-0.15**	**-2.40**
θ_{7_0} (CS)	**3.63**	**1.14**	**-6.04**	**-2.30**	**-0.34**	**-15.77**	**4.86**	**2.26**
θ_{7_1} (CS)	**-3.56**	**-1.72**	**-5.18**	**-5.10**	**-3.50**	**-69.20**	-1.64	-1.53
θ_{7_2} (CS)	**-3.35**	**-2.14**	**-1.07**	**-450.18**	**-0.76**	**-5.58**	-0.08	-0.12
θ_{8_0} (Gold)								
θ_{8_1} (Gold)								
θ_{8_2} (Gold)								
θ_{9_0} (MSCIEMD)								
θ_{9_1} (MSCIEMD)								
θ_{9_2} (MSCIEMD)								
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**	**4.27**			**0.04**	**1.84**		
θ_{11_1} (UMD)	0.06	1.72			0.05	1.15		
θ_{11_2} (UMD)	**0.16**	**4.99**			0.02	1.35		
ω_0	**0.93**	**21.97**	**1.31**	**16.99**	**0.79**	**18.65**	**0.48**	**10.89**
ω_1	**2.35**	**5.11**			**2.74**	**4.85**	**0.97**	**20.35**
p^Z_{00}	**0.99**				**0.98**		**0.98**	
p^Z_{11}	**0.91**				**0.66**		**1.00**	
Pseudo R^2	0.31		0.16		0.25			

Figure 3: **Number of Strategies with Significant Factor Exposures for the Multi-factor Model**

This figure depicts the number of strategies with significant factor exposures for the multi-factor regime-switching model during up-market, normal, and down-market regimes of the S&P 500. The following factors are considered: 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, F_{kt} are other risk factors, and $\omega(Z_t)$ is the volatility of the idiosyncratic risk factor. 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.

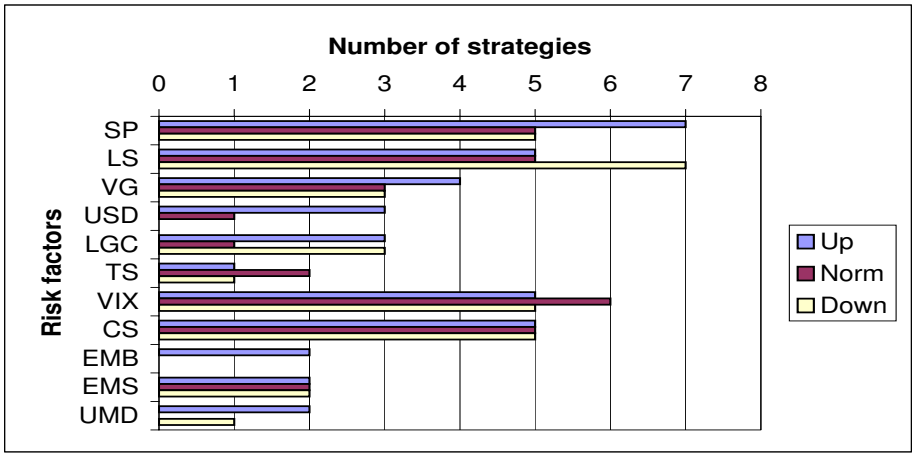


Figure 4: **Probability of Being in a High-Volatility State of the Idiosyncratic Risk Factor for CA, EM, and EM Strategies**

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.

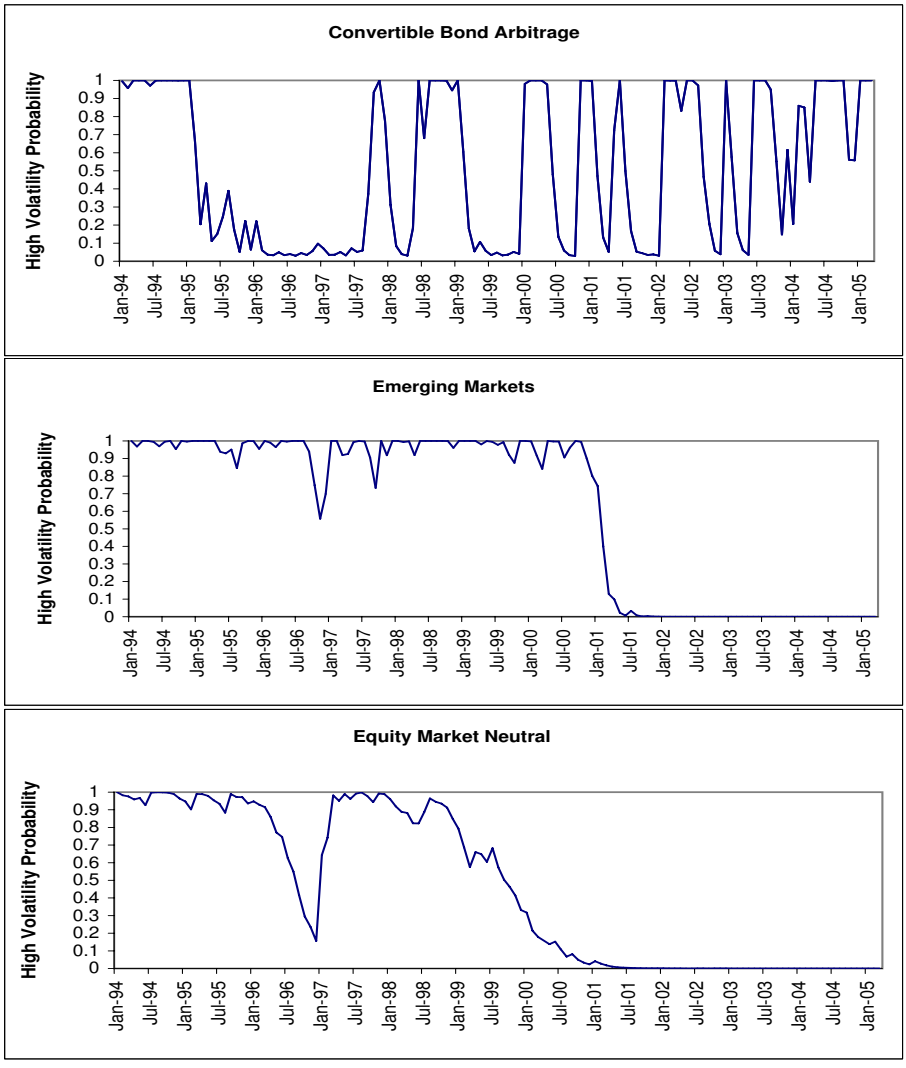


Figure 5: **Probability of Being in a High-Volatility State of the Idiosyncratic Risk Factor for LS, ED and RA Strategies**

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.

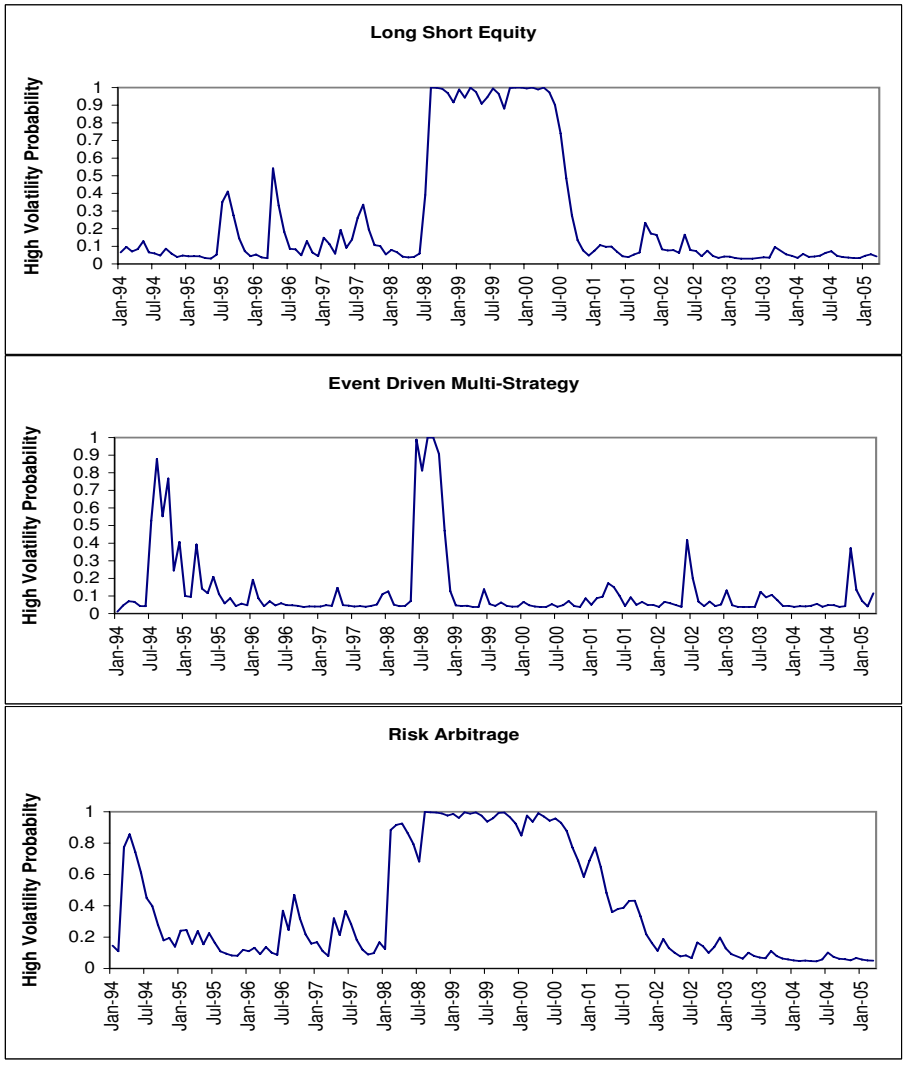
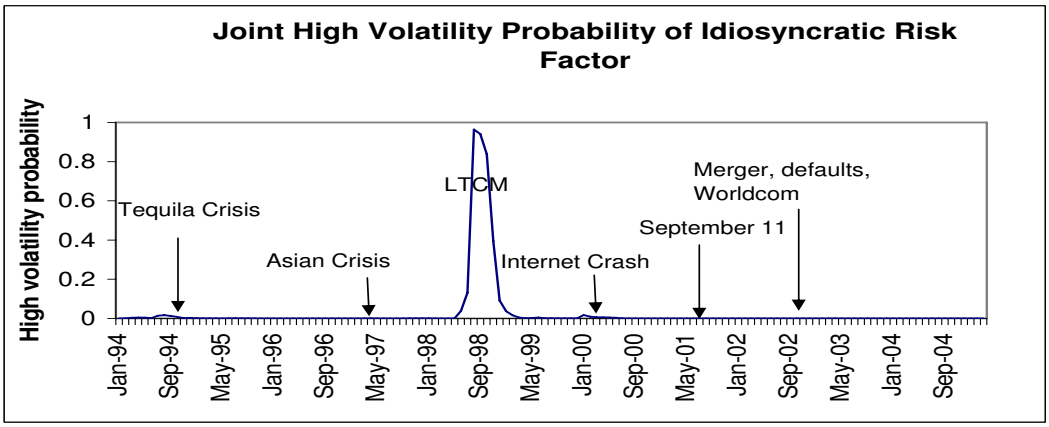


Figure 6: **The Joint Probability of High-Volatility State of the Idiosyncratic Risk Factor for All Hedge Fund Strategies**

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 The Joint Probability of High-Volatility State of the Idiosyncratic Risk Factor for All Hedge Fund Strategies: January 1994 - March 2005



Panel B The Joint Probability of High-Volatility State of the Idiosyncratic Risk Factor for All Hedge Fund Strategies: LTCM crisis of 1998

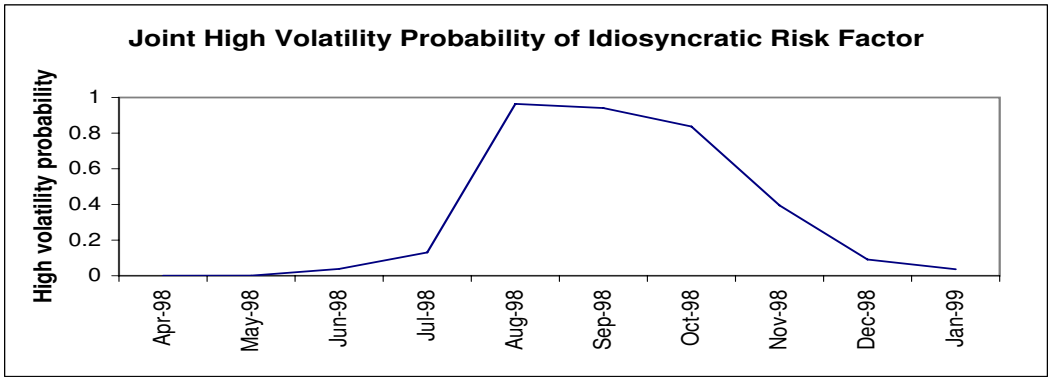
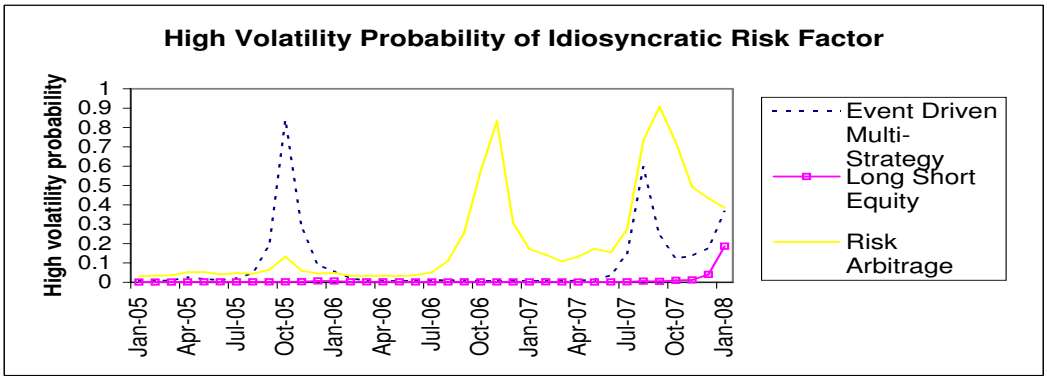


Figure 7: **Evolution of the Idiosyncratic Risk Factor for Individual Strategies: Recent Events**

This figure presents the evolution of the idiosyncratic risk factor for individual strategies from January 2005 to January 2008 (with and without Emerging Markets). Panel A (B) presents the probability of a high-volatility state of the idiosyncratic risk factor for Event Driven Multi-Strategy, Long Short Equity, and Risk Arbitrage (Convertible Bond Arbitrage, Emerging Markets, and Equity Market Neutral) strategies.

Panel A Probability of High-Volatility State of the Idiosyncratic Risk Factor for Event Driven Multi-Strategy, Long Short Equity, and Risk Arbitrage strategies



Panel B Probability of High-Volatility State of the Idiosyncratic Risk Factor for Convertible Arbitrage, Emerging Markets, and Equity Market Neutral strategies

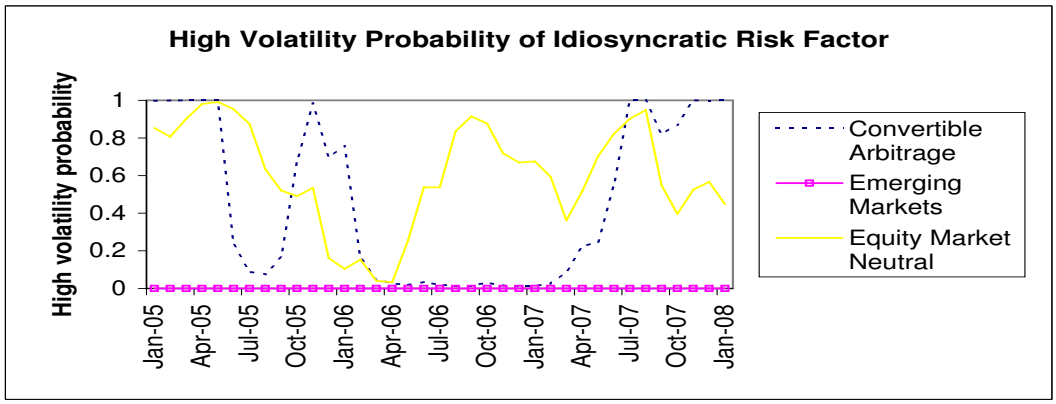
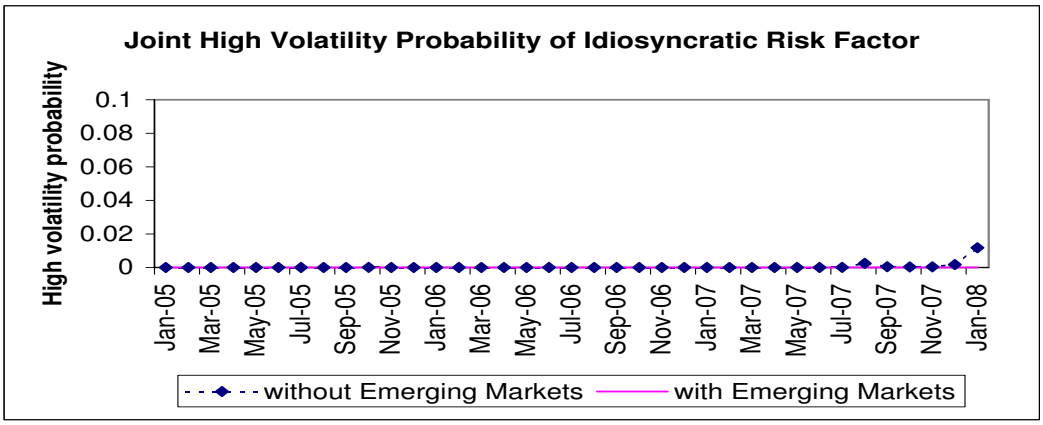


Figure 8: **The Joint Probability of High-Volatility State of the Idiosyncratic Risk Factor for All Hedge Fund Strategies: Recent Events**

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 2005 to January 2008 (with and without Emerging Markets). Panel B presents the joint filtered probability of high-volatility state of the idiosyncratic risk factor for Event Driven Multi-Strategy, Risk Arbitrage, Convertible Bond Arbitrage, and Equity Market Neutral strategies.

Panel A The Joint Probability of High-Volatility State of the Idiosyncratic Risk Factor for All Hedge Fund Strategies: January 2005 - January 2008



Panel B The Joint Probability of High-Volatility State of the Idiosyncratic Risk Factor for Convertible Bond Arb., Risk Arbitrage, Event Driven Multi-Strategy and Equity Market Neutral Strategies: January 1994 - January 2008

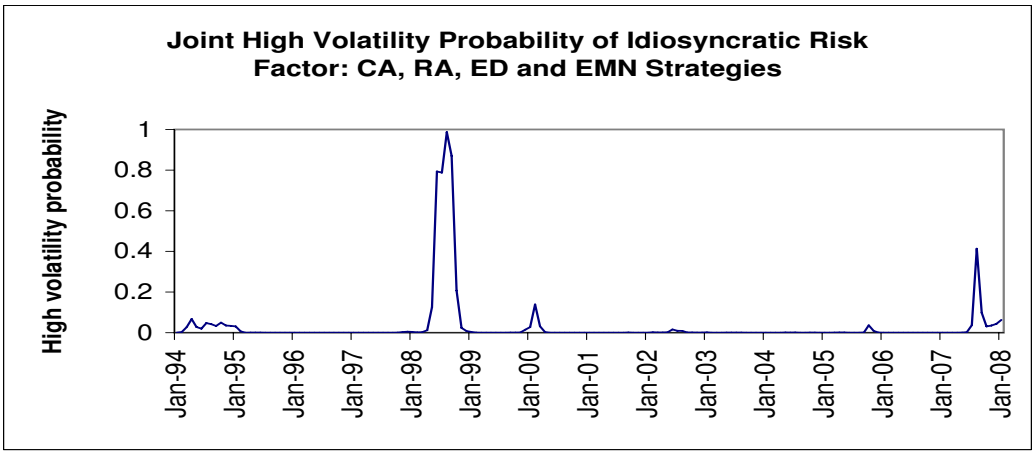


Table 5: **Multi-factor Linear Factor Model (LFM)**

This table presents the results for the 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. ω_0 is the volatility 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	**0.33**	**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	0.09	**0.46**	**3.05**	**0.30**	**2.04**	0.09	1.02
β_0 (SP)	**0.57**	**12.77**	**0.29**	**4.20**	**0.25**	**3.21**	**0.17**	**4.84**
β_1 (LS)	**-0.39**	**-9.41**	**-0.19**	**-4.38**	**-0.15**	**-3.32**	**-0.16**	**-4.86**
β_2 (VG)			**0.11**	**2.29**	**0.10**	**2.20**	**0.08**	**3.03**
β_3 (USD)					**0.20**	**3.66**		
β_4 (L.GC)	**0.14**	**1.82**	**0.24**	**2.54**				
β_5 (TS)	**-0.23**	**-1.78**						
β_6 (dVIX)	**0.09**	**1.67**						
β_7 (CS)	**-4.21**	**-2.32**	**-3.37**	**-2.79**	**-3.74**	**-3.12**		
β_8 (Gold)								
β_9 (MSCIEMD)			**-0.15**	**-2.75**				
β_{10} (MSCIEMS)					**0.06**	**1.72**		
β_{11} (UMD)	**0.23**	**6.41**			**0.07**	**3.10**		
ω_0	**1.36**	**11.09**	**1.42**	**6.22**	**1.28**	**6.63**	**0.93**	**12.74**
Adj. R^2	0.78		0.43		0.45		0.41	
Pseudo R^2	0.23		0.10		0.11		0.11	

Table 6: **Option-Based Model**

This table presents the results for the option-based regression of the CSFB/Tremont hedge-fund index strategies on S&P 500 return (SP), Wilshire 1750 Small Cap - Wilshire 750 Large Cap return (SC-LC), month end-to-month end change in the Federal Reserve's ten year constant maturity yield (10Y), Credit Spread (CS), return of a portfolio of lookback straddles on bond futures (Bd Opt), return of a portfolio of lookback straddles on currency futures (FX Opt), and return of a portfolio of lookback straddles on commodity futures (Com Opt). ω_0 is the volatility of the idiosyncratic risk factor. Panel A presents the results for all eight hedge fund strategies, and Panel B depicts the number of strategies with significant factor exposures for the Fung and Hsieh (FHM) and multi-factor regime-switching (MRSM) models. 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	**0.24**	**2.20**	0.05	0.25	-0.06	-0.21	**0.29**	**4.48**
β1 (SP)	0.03	1.05	**-0.94**	**-16.51**	**0.51**	**7.04**	**0.08**	**5.10**
β2 (SC-LC)	**0.06**	**1.77**	**-0.51**	**-6.51**	**0.31**	**3.67**		
β3 (10Y)	**-1.09**	**-2.04**						
β4 (CS)	**-1.91**	**-1.86**			**-3.89**	**-1.71**		
β5 (Bd Opt)					**-0.05**	**-2.07**		
β6 (FX Opt)							**0.01**	**2.92**
β7 (Com Opt)								
ω_0	**1.30**	**15.71**	**2.54**	**15.04**	**3.91**	**17.42**	**0.75**	**15.39**
Adj. R^2	0.05		0.75		0.34		0.20	
Pseudo R^2	0.02		0.17		0.06		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	**0.23**	**1.52**	**0.47**	**3.69**	**0.33**	**3.31**	**0.11**	**1.36**
β1 (SP)	**0.45**	**12.32**	**0.22**	**7.66**	**0.19**	**4.23**	**0.13**	**4.98**
β2 (SC-LC)	**0.41**	**11.50**	**0.14**	**3.87**	**0.13**	**4.30**	**0.13**	**6.29**
β3 (10Y)	**-1.89**	**-3.42**	**-1.15**	**-1.91**	**-0.84**	**-2.15**		
β4 (CS)			**-2.76**	**-2.44**	**-2.52**	**-2.43**		
β5 (Bd Opt)	**-0.02**	**-1.78**			**-0.03**	**-2.12**	**-0.02**	**-2.78**
β6 (FX Opt)			**-0.03**	**-3.21**				
β7 (Com Opt)			0.02	1.63				
ω_0	**1.80**	**16.44**	**1.40**	**14.93**	**1.16**	**7.00**	**0.92**	**13.86**
Adj. R^2	0.63		0.44		0.50		0.42	
Pseudo R^2	0.15		0.10		0.15		0.11	

Panel B

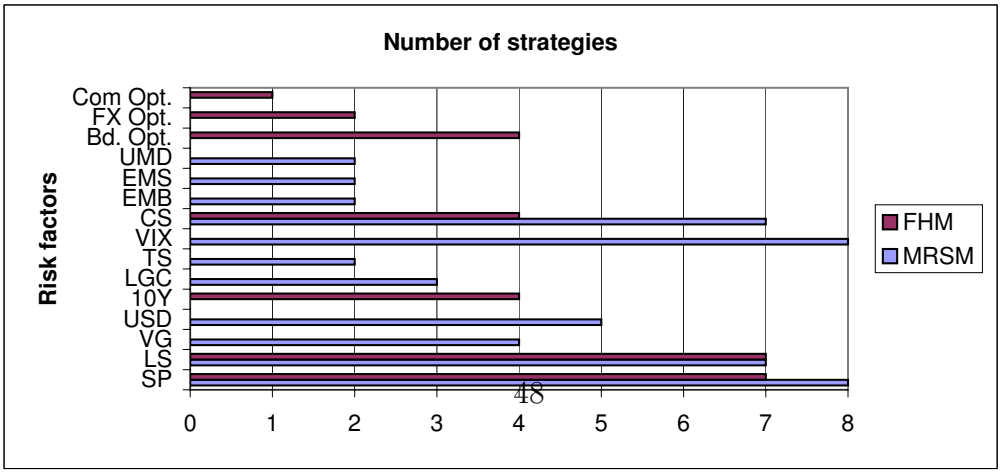


Table 7: **Linear Factor Model with a Crisis Dummy**

This table presents the results for the 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), and interactions of these risk factors with a crisis dummy. The crisis dummy is equal to one when the Mexican, Asian, Russian and LTCM, Brazilian, Argentinean, and Internet crises are observed (the crises periods are identified by Rigobon (2003), Table 2). Hedge fund returns, S&P 500, USD, Lehman Government Credit and Gold are used in excess of LIBOR returns. ω_0 is the volatility of the idiosyncratic risk factor. 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	**0.43**	**4.89**	-0.09	-0.45	-0.02	-0.10	**0.30**	**4.51**
β_0 (SP)	0.01	0.38	**-0.86**	**-16.11**	**0.17**	**2.12**	**0.07**	**4.62**
β_0 (SP) dummy	**0.09**	**1.83**			**-0.39**	**-3.36**		
β1 (LS)	**-0.08**	**-2.67**	**0.61**	**8.38**			-0.03	-1.35
β1 (LS) dummy			**-0.43**	**-3.50**			**0.08**	**2.07**
β_2 (VG)			**0.22**	**3.76**				
β_2 (VG) dummy								
β_3 (USD)								
β_3 (USD) dummy	**0.38**	**4.12**						
β_4 (L.GC)	**0.20**	**2.69**						
β_4 (L.GC) dummy								
β5 (TS)	**-0.25**	**-1.80**			**1.00**	**4.54**	**-0.18**	**-2.03**
β5 (TS) dummy	**1.09**	**4.76**					**0.32**	**2.09**
β_6 (dVIX)					**0.25**	**3.52**		
β_6 (dVIX) dummy								
β_7 (CS)								
β_7 (CS) dummy	**1.13**	**16.01**						
β_8 (Gold)			**-0.11**	**-2.32**	**-0.09**	**-1.59**		
β_8 (Gold) dummy					**-0.45**	**-3.28**		
β_9 (MSCIEMD)					**0.36**	**4.04**		
β9 (LHEMEMD) dummy					**0.32**	**2.58**		
β_{10} (MSCIEMS)					**0.46**	**9.10**		
β_{10} (MSCIEMS) dummy								
β_{11} (UMD)					**0.19**	**4.48**		
β_{11} (UMD) dummy								
ω_0	**1.11**	**11.05**	**2.36**	**16.58**	**2.34**	**16.80**	**0.76**	**16.76**
Adj. R^2	0.19		0.78		0.75		0.16	
Pseudo R^2	0.07		0.19		0.19		0.05	

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	0.08	0.81	**0.59**	**5.55**	**0.45**	**4.94**	**0.17**	**2.27**
β_0 (SP)	**0.47**	**9.78**	**0.16**	**5.01**	**0.11**	**2.95**	**0.12**	**5.17**
β_0 (SP) dummy			**0.26**	**2.95**	**0.18**	**3.26**		
β1 (LS)	**-0.35**	**-10.15**	**-0.14**	**-4.33**	**-0.13**	**-4.68**	**-0.15**	**-7.07**
β1 (LS) dummy								
β_2 (VG)	**-0.11**	**-2.92**	**0.07**	**2.26**				
β_2 (VG) dummy							**0.11**	**2.55**
β_3 (USD)								
β_3 (USD) dummy			**0.31**	**3.29**				
β_4 (L.GC)								
β_4 (L.GC) dummy								
β5 (TS)	**-0.46**	**-4.82**						
β5 (TS) dummy	**0.48**	**2.18**	**0.51**	**1.87**	**0.76**	**4.13**	**0.38**	**2.77**
β_6 (dVIX)	**0.14**	**3.12**			**0.07**	**1.93**	**0.07**	**2.16**
β_6 (dVIX) dummy							**-0.20**	**-5.13**
β_7 (CS)	**-2.64**	**-1.86**						
β_7 (CS) dummy			**-8.11**	**-1.71**	**-5.27**	**-2.00**		
β_8 (Gold)								
β_8 (Gold) dummy			**0.24**	**2.53**			**-0.10**	**-1.82**
β_9 (MSCIEMD)	**0.16**	**4.39**	**0.14**	**3.80**	**0.10**	**2.59**		
β_9 (MSCIEMD) dummy					**0.18**	**2.85**		
β_{10} (MSCIEMS)					0.04	1.64		
β_{10} (MSCIEMS) dummy			**-0.10**	**-1.65**	**-0.13**	**-2.73**		
β_{11} (UMD)	**0.20**	**7.06**						
β_{11} (UMD) dummy								
ω_0	**1.23**	**16.17**	**1.19**	**14.43**	**0.96**	**15.98**	**0.84**	**16.45**
Adj. R^2	0.82		0.59		0.64		0.50	
Pseudo R^2	0.26		0.16		0.21		0.15	

Table 8: **Out-of-Sample Tests**

The table presents results for out-of-sample mimicking performance tests. An out-of-sample of 33 months (from November 2004 to July 2007) is used. Mean Absolute Error is calculated as the mean of absolute differences between the actual hedge fund index returns and returns of replicating portfolios. Replicating portfolios for each hedge fund index strategy are constructed using the factor loadings obtained from the multi-factor regime-switching beta model (MRSM). At each time t, factor loadings are estimated, and are combined with values of risk factors at t+1 to construct returns of the replicating portfolios. The procedure is repeated 33 times. Results for Mean Absolute Error (MAE) tests for Linear factor model (LFM), Random Walk (RW), Multi-factor Regime-Switching Beta (MRSM), and Fung and Hsieh option-based model (FHM) are presented.

Strategy/Test	MAE			
	LFM	RW	MRSM	FHM
Conv. Bond Arb.	0.83	0.80	0.75	0.74
Dedicated Shortseller	1.78	3.13	1.71	1.73
Emerging Markets	0.92	2.00	0.69	1.54
Equity Mkt Neutral	0.46	0.50	0.45	0.46
Long/Short Equity	0.69	1.74	0.79	0.95
Distressed	0.51	0.83	0.49	0.56
Event Driven MS	0.72	1.15	0.59	0.63
Risk Arb	0.51	0.76	0.49	0.57

Figure 9: **The Joint Probability of High-Volatility State of the Idiosyncratic Risk Factor for All Hedge Fund Strategies: Linear Factor and Fung and Hsieh Models**
This figure 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 January 2008 for a linear factor idiosyncratic switching volatility model (LFIM) and Fung and Hsieh idiosyncratic switching volatility model (FHIM). LFIM: $R_t = \alpha(Z_t) + \lambda_k L_{k,t} + \omega(Z_t)$ and FHIM: $R_t = \alpha(Z_t) + \lambda_k H_{k,t} + \omega(Z_t)$, where R_t is the return of a hedge-fund index in period t, $L_{k,t}$ are k linear factors, $H_{k,t}$ are k Fung and Hsieh option-based factors, and ω is the volatility of the idiosyncratic risk factor. The Markov chain Z_t characterizes the change in volatility of the idiosyncratic risk factor.