Crises and Hedge Fund Risk*

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This Draft: May 1, 2009

Abstract

We study the effect of financial crises on hedge fund risk. Specifically, we are interested in identifying common risk factors across different hedge fund strategies that are prevalent during financial crises. We find that during crises most strategies are negatively and significantly exposed to the Large-Small, Change in VIX and Credit Spread risk factors. This suggests that liquidity risk and credit risk are potentially common factors for different hedge fund strategies in crises periods. We further explore the possibility that all hedge fund strategies simultaneously exhibit an increase in idiosyncratic risk volatility, which could be attributed to the presence of a latent factor common to all hedge fund strategies. In our sample this event happened only during the Long-Term Capital Management (LTCM) crisis of August 1998 and September 2008 global financial crisis. Other crises including the mortgage crisis of August 2007 affected the hedge fund industry only through systematic risk factors.

Keywords: Hedge Funds; Risk Management; Liquidity; Financial Crises;

JEL Classification: G12, G29, C51

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

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1 Introduction

Recent years have seen the number of hedge funds, as well as assets managed by these funds, increase dramatically. However, the recent 2007-08 financial crisis has significantly undermined returns to various hedge fund strategies. Hedge funds play a significant role in financial markets, and it is extremely relevant for investors, risk managers, and regulators to understand how financial crises affect this industry. More specifically, in our research we identify common risk factors across different hedge fund strategies that are prevalent during financial crises. We further determine whether risk exposures to these common risk factors depend on different crisis periods we consider.

An important insight from this paper is that hedge fund strategy exposures to systematic risk factors change during crisis periods and are very similar among all different crisis periods. However, the idiosyncratic volatility of hedge fund strategies strongly depends on the type of financial crises. Specifically, currency and market crises affect hedge fund strategies differently compared to financial institution crises.

As highlighted by Brunnermeier (2008) and Boyson, Stahel, and Stulz (2008) hedge funds could be affected by financial crises through many mechanisms: direct exposure, funding liquidity, market liquidity, loss and margin spirals, runs on hedge funds, and aversion to Knightian uncertainty. Some of these mechanisms, like direct exposure and market liquidity could be captured by the dynamic risk exposure of hedge funds to market risk factors. Funding liquidity, margin spirals, runs on hedge funds, and aversion to Knightian uncertainty are potentially affecting the idiosyncratic volatility of hedge fund returns. In fact, as stressed by Khandani and Lo (2007), a forced liquidation of a given strategy should increase the strategy volatility through the increase of the volatility of the idiosyncratic risk component.

The aim of this paper is to study the effects of different mechanisms on hedge fund risk during financial crises periods. Both systematic and idiosyncratic risk factors are analyzed. We identify the presence of a common latent factor among hedge fund strategies by analyzing the 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 market risk factor exposure, but also through a latent factor not usually included in the analysis of 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 during crisis periods is smaller or negative compared to tranquil periods. 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. We found that this result also applies during August 2007 subprime mortgage and September 2008 global financial crises.

We find that the common exposures of different hedge fund indices to risk factors in crisis periods 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 whole hedge fund industry during market downturns. The recent subprime mortgage crisis of August 2007 and global financial crisis of September 2008 emphasized the importance of credit and liquidity for hedge fund returns.[1] Our findings are consistent with Khandani and Lo (2007) who find an increased correlation between hedge fund styles in this period and 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 presence of a latent factor that is common among all hedge fund strategies in our sample. Specifically, we calculate the joint probability of being in a high volatility state for all hedge fund strategies. 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, during the LTCM crisis the hedge fund industry has been affected by a common latent factor that cannot be identified with classical risk factors used in hedge fund risk models. We found similar results for the recent September 2008 global financial crisis.

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

[1] The global financial crisis of 2008 emerged in September 2008 with the failure, merger, or conservatorship of several large United States-based financial firms and spread with the insolvency of additional companies, governments in Europe, recession, and declining stock market prices around the globe.

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 up 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. Adrian (2007) and Khandani and Lo (2007) show that hedge fund risk profile during the LTCM crisis was drastically different from other financial crises. Our work is consistent with this finding. In addition we show that September 2008 global financial crisis was similar with the LTCM crisis. Modest (2008) presents similarities between the LTCM and September 2008 crises.

By comparing mutual funds to hedge funds, we find that the presence of the latent factor is unique to the hedge fund industry. Specifically, during the period considered, mutual funds have never exhibited a joint increase in the volatility of the idiosyncratic risk component. We further test the significance of our results by proposing alternative models that analyze hedge fund risk exposures: 1) Multi-factor regime-switching model; 2) Option-based factor model (Fung and Hsieh (2004, 2002) and Agarwal and Naik (2004)); and 3) Asymmetric beta and threshold models. Our results are robust to using these alternative specifications.

The rest of the paper is organized as follows. In Section 2 we develop a theoretical framework for capturing a latent factor. Section 3 describes data and presents results. Section 4 provides a mutual fund analysis. Section 5 provides alternative model specifications. Section 6 provides robustness checks. Section 7 concludes.

2 Theoretical Framework

2.1 Linear Model with a Crisis Dummy

Linear factor models such as the capital asset pricing model (CAPM), Fama and French model (1993), 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 strategy index returns i could be represented as:

$$R_{i,t} = \alpha_i + \sum_{k=0}^{K} \beta_k F_{k,t} + \omega u_t \tag{1}$$

where R_t is the return of a hedge-fund index in period t, $F_{k,t}$ are k risk factors, ω is the volatility of the idiosyncratic risk factor, and u_t is IID.

We extend this model by introducing a dummy variable D_t that is equal to 1 during crisis periods. More formally the model could be represented as:

$$R_t = \alpha + \sum_{k=0}^{K} \beta_{i,k} F_{k,t} + \sum_{k=0}^{K} \beta_{i,D,k} D_t F_{k,t} + \omega_i u_t \tag{2}$$

2.2 Common Latent Factor

In order to investigate an increase in the idiosyncratic risk of hedge fund strategies, we extend the above model by introducing a dynamic component in the volatility of the idiosyncratic risk factor. More formally, we measure the idiosyncratic risk factor as a residual of the linear factor model with a crisis dummy:

$$r_{i,t} = R_{i,t} - \alpha_i + \sum_{k=0}^{K} \beta_{i,k} F_{k,t} + \sum_{k=0}^{K} \beta_{i,D,k} D_t F_{k,t} \tag{3}$$

The idiosyncratic risk factor is characterized by a switching mean α_i and a switching volatility ω_i:

$$r_{i,t} = \alpha_i(Z_{i,t}) + \omega_i(Z_{i,t}) u_{i,t} \tag{4}$$

where $\omega_i(Z_{i,t})$ is the volatility of the idiosyncratic risk factor, $u_{i,t}$ is IID, and $Z_{i,t}$ is a Markov chain with 2 states (0 = low volatility state and 1 = high volatility state) and a transition probability matrix $\mathbf{P}_{z,i}$.

Despite the fact that the regimes of $Z_{i,t}$ 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. In particular, because the n-step transition matrix of a Markov chain $Z_{i,t}$ is given by $\mathbf{P}^n_{z,i}$, the conditional probability of regime $Z_{i,t+n}$ given date-t data $\mathcal{R}_{i,t} \equiv (r_{i,t}, r_{i,t-1}, \ldots, r_{i,1})$ for strategy i is the following:

$$\text{Prob}\left(Z_{i,t+n} = 0|\mathcal{R}_{i,t}\right) \quad = \quad \mathbf{P}^n_{z,i}{}'\mathbf{b}_{i,t} \tag{5}$$

$$\mathbf{b}_{i,t} = \left[\begin{array}{ccc} \text{Prob}\left(Z_{i,t} \right. & = & \left. 0|\mathcal{R}_{i,t}\right) \;\; \text{Prob}\left(Z_{i,t} = 1|\mathcal{R}_{i,t}\right) \;\; |\mathcal{R}_{i,t}) \end{array} \right]' \tag{6}$$

Our test of the presence of a common latent factor 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:

$$J_p = \prod_{i=1}^{m} \text{Prob}\left(Z_{i,t} = 1|\mathcal{R}_{i,t}\right) \tag{7}$$

In our framework we identify the presence of a common latent factor when we observe a significant change in the joint probability that all hedge funds are in the high volatility regime for the idiosyncratic risk factor, i.e., a large change in J_p.[2]

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 (2008) 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)), hedge funds (Chan et al. (2005)) and foreign exchange markets (Dueker and Neely (2004)).

[2]In order not to impose a common latent factor by construction, a latent factor for each strategy is independently estimated.

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 December 2008. 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 returns (in excess of three-month Treasury Bill rates). 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.

We analyze the following strategies: directional strategies such as Dedicated Shortseller, Long/Short Equity, and Emerging Markets and non-directional strategies such as Distressed, Event Driven Multi-Strategy, Equity Market Neutral, Convertible Bond Arbitrage, and Risk Arbitrage.[3]

For comparison, we also use Morningstar U.S. open-ended mutual fund index returns for the sample period from January 1994 to December 2008. The following strategies are considered: Large Blend, Large Growth, Large Value, Mid-Cap Blend, Mid-Cap Growth, Mid-Cap Value, Small Blend, Small Growth, and Small Value.

[INSERT Table (1) about here]

Categories greatly differ. For example, annualized mean of excess return for the Dedicated Shortseller category is the lowest: -3.33%, and the annualized standard deviation is the highest at 16.96%. Long/Short Equity has the highest mean, 8.11% and a relatively high standard deviation: 10.53%. The lowest annualized standard deviation is reported for the Equity Market Neutral strategy at 2.84% with an annualized mean of 4.81%. Hedge fund strategies also show different third and fourth moments. Specifically, non-directional funds such as Event Driven Multi-Strategy, Distressed, Risk Arbitrage, and Convertible Bond

[3] One common factor we consider is the S&P 500; therefore, we concentrate only on hedge fund styles that either directly or indirectly have the S&P 500 exposure. Therefore, we take out Fixed Income Arbitrage, Funds of Funds, Managed Futures, and Multi-Strategy categories.

Arbitrage all have negative skewness and high excess kurtosis. According to the Jarque-Bera test, which is a goodness-of-fit measure of departure from normality, based on the sample kurtosis and skewness, all hedge fund category returns are not normally distributed except the Equity Market Neutral strategy. For this strategy, normality of returns cannot be rejected. The S&P 500, is characterized by high annualized excess return of 4.36% and high standard deviation of 15.11% 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 described in Table 2. They are also described by Chan et al. (2005) as relevant factors to be used for each hedge fund strategy. Given the limited hedge fund 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, Lehman Emerging Markets Bond Index, and MSCI Emerging Market Stock Index are used in excess of three-month Treasury Bill rates.

[INSERT Table (2) about here]

3.2 Analysis of Systematic Risk During Crises

The objective of our paper is to investigate the impact of financial crises on hedge fund risk. We created a dummy variable that is equal to one when we observe the Mexican (December 1994-March 1995), Asian (June 1997-January 1998), Russian and LTCM (August 1998-October 1998), Brazilian (January 1999 - February 1999), Internet Crash (March 2000 - May 2000), Argentinean (October 2000 - December 2000), September 11 2001, and drying up of merger activities, increase in defaults, and WorldCom accounting problems crises (the crises periods are identified by Rigobon (2003)), the 2007-Subprime crisis and the 2008 global financial crisis.

For each hedge fund strategy we estimate a linear factor model with a dummy crisis specified in equation (2) and the results are contained in Table 3. The following systematic risk factors are considered: S&P 500, Large-Small, Value-Growth, USD, Lehman Government Credit, Term Spread, change in VIX, Credit Spread, Gold, Lehman Emerging Markets Bond Index, MSCI Emerging Markets Stock Index, and Momentum factor.[4]

As Table 3 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.

[INSERT Table (3) about here]

Figure 1 depicts the number of strategies with significant factor exposures for the linear factor model with a crisis dummy during normal and crisis periods.

[INSERT Figure (1) about here]

For all strategies, the exposure to the S&P 500 during crisis periods is smaller or negative compared to normal (tranquil) periods. This suggests that hedge fund managers are able to timely hedge market exposures, especially during financial crises. This is consistent with Brunnermeier and Nagel (2004) finding. 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 crisis exposures on other risk factors shows that Credit Spread and change in VIX are common factors for many hedge fund strategies in the crisis state of the market, as Figure 1 well highlights, suggesting that these factors are important in accessing systematic hedge fund risk, especially during crises.

In particular, we find that LS is a common factor during crisis for six out of eight hedge funds strategies and for five 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 periods, intermediaries, including hedge funds, are well capitalized and liquidity effects are

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

minimal. In the “illiquidity” regime usually related to CRISES, 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.

We also find that during normal times, Credit Spread (CS) is significant for only two strategies: Convertible Bond Arbitrage and Dedicated ShortSeller. However, during crisis periods, CS is negative and significant for six out of eight strategies. 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. Six out of eight strategies show a negative exposure to this variable during crises periods indicating that returns of these strategies are reducing when volatility increases during crisis periods.

3.3 Analysis of Common Latent Factor During Crises

In addition to the analysis of systematic risk exposures during crisis periods, for each hedge fund strategy, we estimate dynamics of the idiosyncratic risk factor using equations (3) and (4). The estimation of the idiosyncratic risk factor is provided in Table 4. We find that the idiosyncratic risk of hedge funds is characterized by two different regimes with high and low volatility for 6 out of 8 strategies. Exceptions are Distressed and Dedicated Shortseller, which are always characterized by a large volatility regime (idiosyncratic volatility is 3.58% for Distressed and 2.53% for Dedicated Shortseller).

[INSERT Table (4) about here]

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. High volatility (ω_1) is estimated to be at least twice the low volatility (ω_0) as depicted in Table 4.

The estimated probability of switching from one regime to another is on average about 5%, but the probability of remaining in the same regime is about 95%, meaning that volatility regimes are quite persistent.

Using the model specification described in equations (3) and (4), we estimate the evolution of the probability of being in the high volatility regime for each strategy. Results for three selected strategies (Convertible bond arbitrage, Equity market neutral, and Long/short equity) are shown in Figure 2. 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.

[INSERT Figure (2) about here]

Figure 2 plots monthly probabilities from January 1994 to December 2008 for 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 Equity Market Neutral index presents a low probability of being in the high volatility regime in the middle part of the sample. A completely different behavior characterizes the Convertible Arbitrage strategy where the volatility dynamically changes throughout the sample. Long/Short Equity presents a high probability in the part of the sample that corresponds to the series of crises that characterized the sample period. Other strategies also exhibit unique patterns of the evolution of the volatility.

We further explore the possibility of the presence of a common latent factor across all hedge fund strategies. Our test of the presence of a common latent factor is based on the determination of the joint probability that all hedge fund strategies are in a high volatility regime for the idiosyncratic risk factor. The measure of the common latent factor is given in equation (7).

Specifically, we calculate the joint filtered probability of being in a high volatility state for all hedge funds and plot them in Figure 3. We find that the joint filtered probability jumps from approximately 0% in May 1998 to 4% in June 1998 to 15% in July 1998 to 98% 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.[5] 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 (see Panel B).

[INSERT Figure (3) about here]

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

3.3.1 2007 Subprime Mortgage Crisis

By concentrating on the last part of the sample we are able to explore whether the volatility of hedge fund idiosyncratic risk was high during the recent subprime mortgage crisis period. We find that 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. In contrast, Long/Short Equity experienced only a slight increase in the probability 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 of August 2007. This means that the latent factor was not present in all strategies during the crisis. Only a selected number of strategies was affected[6].

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 co-movement of the volatility of the idiosyncratic risk factor for these strategies, as shown in Figure 4. In this case, the joint probability of high volatility in August 2007 (subprime mortgage crisis) is below 50%.

[INSERT Figure(4) about here]

3.3.2 2008 Global Financial Crisis

We further concentrate on the most recent September 2008 global financial crisis. We calculate joint probabilities of the high volatility state of the idiosyncratic risk factor for all eight strategies. The obtained evolution of the idiosyncratic risk factor is plotted in Figure 3 Panel C . In this case, the joint probability of high-volatility state of the idiosyncratic factor in September 2008 is above 90%. Both LTCM (joint probability is above 95%) and the September 2008 crisis exhibit similar patterns of behavior (see Panel B and Panel C of Figure 3). Therefore, it is feasible that both these events were affected by similar shocks.

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

4 Mutual Fund Indices

It is possible that our finding of a common latent factor across all different hedge fund strategies is applicable to other investment institutions like mutual funds. In order to answer this question in this section, we conduct the same analysis on classical mutual fund indices. Specifically, we analyze returns for the following U.S. open-ended mutual fund indices obtained from Morningstar for the sample period from January 1994 to December 2008: Large Blend, Large Growth, Large Value, Mid-Cap Blend, Mid-Cap Growth, Mid-Cap Value, Small Blend, Small Growth, and Small Value. Statistics for these mutual fund indices are presented in Table 5.

[INSERT Table (5) about here]

We first estimate an OLS regression of mutual fund indices on all risk factors described in Table 2, and results are described in Table 6 Panel A. We find that all mutual fund indices exhibit positive exposure to the S&P 500. The exposures to Large-Small and Credit Spread are significant for all strategies except Large Growth. Change in VIX is significant only for Large Value and Mid-Cap Blend. The systematic risk factors in this case explain more than 90% of the variability of these indices, therefore the volatility of residuals is very limited.

Next, we calculate residuals for all different indices and capture the dynamics of the idiosyncratic risk using equation (4). Using equation (7) we test for the presence of the common latent factor across all mutual fund strategies. As Table 6 Panel B shows, there is no evidence of any systematic increase of the idiosyncratic risk across different mutual fund strategies. This means that the presence of the common latent factor during LTCM and 2008 global financial crises is unique to the hedge fund industry.

[INSERT Table (6) about here]

5 Alternative Model Specifications

Hedge funds often employ leverage, trade in options and other non-linear instruments, take state-dependent positions, and hedge their positions. Therefore, it is possible that our results are generated due to the inability of the linear risk factor model with a dummy crisis variable to capture the true change in risk exposures of hedge funds. Moreover, it could be that our exogenous identification of the crisis windows is incorrect. For these reasons we consider different model specifications for capturing the exposure of hedge funds to systematic risk factors and investigate the resulting behavior of the idiosyncratic risk. We consider three different models. First we consider a multi-factor regime-switching model where market downturn periods are endogenously identified with a Markov chain that depends on distributional properties of the S&P 500. With this model the dynamic exposure of hedge funds to all systematic risk factors is determined conditional on the volatility of the S&P 500. The second model is the Option-based factor model originally proposed by Fung and Hsieh (2004, 2002) that captures the non-linear exposure of hedge funds to systematic risk factors. Finally, we consider two more models used in the literature to capture the non-linear exposure of hedge funds to systematic risk factors: asymmetric beta and threshold models.

5.1 AMulti-Factor Regime-Switching Model

5.1.1 Theoretical Framework

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.[7] 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.[8]

[7]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.

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

More formally, the model could be represented as:

$$R_t = \alpha(Z_t) + \beta(S_t)I_t + \sum_{k=1}^{K} \theta_k(S_t)F_{k,t} + \omega(Z_t)u_t \quad (8)$$

$$I_t = \mu(S_t) + \sigma(S_t)\epsilon_t \quad (9)$$

where S_t and Z_t are Markov chains with h_s and h_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 $h_s = 3$ (state labels are denoted as 0, 1 or 2), β depends on the state variable S_t:

$$\beta(S_t) = \begin{cases} \beta_0 & \text{if } S_t = 0 \\ \beta_1 & \text{if } S_t = 1 \\ \beta_2 & \text{if } S_t = 2 \end{cases} \quad (10)$$

and the Markov chain S_t (the regime-switching process) is described by the following transition probability matrix $\mathbf{P}_s$:[9]

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

with $p_{02} = 1 - p_{00} - p_{01}$, $p_{12} = 1 - p_{10} - p_{11}$ and $p_{22} = 1 - p_{20} - p_{22}$. The parameters p_{00}, p_{11} and p_{22} determine the probability of remaining in the same regime. This model allows for a change in variance of returns only in response to occasional, discrete events. Despite

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

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 n-step transition matrix of a Markov chain S_t is given by $\mathbf{P}_s^n$, the conditional probability of the regime S_{t+n} 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):

$$\text{Prob}\,(S_{t+n} = 0|\mathcal{R}_t) \;=\; \pi_1 \;+ (p_{00} - (1 - p_{11}))^n \Big[\text{Prob}\,(S_t = 0|\mathcal{R}_t) - \pi_1\Big] \tag{12}$$

$$\pi_1 \;\equiv\; \frac{(1 - p_{11})}{(2 - p_{00} - p_{11})} \tag{13}$$

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

$$\text{Prob}\,(S_{t+n} = 0|\mathcal{R}_t) \;=\; \mathbf{P}_s^{n\prime}\mathbf{a}_t \tag{14}$$

$$\mathbf{a}_t \;=\; \Big[\;\text{Prob}\,(S_t = 0|\mathcal{R}_t)\;\;\text{Prob}\,(S_t = 1|\mathcal{R}_t)\;\;..\text{Prob}\,(S_t = h_s|\mathcal{R}_t)\Big]' \tag{15}$$

5.1.2 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 5.1.3 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. However, in the next section we also describe the results for two regimes.

Using three regimes is also consistent with the literature that well recognizes the presence of normal, rolling-up or downturn regions in equity market returns.[10] Moreover, the use of

[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

three regimes is in line with our objective — disentangling the effects of financial crises on the hedge fund industry. The results of the estimation are shown in Table 7.[11]

[INSERT Table (7) about here]

Table 7 shows that the return pattern of the S&P 500 could be easily captured with three regimes, where regime 0 has a mean of 6.39% and a relatively low volatility of 1.33%. 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}=32%. Regime 1 has a mean statistically different than zero and equal to 0.92% and a volatility of 2.30%, 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 -2.39% and a volatility of 4.94%. The probability of remaining in this regime is 83%.[12] Other results about the dynamics of the S&P500 in the sample are reported in Appendix A.

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 5.1.3 and 5.1.4.

5.1.3 Dynamic Risk Exposure to Systematic Risk Factors

In this section, for each hedge fund strategy we estimate the multi-factor model specified in equation (8) and the results are contained in Table 8.[13] 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, Lehman Emerging

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.

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

Markets Bond Index, MSCI Emerging Markets Stock Index, and Momentum factor.[14] 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 (8) about here]

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 result is in line with our main result found using the linear factor model with the dummy crisis variable and is consistent with the literature (Brunnermeier and Nagel (2004)).

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 5 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.

[INSERT Figure(5) about here]

As Figure 5 shows, during crises the exposure to Change in VIX, Credit Spread, and LS is common for almost all strategies, consistent with the previous result using a linear factor model with a dummy crisis variable. This indicates that allowing the data to endogenously identify crisis periods leads to similar results - the exposure to common risk factors during crises is confirmed.

In order to measure and compare the goodness of fit between regime-switching and a linear model with a crisis dummy, we employ a Pseudo-R^2 analysis.[15]

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

[15]$Pseudo - R^2 = 1 - \frac{logL_{UR}}{logL_R}$ where L_{UR} is the unrestricted (full model) likelihood and L_R is restricted (constants only) likelihood. Pseudo-R^2 has been used by Boyson, Stahel and Stulz (2008) to compare different hedge fund risk models.

We compare the goodness of fit of this model with respect to the linear factor model with a crisis dummy and find that for all strategies the regime-switching model has a much higher Pseudo-R^2 compared to the linear model with a crisis dummy.[16]

5.1.4 Idiosyncratic Risk Factor

Since regime-switching model better captures return variability of hedge fund strategies, can we still capture a common latent factor with this model, or the common latent factor is explained by the regime-switching model? In order to answer this question, we re-estimate idiosyncratic risk for each strategy using equation (4) and investigate the evolution of the idiosyncratic risk for separate hedge fund strategies. The dynamics are very similar to the ones already estimated for the linear factor model with a crisis dummy.

We further explore the probability that all hedge fund strategies exhibit idiosyncratic risk in a high volatility regime. Specifically, we calculate the joint filtered probability of being in a high volatility state for all hedge funds and plot them in Figure 6. As before, we found the presence of the common latent factor across all hedge fund strategies that manifested in 1998 and 2008.

[INSERT Figure(6) about here]

5.2 Option-Based Factor Model

Hedge funds often use options to implement their strategies, for this reason an option-based factor model was originally proposed by Fung and Hsieh (2004, 2002) to explain hedge fund returns. We compare estimates from the Fung and Hsieh's model (FHM) to the linear model with a crisis dummy (LCM), and results are presented in Table 9. Similar to LCM, the option-based factor model (FHM) 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).

Moreover, we observe LCM fits the data better than the FHM. In fact for all styles, the adjusted-R^2 for the LCM is larger than the one for the FHM. Therefore, adjusting for crisis

[16] The Pseudo-R^2 for the linear factor model are: CA 0.09, DS 0.17, EM 0.17 EMN 0.07, LS 0.20, D 0.13, ED 0.10 and RA 0.13.

periods is important in capturing hedge fund risk exposures. The same result applies for the multi-factor regime-switching model (MFRM). In fact for all styles, pseudo-R^2 for the MRSM is larger than the one for the FHM.

[INSERT Table (9) about here]

We also analyze the residuals of the FHM and estimate the evolution of the idiosyncratic risk. The dynamics of idiosyncratic risk and latent factor are again similar to the ones found using LCM. This confirms the fact that the presence of a common latent factor found using LCM model does not come from omitting option-based factors.

5.3 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:

$$R_{it} \;=\; \alpha_i \;+\; \beta_i^+ I_t^+ \;+ \beta_i^0 I_t^0 \;+\; \beta_i^- I_t^- \;+\; \epsilon_{it} \tag{16}$$

where

$$I_t^+ = \begin{cases} I_t & \text{if } I_t > \mu + \sigma \\ 0 & \text{otherwise} \end{cases} \qquad I_t^0 = \begin{cases} I_t & \text{if } \mu - \sigma < I_t < \mu + \sigma \\ 0 & \text{otherwise} \end{cases} \qquad I_t^- = \begin{cases} I_t & \text{if } I_t \leq \mu + \sigma \\ 0 & \text{otherwise} \end{cases} \tag{17}$$

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 (16), the case where $\beta_i^+ = \beta_i^0 = \beta_i^-$. The specification (16) essentially tries to capture asymmetries in the index exposures.

Using the specification (16), we regress hedge fund returns on the S&P 500 index during up (I_t^+), normal (I_t^0), and down (I_t^-) conditions.[17] 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.

Even using these models we still find the presence of a common latent variable in the dynamic of the idiosyncratic risk.

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

6 Robustness Analysis

6.1 Two S&P 500 Regimes

For completeness we re-estimate regime-switching models with only two regimes (instead of three). We find that CS and Change in VIX are still significant, but for a lower number of strategies. The presence of the common latent factor is confirmed in LTCM and September 2008 crisis periods.

6.2 Different Risk Factor Regimes

We also estimate different Markov chains for change in VIX, LS, and CS and allow hedge fund strategy exposures to change conditional on the properties of each of these Markov chains. We still observe the presence of a common latent factor in 1998 and 2008.

6.3 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:

$$\begin{aligned} R_t &= \mu + \beta\Lambda_t + \epsilon_t \ , \quad \mathrm{E}[\Lambda_t] = \mathrm{E}[\epsilon_t] = 0 \ , \quad \epsilon_t \ , \ \Lambda_t \ \sim \ \mathrm{IID} && \text{(18a)} \\ \mathrm{Var}[R_t] &\equiv \sigma^2 \ . && \text{(18b)} \end{aligned}$$

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

$$\begin{aligned} R_t^o &= \theta_0 R_t + \theta_1 R_{t-1} + \cdots + \theta_k R_{t-k} && (19) \\ \theta_j &\in [0,1] \ , \quad j = 0, \ldots, k && (20) \\ 1 &= \theta_0 + \theta_1 + \cdots + \theta_k && (21) \end{aligned}$$

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.[18] 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.[19]

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.

6.4 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.[20]

7 Conclusion

In this paper we study the effect of financial crises on hedge fund risk. We analyze crisis-dependent risk exposures for various hedge fund strategies, identify common risk factors across different hedge fund strategies, especially during crises. We also isolate crisis events where all different hedge fund strategies show a high volatility of idiosyncratic risk.

We characterize the exposure of hedge fund indices to risk factors using a linear factor model with a dummy crisis variable. This approach allows us to analyze the changes in hedge fund exposure during crises.

We have three main results. First, we show that exposures can be strongly different in the crisis periods compared to normal times, suggesting that risk exposures of hedge funds during financial crises, are quite different than those faced during tranquil periods. We find

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

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

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

that in most cases hedge fund exposure to the S&P 500 during crisis of the S&P 500 is smaller than in the normal periods. This suggests that hedge fund managers are able to time hedge market exposures, especially during financial crises.

Second, we find that Credit Spread, Large-Small, and change in VIX are common hedge fund factors during crises, suggesting that these factors are important in accessing hedge fund risk. Specifically, during crisis periods six out of eight strategies are all negatively and significantly exposed to the Credit Spread risk factor versus only two strategies that are exposed to Credit Risk during normal period. 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 ten months among the 180 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 of August 1998 and the global financial crisis of September 2008. These crises periods uncover a common latent factor that affected all different hedge fund strategies. Other crises periods, including the recent subprime mortgage crisis of August 2007 affected the hedge fund industry only through systematic risk factors.

Understanding hedge fund risk exposure and latent factors is important for investors, risk managers, and regulators. The presence of a common latent factor among hedge funds eliminates the benefits of portfolio diversification and may lead to diversification implosion.[21] Moreover, it can lead to potential margin calls for hedge fund investors. Furthermore, 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 the presence of common latent factors among hedge funds can help address regulators' concern regarding the potential risk hedge funds may pose for stability of financial markets.

8 APPENDIX A

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

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

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 part of the sample from 2003 through the third quarter of 2007 is characterized by the normal regime 1 (100%). Finally, in 2008 the S&P 500 returns are again almost exclusively in regime 2 (89.7% of time in the down-market and 6.9% in normal regime). This clearly captures the effects of the Sub-prime crisis and the beginning of the current economic downturn. 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.[22]

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 (7) about here]

Figure 7 depicts unconditional distributions of the S&P 500 overall, in down-market, normal and up-market regimes. First, during the time period analyzed in this 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 7 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.

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

[INSERT Figure (8) about here]

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

Figure 8 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 (32%), but there is also a large left-tail probability of moving to a down-market (59%). It looks like the up-market regime is often transitory, frequently followed by a down-market regime. Conditional on being in a normal regime, the total distribution is almost identical to the conditional probability of a normal regime. Therefore, if a market is in the normal regime, it is more likely to be persistent (98%). The conditional distributions for all regimes are very close to normal in this case. Nevertheless, there is a small probability of 2% of moving to an up-market regime that is more likely (59%) followed by a down-market.

Overall, the results confirm that during the period of January 1994 to December 2008, 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 7 and 8, 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.

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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 December 2008. All returns are in excess of three-month Treasury Bill rates. 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. The returns are in percentage terms. Skew measures skewness and Kurt measures excess kurtosis. JB p-value is p-value of the Jarque-Bera statistic.

Strategy	N	$\beta_{S\&P500}$	Ann. Mean	Ann. SD	Min	Med	Max	Skew	Kurt	JB p-value
Convertible Bond Arbitrage	180	0.16	1.31	6.76	-12.81	0.55	3.05	-3.61	19.55	0.00
Dedicated Shortseller	180	-0.84	-3.33	16.96	-9.14	-0.62	22.24	0.74	1.57	0.00
Emerging Markets	180	0.55	3.54	15.88	-23.50	1.02	16.01	-0.77	4.48	0.00
Equity Market Neutral	180	0.08	4.81	2.84	-2.05	0.38	2.79	0.00	0.76	0.14
Long/Short Equity	180	0.18	8.11	10.53	-11.99	0.77	10.11	-0.11	2.94	0.00
Distressed	180	0.27	6.18	6.71	-12.92	0.78	3.79	-2.43	12.73	0.00
Event Driven MS	180	0.24	5.22	6.06	-12.24	0.69	3.42	-2.77	15.30	0.00
Risk Arbitrage	180	0.14	2.68	4.23	-6.62	0.19	3.34	-1.19	5.55	0.00
S&P 500	180	1.00	4.36	15.11	-16.87	0.92	9.34	-0.76	1.29	0.00

Table 2: **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	LGC	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
Lehman Emerging Bond	LEHMEMD	Monthly return of the Lehman Emerging Markets Bond Index
MSCI Emerging Stock	MSCIEMS	Monthly return of the MSCI Emerging Markets Stock Index
Momentum Factor	UMD	Momentum factor

Table 3: **Linear Factor Model with a Crisis Dummy**

This table presents results for the regression of the CSFB/Tremont hedge-fund index strategy returns on S&P 500 (SP), Large-Small (LS), Value-Growth (VG), USD, Lehman Government Credit (LGC), Term Spread (TS), Change in VIX (dVIX), Credit Spread (CS), Lehman Emerging Market Bond (LEHMEMD), MSCI Emerging Market 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, Internet Crash, Argentinean, September 11, 2001, Defaults/WorldCom, Subprime and the global financial crises are observed. Hedge fund returns, S&P 500, USD, and Lehman Government Credit are used in excess of three-month Treasury Bill rates. The following model is estimated: $R_t = \alpha + \sum_{k=0}^{K} \beta_{i,k} F_{k,t} + \sum_{k=0}^{K} \beta_{i,D,k} D_t F_{k,t} + \omega_i u_t$. F_{kt} represents all risk factors, D_t is a crisis dummy, and $\omega(Z_t)$ 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	**1.37**	**4.08**	**1.46**	**2.50**	**0.97**	**1.74**	**0.36**	**2.29**
β_0 (SP)	0.07	1.46	**-1.01**	**-12.42**	0.05	0.61	**0.06**	**2.83**
β_1 (LS)	**-0.12**	**-2.93**	**0.61**	**8.39**			-0.02	-1.05
β_2 (VG)	0.05	1.11	**0.15**	**2.05**				
β_3 (USD)			0.07	0.58	0.12	1.02		
β_4 (LGC)	**0.21**	**2.05**						
β_5 (TS)							**-0.12**	**-2.56**
β_6 (dVIX)	0.02	0.35	**-0.24**	**-2.66**	**0.22**	**2.57**	0.01	0.25
β_7 (CS)	**-1.28**	**-3.39**	**-1.16**	**-1.75**	-0.85	-1.35	0.18	0.99
β_8 (LEHMEMD)					**0.34**	**4.12**		
β_9 (MSCIEMS)					**0.44**	**8.96**		
β_{10} (UMD)								
β_0 (SP) dummy	**-0.14**	**-1.73**	0.00	-0.03	**-0.27**	**-2.06**	0.02	0.56
β_1 (LS) dummy	**0.22**	**2.85**	**-0.22**	**-1.66**			**0.07**	**1.76**
β_2 (VG) dummy	0.03	0.37	0.05	0.34				
β_3 (USD) dummy			-0.21	-0.88	**0.50**	**2.27**		
β_4 (LGC) dummy	**0.42**	**2.16**						
β_5 (TS) dummy							**0.27**	**2.35**
β_6 (dVIX) dummy	**-0.23**	**-3.09**	0.09	0.67	0.01	0.06	-0.02	-0.52
β_7 (CS) dummy	**-1.20**	**-3.80**	**-1.18**	**-2.16**	0.18	0.33	**-0.28**	**-1.73**
β_8 (LEHMEMD) dummy					**0.14**	**0.98**		
β_9 (MSCIEMS) dummy					0.12	1.18		
β_{10} (UMD) dummy								
ω_0	**1.47**	**6.41**	**2.53**	**3.82**	**2.35**	**4.26**	**0.72**	**6.64**
Adj. R^2	0.39		0.71		0.72		0.34	

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	0.67	1.10	**0.96**	**3.28**	**0.59**	**2.00**	0.10	0.52
β_0 (SP)	**0.34**	**3.78**	**0.24**	**5.78**	**0.19**	**4.81**	**0.12**	**4.22**
β_1 (LS)	0.01	0.12	**-0.15**	**-3.94**	**-0.16**	**-4.32**	**-0.12**	**-4.90**
β_2 (VG)	0.08	1.05	**0.09**	**2.47**			0.04	1.58
β_3 (USD)					-0.04	-0.68		
β_4 (LGC)			**0.15**	**1.66**				
β_5 (TS)	-0.17	-0.94						
β_6 (dVIX)	0.05	0.55	**0.08**	**1.65**	**0.09**	**1.93**	0.05	1.50
β_7 (CS)	0.08	0.11	-0.35	-1.06	-0.05	-0.15	0.19	0.85
β_8 (LEHMEMD)								
β_9 (MSCIEMS)								
β_{10} (UMD)	**0.13**	**2.67**						
β_0 (SP) dummy	**-0.26**	**-1.75**	-0.02	-0.26	0.02	0.34	-0.03	-0.64
β_1 (LS) dummy	-0.01	-0.10	0.02	0.31	0.02	0.22	0.02	0.37
β_2 (VG) dummy	**0.34**	**2.02**	**-0.13**	**-1.77**			0.06	1.12
β_3 (USD) dummy					**0.48**	**3.98**		
β_4 (LGC) dummy			-0.24	-1.44				
β_5 (TS) dummy	**0.81**	**1.81**						
β_6 (dVIX) dummy	-0.19	-1.42	**-0.16**	**-2.40**	**-0.23**	**-3.58**	**-0.18**	**-4.16**
β_7 (CS) dummy	**-1.50**	**-2.37**	**-0.76**	**-2.75**	**-0.46**	**-1.68**	-0.25	-1.41
β_8 (LEHMEMD) dummy								
β_9 (MSCIEMS) dummy								
β_{10} (UMD) dummy	**0.27**	**2.23**						
ω_0	**2.67**	**3.50**	**1.29**	**6.74**	**1.29**	**6.74**	**0.87**	**6.92**
Adj. R^2	0.20		0.56		0.51		0.47	

Figure 1: **Number of Strategies with Significant Factor Exposures for the Linear Factor Model with a Crisis Dummy**

This figure depicts the number of strategies with significant factor exposures for the linear factor model with a crisis dummy during normal and crisis periods. The following factors are considered: S&P 500 (SP), Large-Small (LS), Value-Growth (VG), USD, Lehman Government Credit (LGC), Term Spread (TS), Change in VIX (dVIX), Credit Spread (CS), Lehman Emerging Bond (LEHMEMD), MSCI Emerging Stock (MSCIEMS), and Momentum Factor (UMD).

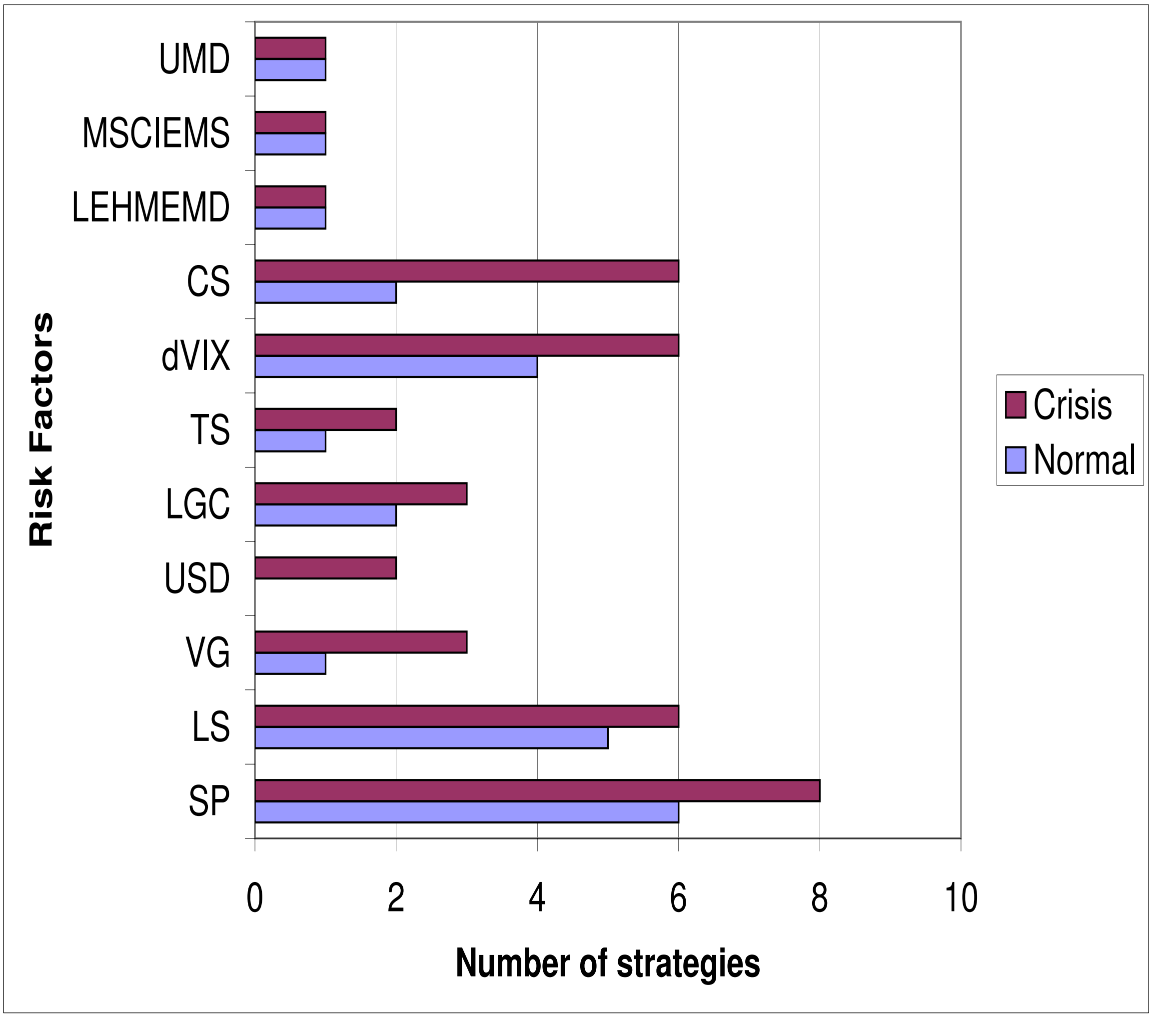


Table 4: **Estimation of Idiosyncratic Risk Factor**

This table characterizes idiosyncratic risk of six hedge fund strategy returns. Idiosyncratic risk factor is calculated using a linear model with a crisis dummy: $r_{i,t} = R_{i,t} - \alpha_i + \sum_{k=0}^{K} \beta_{i,k} F_{k,t} + \sum_{k=0}^{K} \beta_{i,D,k} D_t F_{k,t}$. $R_{i,t}$ is a hedge fund strategy return, $F_{k,t}$ represents all risk factors, and D_t is a crisis dummy. The idiosyncratic risk factor is characterized by a switching mean α_i and a switching volatility ω_i: $r_{i,t} = \alpha_i(Z_{i,t}) + \omega_i(Z_{i,t}) u_{i,t}$. $Z_{i,t}$ is a Markov chain with 2 states (0 = low volatility state and 1 = high volatility state) and a transition probability matrix $\mathbf{P}_{z,i}$. $u_{i,t}$ is IID. α, ω, and $\mathbf{P}$ are provided for each state of the idiosyncratic risk factor. Parameters that are significant at the 10% level are shown in bold type.

Panel A

Variable	Convertible Bond Arb		Emerging Markets		Equity Market Neutral	
	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat
α_0	**0.68**	**8.29**	**0.94**	**3.50**	**0.45**	**7.61**
α_1	**-1.72**	**-2.74**	-0.35	-0.53	**0.31**	**1.94**
ω_0	**0.77**	**8.13**	**2.32**	**11.18**	**0.56**	**13.88**
ω_1	**3.10**	**8.37**	**5.97**	**11.36**	**1.13**	**9.46**
P_0	**0.94**		**0.98**		**0.98**	
P_1	**0.78**		**0.99**		**0.98**	

Panel B

Variable	Long/Short Equity		Event Driven MS		Risk Arb	
	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat
α_0	**0.83**	**7.11**	**0.65**	**5.37**	**0.34**	**4.45**
α_1	0.56	1.39	**-3.21**	**-1.84**	-0.18	-0.48
ω_0	**0.99**	**10.14**	**1.37**	**14.68**	**0.78**	**9.70**
ω_1	**3.97**	**13.75**	**3.50**	**4.40**	**2.06**	**7.02**
P_0	**0.98**		**0.99**		**0.93**	
P_1	**0.99**		**0.77**		**0.73**	

Figure 2: **Dynamics of a Latent Factor for Individual Hedge Fund Strategies**
These figures depict the probability of being in a high-volatility state of the idiosyncratic risk factor for Convertible Bond Arbitrage, Equity Market Neutral, and Long/Short Equity strategies from January 1994 to December 2008.

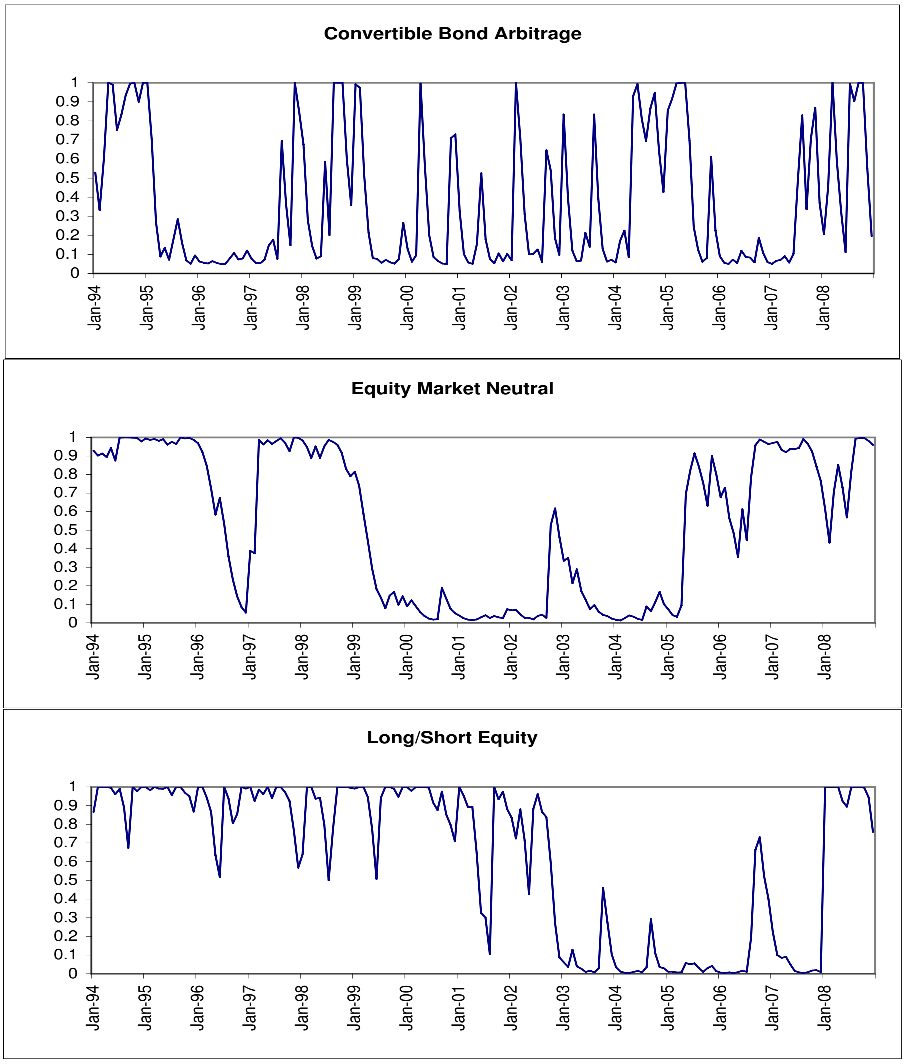
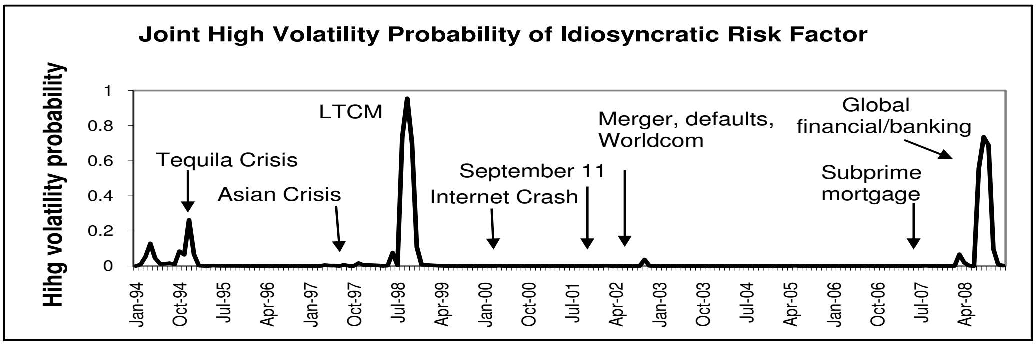
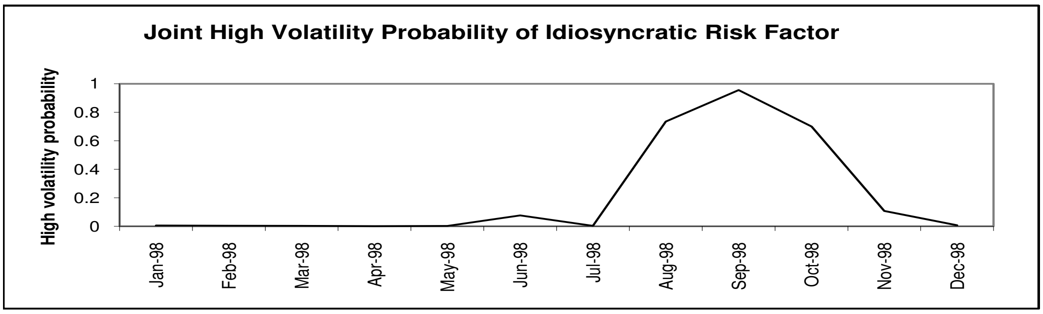


Figure 3: **Common Exposure to a Latent Factor for All Hedge Fund Strategies**
Panel A presents the joint filtered probability of high-volatility state of the idiosyncratic risk factor for all CSFB/Tremont hedge-fund index strategies from January 1994 to December 2008. Panel B concentrates on the joint 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 C concentrates on the global financial crisis of 2008.

Panel A The Joint Probability of High-Volatility State of the Idiosyncratic Risk Factor for All Hedge Fund Strategies: January 1994 - December 2008



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



Panel C The Joint Probability of High-Volatility State of the Idiosyncratic Risk Factor for All Hedge Fund Strategies: Global Financial Crisis of 2008

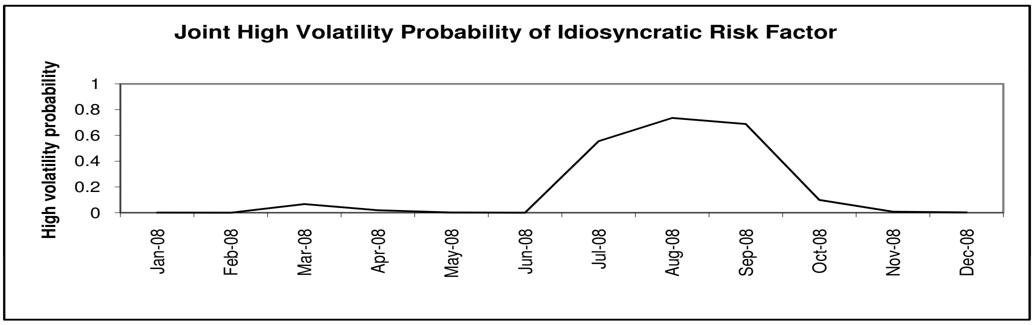


Figure 4: **Common Exposure to a Latent Factor for Four Hedge Fund Strategies: 2007 Subprime Mortgage Crisis**

This figure 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 for the year 2007. August 2007 marks the Subprime mortgage financial crisis.

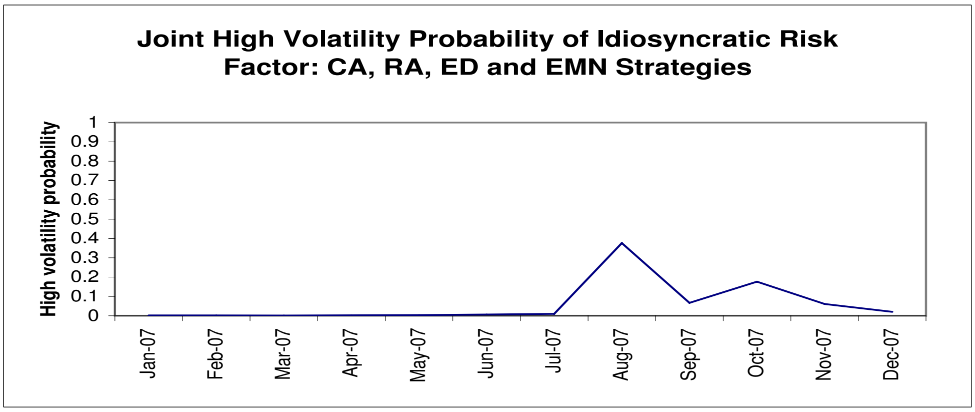


Table 5: **Mutual Fund Summary Statistics**

This table presents summary statistics for monthly Morningstar open-ended US mutual fund index returns from January 1994 to December 2008. All returns are in excess of three-month Treasury Bill rates. 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. The returns are in percentage terms. Skew measures skewness and Kurt measures excess kurtosis. JB p-value is p-value of the Jarque-Bera statistic.

Strategy	N	$\beta_{S\&P500}$	Ann. Mean	Ann. SD	Min	Med	Max	Skew	Kurt	JB p-value
Large Blend	180	0.95	0.14	4.19	-17.54	0.91	7.64	-0.96	1.85	0.00
Large Growth	180	1.10	0.13	5.05	-17.76	0.54	11.52	-0.73	1.03	0.00
Large Value	180	0.84	0.19	3.93	-17.32	0.70	9.70	-0.96	2.52	0.00
Mid-Cap Blend	180	0.96	0.31	4.56	-21.28	0.75	8.04	-1.19	3.09	0.00
Mid-Cap Growth	180	1.16	0.28	6.02	-20.61	0.73	19.65	-0.49	1.53	0.00
Mid-Cap Value	180	0.85	0.33	4.20	-20.91	0.88	10.27	-1.23	4.06	0.00
Small Blend	180	0.94	0.36	5.05	-21.43	0.85	10.11	-1.02	2.45	0.00
Small Growth	180	1.15	0.34	6.55	-22.41	0.90	23.82	-0.30	1.45	0.00
Small Value	180	0.80	0.38	4.48	-20.19	0.76	9.13	-1.17	3.29	0.00

Table 6: **Mutual Fund Analysis**

Panel A presents results for the regression of Morningstar open-ended US mutual fund index returns on S&P 500 (SP), Large-Small (LS), Value-Growth (VG), USD, Lehman Government Credit (LGC), Term Spread (TS), Change in VIX (dVIX), Credit Spread (CS), Lehman Emerging Market Bond (LEHMEMD), MSCI Emerging Market Stock (MSCIEMS), and Momentum Factor (UMD). Large Blend, Large Growth, Large Value, Mid-Cap Blend, Small Blend, Small Growth, Small Value, Mid-Cap Growth, and Mid-Cap Value strategies are analyzed. Mutual fund returns, S&P 500, USD, and Lehman Government Credit are used in excess of three-month Treasury Bill rates. ω_0 is the volatility of the idiosyncratic risk factor. Panel B presents the joint filtered probability of high-volatility state of the idiosyncratic risk factor for all mutual fund strategies presented in Panel A. The sample is from January 1994 to December 2008. Parameters that are significant at the 10% level are shown in bold type.

Panel A

Variable/	Large Blend		Large Growth		Large Value		Mid-Cap Blend	
	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat
α_0	-0.03	-0.38	-0.11	-0.69	0.11	1.00	**0.44**	**2.16**
β_0 (SP)	**0.90**	**72.24**	**0.99**	**42.93**	**0.88**	**55.74**	**0.89**	**30.36**
β_1 (LS)	**-0.07**	**-7.40**	-0.18	-10.57	**-0.08**	**-6.80**	**-0.41**	**-18.38**
β_2 (VG)	0.01	0.58	**-0.33**	**-18.09**	**0.37**	**29.95**	**0.09**	**4.03**
β_3 (USD)	**-0.04**	**-2.36**	-0.02	-0.62	-0.02	-1.13	**-0.07**	**-1.68**
β_4 (LGC)	0.01	0.22	-0.04	-0.87	0.04	1.06	0.07	1.06
β_5 (TS)	-0.01	-0.57	**-0.08**	**-1.93**	-0.02	-0.84	0.02	0.45
β_6 (dVIX)	-0.02	-1.47	0.00	-0.07	**-0.03**	**-2.16**	**-0.05**	**-1.85**
β_7 (CS)	**-0.17**	**-1.93**	-0.09	-0.55	**-0.20**	**-1.77**	**-0.58**	**-2.72**
β_8 (LEHMEMD)	**-0.02**	**-1.90**	-0.03	-1.52	**-0.04**	**-2.30**	**-0.05**	**-1.80**
β_9 (MSCIEMS)	**0.04**	**5.21**	**0.04**	**2.95**	**0.04**	**4.08**	**0.07**	**3.97**
β_{10} (UMD)	0.00	-0.76	**0.06**	**5.17**	**-0.06**	**-8.01**	0.00	0.22
ω_0	1.16		1.16		1.16		1.16	
Adj. R^2	0.99		0.98		0.99		0.96	

Variable/	Small Blend		Small Growth		Small Value		Mid-Cap Growth		Mid-Cap Value	
	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat
α_0	**0.40**	**1.96**	0.09	0.29	**0.38**	1.57	0.22	0.71	**0.51**	**2.28**
β_0 (SP)	**0.92**	**31.26**	**1.07**	**25.21**	**0.86**	**24.54**	**1.02**	**22.82**	**0.83**	**25.95**
β_1 (LS)	**-0.81**	**-36.51**	**-1.02**	**-31.86**	**-0.71**	**-26.66**	**-0.65**	**-19.33**	**-0.29**	**-11.89**
β_2 (VG)	**0.13**	**5.54**	**-0.37**	**-11.12**	**0.38**	**13.76**	**-0.41**	**-11.74**	**0.41**	**16.30**
β_3 (USD)	-0.05	-1.30	**-0.11**	**-1.98**	-0.02	-0.40	-0.07	-1.18	-0.03	-0.78
β_4 (LGC)	-0.02	-0.36	**-0.15**	**-1.67**	0.01	0.08	-0.03	-0.30	0.08	1.15
β_5 (TS)	0.05	0.92	-0.12	-1.47	**0.12**	**1.92**	**-0.13**	**-1.61**	0.02	0.36
β_6 (dVIX)	-0.01	-0.45	0.03	0.95	-0.01	-0.19	0.00	-0.07	**-0.07**	**-2.46**
β_7 (CS)	**-0.51**	**-2.39**	-0.18	-0.57	**-0.45**	**-1.80**	-0.33	-1.02	**-0.53**	**-2.30**
β_8 (LEHMEMD)	-0.02	-0.73	0.01	0.26	-0.04	-1.02	-0.04	-0.85	-0.05	-1.49
β_9 (MSCIEMS)	**0.05**	**2.69**	0.03	1.35	**0.04**	**1.69**	**0.07**	**2.67**	**0.07**	**3.47**
β_{10} (UMD)	-0.01	-0.50	**0.11**	**5.24**	**-0.07**	**-3.70**	**0.12**	**5.31**	**-0.07**	**-4.63**
ω_0	1.16		1.16		1.16		1.16		1.16	
Adj. R^2	0.97		0.96		0.94		0.95		0.95	

Panel B

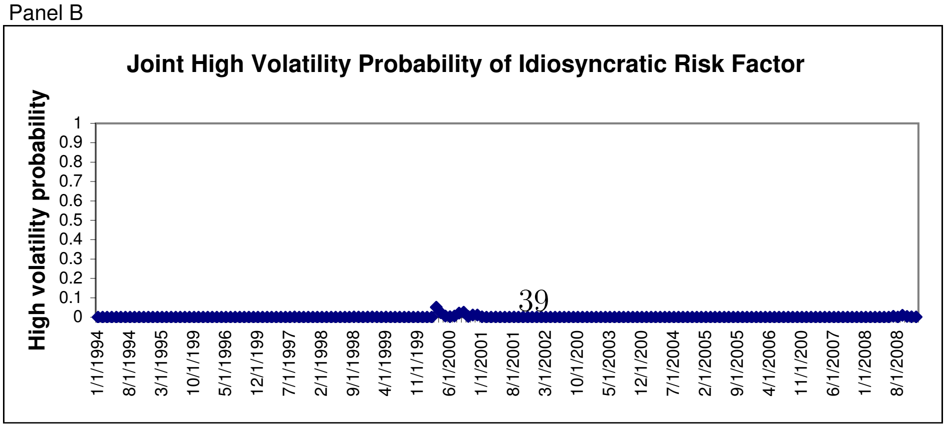


Table 7: **Regime-Switching Model for the Market Risk Factor, S&P 500**

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 three-month Treasury Bill rates. 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 December 2008 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
6.39	**17.80**	**0.92**	**3.72**	**-1.62**	**-2.39**

Standard Deviation (%)

Regime 0 (σ_0)		Regime 1 (σ_1)		Regime 2 (σ_2)	
Estimate	t-stat	Estimate	t-stat	Estimate	t-stat
1.33	**10.74**	**2.30**	**22.83**	**4.94**	**54.73**

Frequency of S&P500 regimes from 1994-2008 (%)

Regime 0	Regime 1	Regime 2
13%	**48%**	**39%**

Transition Probabilities

	Regime 0	Regime 1	Regime 2
Regime 0	**0.32**	0.09	**0.59**
Regime 1	0.02	**0.98**	0.00
Regime 2	**0.17**	0.00	**0.83**

Table 8: **Multi-Factor Regime-Switching Model**

This table presents the nonlinear exposure of CSFB/Tremont hedge-fund index strategies to the S&P 500 (SP), Large-Small (LS), Value-Growth (VG), USD, Lehman Government Credit (LGC), Term Spread (TS), Change in VIX (dVIX), Credit Spread (CS), Lehman Emerging Bond (LEHMEMD), 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 Arbitrage		Dedicated Shortseller		Emerging Markets		Equity Market Neutral	
	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat
α_0	**2.06**	**8.38**			-0.41	-0.63	**0.85**	**4.60**
α_1	**0.80**	**2.10**	**1.15**	**1.82**	0.08	0.16	**0.39**	**1.66**
β_0 (SP)	-0.11	-1.02	**-1.07**	**-2.50**	0.61	1.33	**0.31**	**2.81**
β_1 (SP)	0.04	1.10	**-1.06**	**-7.76**	**-0.17**	**-2.37**	**0.09**	**2.15**
β_2 (SP)	**-0.10**	**-2.86**	**-0.74**	**-8.68**	-0.02	-0.14	**-0.01**	**-0.41**
θ_{1_0} (LS)	-0.02	-0.34	0.29	1.17			0.02	0.26
θ_{1_1} (LS)	-0.04	-0.92	**0.71**	**5.42**			-0.02	-0.57
θ_{1_2} (LS)	**-0.11**	**-5.59**	**0.37**	**4.30**			0.02	0.93
θ_{2_0} (VG)	**0.13**	**1.63**	-0.06	-0.22				
θ_{2_1} (VG)	0.05	0.81	**0.38**	**2.05**				
θ_{2_2} (VG)	**0.06**	**3.51**	**0.21**	**2.74**				
θ_{3_0} (USD)			0.38	1.10	**0.89**	**2.33**		
θ_{3_1} (USD)			**0.29**	**1.72**	0.01	0.07		
θ_{3_2} (USD)			**-0.33**	**-1.88**	0.08	0.46		
θ_{4_0} (LGC)	-0.09	-0.57						
θ_{4_1} (LGC)	-0.02	-0.28						
θ_{4_2} (LGC)	**0.37**	**5.24**						
θ_{5_0} (TS)							-0.15	-0.89
θ_{5_1} (TS)							-0.02	-0.46
θ_{5_2} (TS)							0.04	0.67
θ_{6_0} (dVIX)	0.10	1.59			**0.55**	**2.15**	**0.11**	**1.85**
θ_{6_1} (dVIX)	-0.01	-0.30			0.06	0.94	0.06	1.65
θ_{6_2} (dVIX)	**-0.20**	**-5.03**			**0.27**	**2.07**	**-0.09**	**-3.92**
θ_{7_0} (CS)	0.61	0.82	0.23	0.08	-2.49	-0.77	-1.36	-1.87
θ_{7_1} (CS)	**-1.74**	**-5.59**	-0.68	-0.75	0.63	0.82	**-0.60**	**-2.52**
θ_{7_2} (CS)	**-1.70**	**-6.59**	**-1.28**	**-2.39**	-0.27	-0.56	**-0.38**	**-2.44**
θ_{8_0} (LEHMEMD)					-0.08	-0.20		
θ_{8_1} (LEHMEMD)					**0.22**	**3.49**		
θ_{8_2} (LEHMEMD)					**0.62**	**5.56**		
θ_{9_0} (MSCIEMS)					**0.71**	**3.28**		
θ_{9_1} (MSCIEMS)					**0.43**	**14.17**		
θ_{9_2} (MSCIEMS)					**0.35**	**6.83**		
θ_{10_0} (UMD)								
θ_{10_1} (UMD)								
θ_{10_2} (UMD)								
ω_0	**0.41**				**0.69**		**0.55**	**15.46**
ω_1	**2.01**		**2.53**	**18.97**	**2.84**		**0.98**	**7.62**
p^{Z}_{00}	**0.87**				**0.98**		**0.98**	**75.21**
p^{Z}_{11}	**0.83**				**0.99**		**0.98**	**37.99**
PseudoR^2	0.15		0.21		0.23		0.10	

Panel B

Variable/ Strategy	Long/Short Equity		Distressed		Event Driven Multi-Strategy		Risk Arb	
	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat
α_0	**1.22**	**1.87**	**2.75**	**9.63**	**1.02**	**3.82**	0.08	0.60
α_1	0.08	0.11	**1.47**	**4.19**	-0.31	-0.58	0.21	1.53
β_0 (SP)	**1.42**	**3.19**	-0.01	-0.04	**0.29**	**2.20**	**0.26**	**2.94**
β_1 (SP)	**0.29**	**3.27**	**0.26**	**6.95**	**0.25**	**3.69**	**0.19**	**4.16**
β_2 (SP)	-0.12	-1.37	**0.12**	**2.40**	**0.15**	**3.31**	0.04	0.97
θ_{1_0} (LS)	-0.11	-0.51	-0.10	-0.96	**-0.20**	**-2.57**	**-0.14**	**-1.75**
θ_{1_1} (LS)	0.08	1.09	**-0.15**	**-5.06**	**-0.12**	**-2.48**	**-0.10**	**-2.90**
θ_{1_2} (LS)	-0.03	-0.64	**-0.15**	**-4.84**	**-0.14**	**-4.60**	**-0.16**	**-4.78**
θ_{2_0} (VG)	**0.41**	**2.00**	**0.26**	**2.08**			**0.25**	**2.33**
θ_{2_1} (VG)	**0.17**	**1.87**	0.02	0.38			-0.02	-0.32
θ_{2_2} (VG)	0.00	-0.02	0.04	1.27			**0.06**	**2.15**
θ_{3_0} (USD)					0.20	1.48		
θ_{3_1} (USD)					-0.04	-0.47		
θ_{3_2} (USD)					-0.01	-0.14		
θ_{4_0} (LGC)			0.50	1.32				
θ_{4_1} (LGC)			-0.06	-0.99				
θ_{4_2} (LGC)			0.07	0.76				
θ_{5_0} (TS)	**2.01**	**2.29**						
θ_{5_1} (TS)	-0.08	-0.78						
θ_{5_2} (TS)	-0.13	-0.55						
θ_{6_0} (dVIX)	**1.16**	**5.31**	**0.19**	**2.06**	**0.25**	**3.17**	-0.36	-1.38
θ_{6_1} (dVIX)	**0.15**	**1.87**	**0.08**	**2.21**	0.06	0.82	0.05	0.76
θ_{6_2} (dVIX)	**-0.22**	**-2.74**	**-0.13**	**-3.19**	-0.05	-1.12	**-0.13**	**-1.77**
θ_{7_0} (CS)	**-4.29**	**-1.68**	0.79	0.80	-0.40	-0.41	0.02	0.22
θ_{7_1} (CS)	-0.93	-1.23	**-2.41**	**-6.95**	-0.33	-0.88	**0.08**	**1.92**
θ_{7_2} (CS)	0.22	0.31	**-1.46**	**-4.61**	**-0.55**	**-2.07**	**-0.13**	**-3.03**
θ_{8_0} (LEHMEMD)								
θ_{8_1} (LEHMEMD)								
θ_{8_2} (LEHMEMD)								
θ_{9_0} (MSCIEMS)								
θ_{9_1} (MSCIEMS)								
θ_{9_2} (MSCIEMS)								
θ_{10_0} (UMD)	**0.34**	**2.81**						
θ_{10_1} (UMD)	**0.23**	**3.42**						
θ_{10_2} (UMD)	-0.02	-0.62						
ω_0	**0.92**		**0.42**		**0.80**		**0.53**	
ω_1	**3.34**		**1.78**		**2.21**		**1.10**	
p^Z_{00}	**0.98**		**0.88**		**0.97**		**0.96**	
p^Z_{11}	**0.99**		**0.89**		**0.89**		**0.97**	
PseudoR^2	0.31		0.15		0.25		0.17	

Figure 5: **Number of Strategies with Significant Factor Exposures for the Multi-Factor Regime-Switching Model**

This figure depicts the number of strategies with significant factor exposures for the multi-factor regime-switching model during normal, up, and down states. The following factors are considered: S&P 500 (SP), Large-Small (LS), Value-Growth (VG), USD, Lehman Government Credit (LGC), Term Spread (TS), Change in VIX (dVIX), Credit Spread (CS), Lehman Emerging Bond (LEHMEMD), MSCI Emerging Stock (MSCIEMS), and Momentum Factor (UMD).

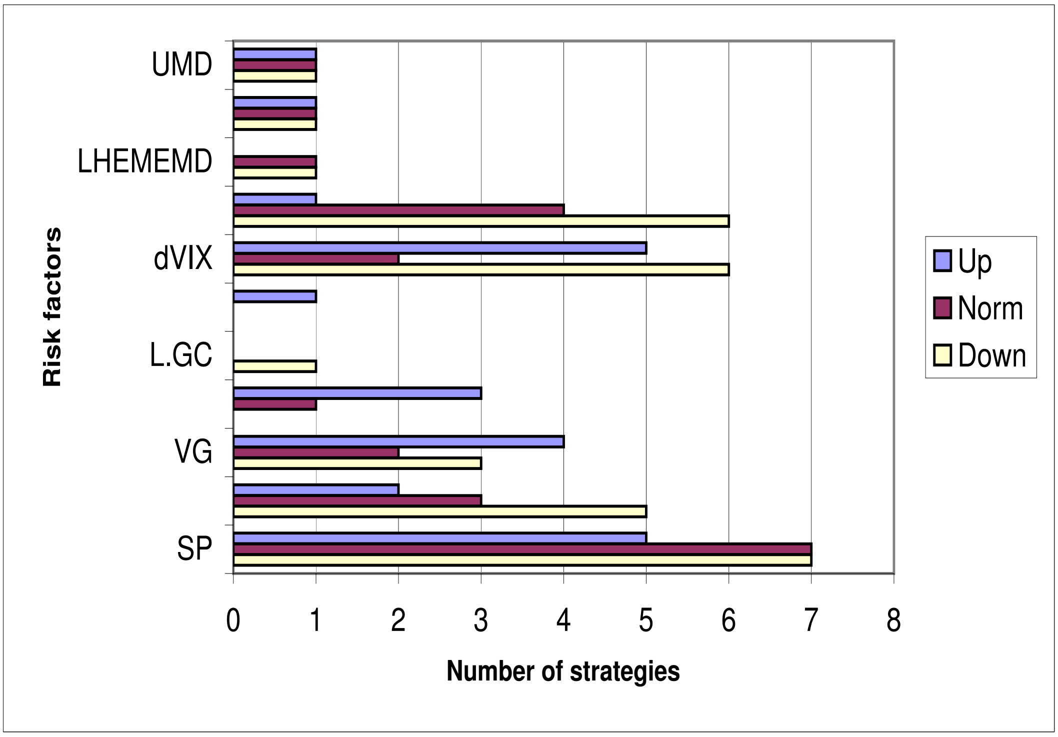


Figure 6: **Common Exposure to a Latent Factor for All Hedge Fund Strategies: Multi-Factor Regime-Switching Model**

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 December 2008. 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.

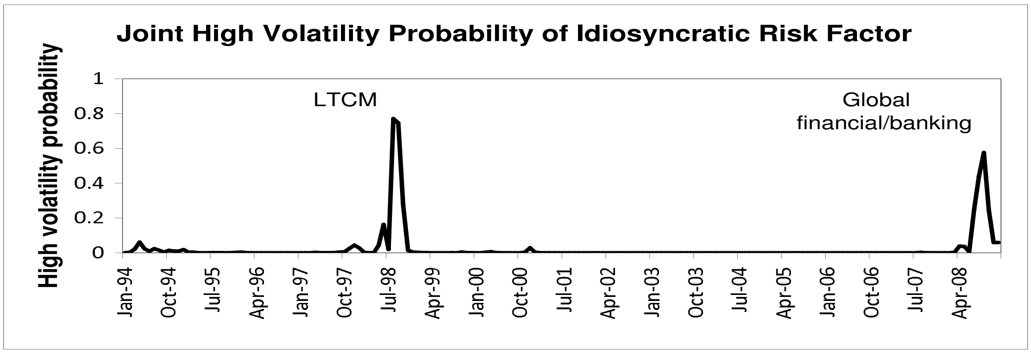


Table 9: **Option-Based Model**

This table presents results for the option-based regression of the CSFB/Tremont hedge-fund index strategy returns 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. 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	**1.51**	**4.62**	**1.41**	**2.67**	**-0.03**	**-0.12**	**0.41**	**7.41**
β1 (SP)	**0.10**	**3.46**	**-0.90**	**-18.39**	**0.57**	**8.70**	**0.08**	**6.21**
β2 (SC-LC)	**0.09**	**2.32**	**-0.48**	**-7.92**	**0.30**	**3.67**		
β3 (10Y)	**-1.56**	**-4.65**	**-1.42**	**-2.63**				
β4 (CS)					**0.11**	**2.04**		
β5 (Bd Opt)					**-0.04**	**-2.33**		
β6 (FX Opt)	**-0.01**	**-1.81**						
β7 (Com Opt)			**-0.03**	**-2.00**			0.01	1.60
ω_0	**1.66**	**5.98**	**2.71**	**3.42**	**3.62**	**1.84**	**0.74**	**6.69**
Adj. R^2	0.25		0.68		0.36		0.36	
Pseudo R^2	0.05		0.15		0.06		0.06	

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	**0.59**	**2.29**	**1.15**	**4.26**	**0.29**	**2.76**	**0.20**	**2.79**
β1 (SP)	**0.22**	**4.45**	**0.23**	**9.37**	**0.23**	**9.02**	**0.13**	**7.83**
β2 (SC-LC)			**0.14**	**4.75**	**0.14**	**4.60**	**0.12**	**5.59**
β3 (10Y)			**-0.79**	**-2.88**				
β4 (CS)	**0.15**	**3.50**			**0.04**	**1.71**		
β5 (Bd Opt)			**-0.02**	**-3.38**	**-0.03**	**-3.82**	**-0.02**	**-3.09**
β6 (FX Opt)								
β7 (Com Opt)								
ω_0	**2.83**	**3.16**	**1.37**	**6.60**	**1.40**	**6.56**	**0.95**	**6.97**
Adj. R^2	0.16		0.52		0.45		0.40	
Pseudo R^2	0.02		0.11		0.08		0.10	

Figure 7: **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 three-month Treasury Bill rates. 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.

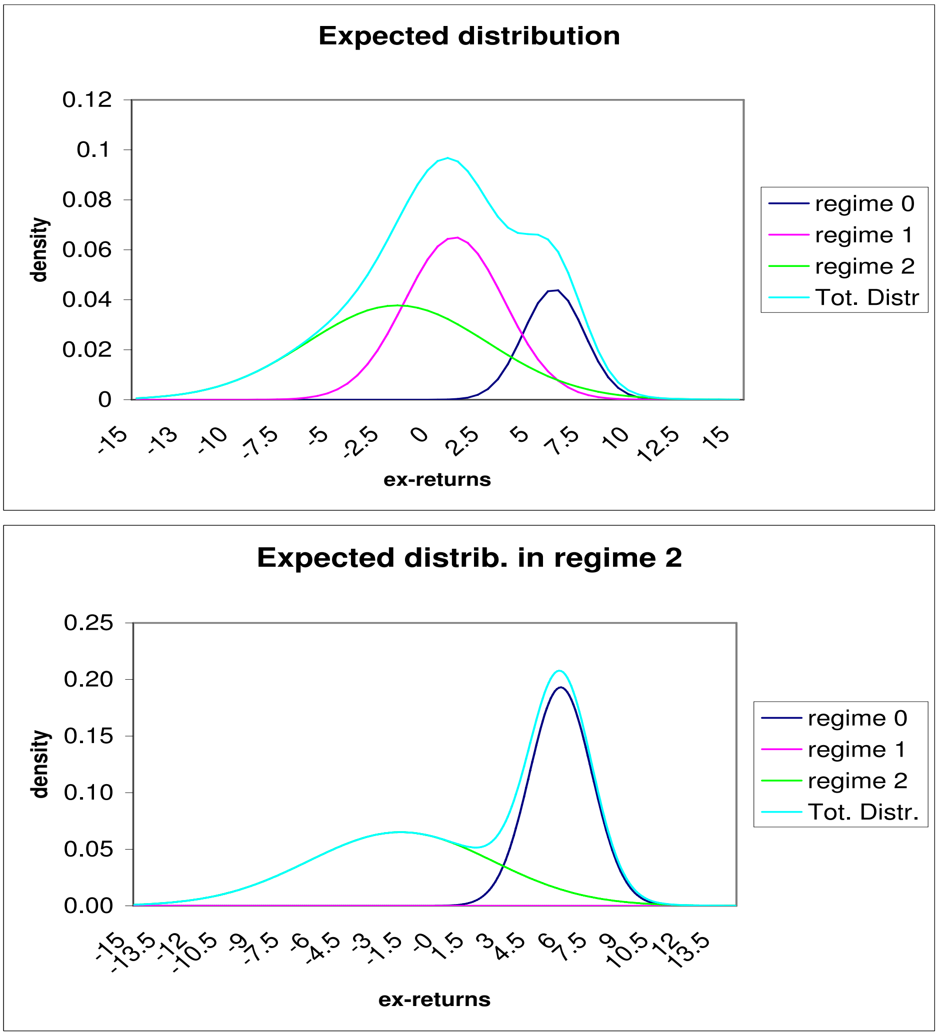


Figure 8: **Conditional Distributions of the S&P 500 in 3 Regimes**
The first panel describes the distribution of the S&P 500 conditional on the up-market regime. S&P 500 returns are in excess of three-month Treasury Bill rates. The second panel describes the distribution of the S&P 500 conditional on 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.