Crises and Hedge Fund Risk[*]

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Abstract

We study the effects of financial crises on hedge fund risk and show that liquidity, credit, equity market, and volatility are common risk factors during crises for various hedge fund strategies. We also apply a novel methodology to identify the presence of a common latent (idiosyncratic) risk factor exposure across all hedge fund strategies. If the latent risk factor is omitted in risk modeling, the resulting effect of financial crises on hedge fund risk is greatly underestimated. The common latent factor exposure across the whole hedge fund industry was present during the Long-Term Capital Management (LTCM) crisis of 1998 and the 2008 Global financial crisis. Other crises including the subprime mortgage crisis of 2007 affected the whole hedge fund industry only through classical systematic risk factors.

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1   Introduction

Hedge funds have become an increasingly large share of professionally managed money in recent years. One attraction of hedge funds as investment vehicles is their perceived low exposure to market risk. Additionally, pension funds, endowments, and individuals have invested in hedge funds to diversify their portfolios. Furthermore, the proliferation of multi-strategy funds and funds of hedge funds has allowed investors to diversify within the hedge fund industry (Learned and Lhabitant (2003)).

The recent financial crisis of 2008 has called into question the view that hedge funds are really "hedged", and that diversification across hedge fund styles is beneficial. The 2008 financial crisis has significantly reduced returns to all hedge fund strategies, leaving no safe place for investors. During this crisis period, all hedge fund strategies performed poorly. Furthermore, correlations increased — specifically, we find that an average correlation among hedge fund strategies in our sample jumped from 0.32 (August 2008) to 0.52 (September 2008), a 64% increase.

The goal of this paper is to study the effects of financial crises on hedge fund risk. Specifically, we investigate the presence of common hedge fund exposures to classical (systematic) and latent (idiosyncratic) risk factors during financial crises. The presence of common classical systematic risk factor exposures sheds light on common risk factors that lead to increases in volatility and correlation during financial crises, and the ability of hedge fund managers to hedge these risks. The presence of common latent risk factor exposures limits diversification benefits, contributes to increases in volatility and correlation, and uncovers crisis periods during which hedge fund managers cannot maintain their arbitrage positions and engage in eliminating price inefficiencies. Therefore, in this paper we show that assuming that only systematic risk factor exposures are important during crisis periods greatly underestimates the impact of financial crises on hedge fund risk.

We investigate eight hedge fund index strategies and find that hedge fund volatilities increased by almost a factor of two on average during financial crises. Out of that, 15% comes from the increase in the variance-covariance of classical systematic risk factors, 46% is due to the increase in hedge fund exposures to common classical systematic risk factors during crisis periods, and the remaining 39% is due to the increase in the idiosyncratic volatility.

The increase in correlation during crisis periods is equally explained by the following factors: 34% is attributed to the increase in the variance-covariance of classical systematic risk factors, 33% is due to the increase in hedge fund exposures to common classical systematic

factors during crisis periods, and 33% is due to the increase in correlation of the idiosyncratic returns.

The 46% increase in volatility and the 33% increase in correlation can be attributed to the increases in hedge fund exposures to liquidity, credit, and volatility factors, which are common risk factors during crisis periods. We proxy market liquidity with Large-Small risk factor (the return difference between Russell 1000 and Russell 2000 indexes) given that small stocks have higher sensitivity to market illiquidity compared to large stocks. Credit Spread (the difference between BAA and AAA corporate bond yields) proxies for credit and funding liquidity risks; and change in VIX (Chicago Board Options Exchange Volatility Index) proxies for volatility risk. The exposures to all these factors are often double or triple the "tranquil" period exposures. This means that liquidity, volatility, and credit risk are greatly relevant for hedge fund risk analysis during crises as the recent subprime mortgage crisis of 2007 and the Global financial crisis of 2008 emphasized.

While the hedge fund exposures to the Large-Small, Credit Spread, and change in VIX increased, we find that hedge fund exposures to the S&P 500 during crisis periods are smaller or negative compared to tranquil periods. This suggests that hedge fund managers are able to reduce equity market exposures during financial crises.

We also find that idiosyncratic volatility increases and idiosyncratic returns are on average positively correlated during crisis periods. If all common hedge fund risk exposures are captured by the classical systematic hedge fund risk factors, then we should not observe these properties of idiosyncratic returns. Moreover, we should not find the presence of a latent factor that is a common driver of idiosyncratic returns and volatilities for all hedge fund strategies.

We investigate this hypothesis by introducing a novel methodology to identify the presence of a common latent factor exposure across all idiosyncratic components of hedge fund strategies. We measure the presence of the common latent risk factor exposure by calculating the joint probability of an increase in the idiosyncratic volatility for all hedge fund strategies using a regime-switching approach.

We find a strong presence of a common (i.e., across all hedge fund strategies) latent risk factor exposure in August-October 1998 (during the Long-Term Capital Management (LTCM)/Russian crisis) and in August-September 2008 (during the recent global financial crisis). The peak in our "commonality" measure coincides with the peak of both crises. This provides evidence that even after accounting for market and other classical systematic factor exposures, during the LTCM and the Global financial crises of 2008, the hedge fund industry was affected by a common latent factor that cannot be captured with classical risk factors used in hedge fund risk models.

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Both of these crises were precipitated by the failure of financial institutions: LTCM (in 1998) and Lehman Brothers (in 2008). LTCM and Lehman Brothers were large companies that were not too big to fail contrary to popular opinions and market expectations. As a result, the fragility of other financial institutions, especially hedge funds, was exacerbated, which led to runs on hedge funds, massive redemptions, credit freeze, and subsequently poor performance and failure of many hedge funds. Faced with redemptions, restrictions on short selling, increases in funding costs, and inability to obtain leverage, many hedge funds across different strategies could not maintain their arbitrage positions and engage in eliminating price inefficiencies in the system.

Moreover, we show that this common latent factor induces a positive correlation among hedge fund strategy residuals during these two crises. As a result, the presence of the common latent factor exposure impedes diversification benefits that can usually be obtained by investing across different hedge fund strategies in tranquil times.

We also considered other financial crises in our analysis. However, the common latent factor exposure across the whole hedge fund industry was absent during those crisis periods.

We also apply our methodology to mutual fund returns to verify whether the latent factor exposure is peculiar to investment institutions characterized by arbitrage and leverage. Unlike hedge funds, we do not find exposure to a common latent factor. We further test the significance of our results by proposing alternative models that analyze hedge fund risk exposures. We also consider other liquidity and volatility variables and investigate whether the latent factor exposure can be captured by these variables. None of these alternative specifications and inclusion of other liquidity and volatility variables can fully account for the presence of the common latent factor exposure.

The rest of the paper is organized as follows: Section 2 describes related literature. In Section 3 we develop methodology for capturing a latent factor exposure. Section 4 describes data and presents results. Section 5 provides a mutual fund analysis. Section 6 provides alternative model specifications. Section 7 provides robustness checks. Section 8 presents our conclusion.

2   Related Literature

Our paper contributes to a growing literature on hedge funds and crises. Chan, Getmansky, Haas, and Lo (2006) use aggregate measures of volatility and distress for hedge funds based on regime-switching models and suggest that during the LTCM crisis of 1998 the whole

hedge fund industry was in distress and had a significant systemic risk exposure. [1] Boyson, Stahel, and Stulz (2008) study potential explanations for clustering of hedge funds' worst returns and find that adverse shocks to asset and funding liquidity as well as contagion may potentially explain this tail risk. We propose an additional perspective by analyzing characteristics of hedge fund risk during financial crises.

Chan, Getmansky, Haas, and Lo (2006), Adrian (2007), and Khandani and Lo (2007) show that hedge funds' risk profile during the LTCM crisis was drastically different from other financial crises. Khandani and Lo (2007) find an increased correlation among 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. Our findings provide evidence for these hypotheses.

The role of hedge funds in financial crises has been well studied by Eichengreen, Mathieson, Chadha, Jansen, Kodres, and Sharma (1998), Brown, Goetzmann, and Park (2000), Fung, Hsieh, and Tsatsoronis (2000), Brunnermeier and Nagel (2004), and Chen and Liang (2007), and hedge fund liquidation and failures were covered by Getmansky, Lo, and Mei (2004) and Liang and Park (2007).

The asymmetry of hedge fund factor loadings in up-market versus down-market conditions has been well-documented in the literature (Mitchell and Pulvino (2001), Asness, Krail, and Liew (2001), Agarwal and Naik (2004), and Chan, Getmansky, Haas, and Lo (2006)). Fung and Hsieh (2004), Agarwal, Fung, Loon, and Naik (2006), and Fung, Hsieh, Naik, and Ramadorai (2006) use breakpoint analysis to study changes in factor exposures during different time-periods. For example, they found that September 1998 and March 2000 are major break-points for hedge fund strategies and are associated with the LTCM failure and the bursting of the Internet bubble, respectively. The time-varying properties of hedge fund returns have also been studied by Bollen and Whaley (2009). The authors use discrete structural change and stochastic beta approaches in analyzing performance appraisal. All these papers find that hedge fund strategy risk exposures change over time, and that these changes are mostly related to crisis periods. Our paper is in line with the literature and contributes with an analysis of common risk exposures of hedge funds during crisis periods.

Risk factors for hedge fund analysis are introduced by Fung and Hsieh (1997, 2002, 2004), Agarwal and Naik (2004), Chan, Getmansky, Haas, and Lo (2006), Bali, Gokcan and Liang (2007), Bondarenko (2007), and Buraschi, Kosowski and Trojani (2009). Fung and Hsieh (2001) create "style factors" that embed option-like characteristics of hedge funds. Similarly, Agarwal and Naik (2004) propose option-based risk factors consisting of highly liquid at-

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[1]Regime-switching models have been used in the financial economics literature by Bekaert and Harvey (1995), Ang and Bekaert (2002) and Guidolin and Timmermann (2006) among others.

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the-money and out-of-the-money call and put options to analyze dynamic risk exposures of hedge funds. Bondarenko (2007) and Buraschi, Kosowski and Trojani (2009) introduce and analyze variance and correlation risk factors for hedge funds. Chan, Getmansky, Haas, and Lo (2006) propose a series of risk factors that are relevant for most of hedge fund strategies. In our paper we refer to these risk factors as "classical systematic risk factors" and use them to investigate a commonality of risk exposures to systematic risk factors among hedge fund strategies during financial crisis periods.

Theory offers a useful guide for understanding the origin of hedge fund latent exposures. Brunnermeier (2009) argues that 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 hedge fund exposures to market risk factors. Others, however — such as funding liquidity, margin spirals, runs on hedge funds, and aversion to Knightian uncertainty — are hedge-fund-specific and affect the idiosyncratic volatility of hedge fund returns (Krishnamurthy (2008)). For example, Khandani and Lo (2007) argue that a forced liquidation of a given strategy should increase the strategy volatility through the increase in the idiosyncratic volatility of hedge fund returns. We investigate idiosyncratic volatility of hedge fund strategies and show that the increase in this volatility is common among all hedge fund strategies we consider during the LTCM crisis of 1998 and the Global financial crisis of 2008.

3   Theoretical Framework

In this section we present a methodology for identifying common hedge fund risk exposures during financial crises. We first describe a linear model with a crisis dummy that is used to analyze common exposures to classical systematic risk factors. Second, we develop a methodology for capturing a common latent (idiosyncratic) factor exposure.

3.1   Linear Model with a Crisis Dummy

Linear factor models such as the capital asset pricing model (CAPM), Fama and French (1993) model, and the arbitrage pricing theory (APT) have been the foundation of most of the theoretical and empirical asset pricing literature.

As in Chan, Getmansky, Haas, and Lo (2006), a simple multi-factor model applied to hedge fund strategy i index returns could be represented as:

$$R_{i,t} = \alpha_i + \sum_{k=0}^{K} \beta_{i,k} F_{k,t} + \omega_i u_{i,t} \tag{1}$$

where $R_{i,t}$ is the return of a hedge fund index $i = 1, ..., m$ in period t, $F_{k,t}$, $k = 0, 1, ..., K$ are $K + 1$ risk factors, ω_i is the idiosyncratic volatility, and $u_{i,t}$ is an uncorrelated noise term with zero mean and unit variance.

We extend the model by introducing a dummy variable D_t that is equal to 1 during exogenously defined crisis periods and 0 otherwise.[2]

More formally the model could be represented as:

$$R_{i,t} = \alpha_i + \sum_{k=0}^{K} \beta_{i,k} F_{k,t} + \sum_{k=0}^{K} \beta_{i,D,k} D_t F_{k,t} + \omega_i u_{i,t} \tag{2}$$

where $\beta_{i,D,k}$ represents the change in factor k risk exposure during crisis periods.

3.2   Common Latent Factor Identification

In order to investigate the presence of a common latent factor exposure for hedge fund strategies, we extend Model (2) by introducing a dynamic component in the volatility of the idiosyncratic returns. More formally, we measure the idiosyncratic returns 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 residual $r_{i,t}$ is relative to the empirical model specified in Equation (2) and is not necessarily "idiosyncratic" or fund-strategy-specific. We use an extensive list of systematic factors, and in Section 6 we consider other alternative models with dynamic risk factor

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[2]The exogenous definition of crisis periods is provided in Section 4.1. We also provide an endogenous specification in Section 6.1.

exposures, but it is still possible that the residual contains systematic risk that is not picked up by any of the factors or the models used. In this way we are in line with the literature that investigates stock residuals (see Ang, Hodrick, Xing, and Zhang (2009) and Bekaert, Hodrick, and Zhang (2009)).

In order to investigate the presence of a latent (idiosyncratic) factor, we characterize the idiosyncratic returns of a hedge fund strategy i by a switching mean and a switching volatility:

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

where $\mu_i(Z_{i,t})$ is the idiosyncratic mean, $\omega_i(Z_{i,t})$ is the idiosyncratic volatility, both function of $Z_{i,t}$ that is a Markov chain with 2 states (State 0 = low idiosyncratic volatility state and State 1 = high idiosyncratic volatility state) and a transition probability matrix $\mathbf{P}_{z,i}$ with $i = 1, ..., m$. $u_{i,t}$ is an IID noise term, which is normally distributed with zero mean and unit variance within each regime. $Z_{i,t}$ is our proxy for a latent (idiosyncratic) risk factor specific to strategy i. The model could also be written as:

$$r_{i,t} = \mu_{0,i} + \mu_{1,i}Z_{i,t} + \omega_i(Z_{i,t})u_{i,t} \tag{5}$$

where $\mu_{0,i}$ is the mean of idiosyncratic returns when $Z_{i,t}$ is equal to 0, and $\mu_{1,i}$ is the change in this mean when $Z_{i,t}$ is equal to 1.[3] From the economic point of view, $\mu_{1,i}$ is the change in the mean of idiosyncratic residuals that is related to the change in the idiosyncratic volatility, i.e. when the idiosyncratic volatility is increasing, hedge fund strategies on average may face higher or lower idiosyncratic returns.

Despite the fact that the regimes of $Z_{i,t}$ are unobservable, they can be econometrically estimated (see for example Hamilton (1990, 1994)).[4] More specifically, once parameters are

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[3]By construction, the average of idiosyncratic returns is equal to zero in the sample. This allows for both $\mu_{0,i}$ and $\mu_{1,i}$ be equal to zero or be of opposite sign.

[4]The importance of using regime-switching models is well established in the financial economics literature. Examples are found in Bekaert and Harvey's (1995) regime-switching asset pricing model, Ang and Bekaert's

estimated, the likelihood of regime changes can be readily obtained. In particular, since the n-step transition matrix of a Markov chain $Z_{i,t}$ is given by $\mathbf{P}_{z,i}^n$, the conditional probability of the regime $Z_{i,t+n}$ 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):

$$\text{Prob}\,(Z_{i,t+n} = 0 | \mathcal{R}_{i,t}) \;\; = \;\; \pi_{i,1} \; + [(p_{i,00} - (1 - p_{i,11})]^n \left[\text{Prob}\,(Z_{i,t} = 0 | \mathcal{R}_{i,t}) - \pi_{i,1}\right] \quad (6)$$

$$\pi_{i,1} \;\; \equiv \;\; \frac{(1 - p_{i,11})}{(2 - p_{i,00} - p_{i,11})} \quad (7)$$

where $\pi_{i,1}$ is the unconditional probability of being in state 1 for strategy i and $\text{Prob}\,(Z_{i,t} = 0 | \mathcal{R}_t)$ is the probability that the date-t, $Z_{i,t}$ is equal to 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).

In order to investigate the presence of the common latent (idiosyncratic) risk factor exposure, we propose a novel approach based on the determination of the joint probability that idiosyncratic volatilities of hedge fund returns for all m hedge fund strategies are in a high volatility regime, given the historical data up to and including data t:

$$J_{p,t} = \prod_{i=1}^{m} \text{Prob}\,(Z_{i,t} = 1 | \mathcal{R}_{i,t}) \quad (8)$$

In our framework we identify the presence of a common latent (idiosyncratic) risk factor exposure when we observe a significant joint increase in the idiosyncratic volatility of hedge fund returns for all hedge fund strategies, i.e., a large $J_{p,t}$.

In order not to impose a common latent factor exposure by construction, a latent factor exposure for each strategy is independently estimated. If an increase in idiosyncratic volatility for each strategy is truly independent, then $J_{p,t}$ should be close to the following probability $A_{p,t}$:

(2002) and Guidolin and Timmermann's (2008) regime-switching asset allocation models, Lettau, Ludvigson, and Wachter's (2008) regime-switching equity premia model, Bollen, Gray and Whaley's (2000) analysis of regimes in currency options, and Billio and Pelizzon's (2000, 2003) 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, Getmansky, Haas, and Lo (2006)), and foreign exchange markets (Dueker and Neely (2004)).

$$A_{p,t} = \prod_{i=1}^{m} \pi_{i,1} \tag{9}$$

where $A_{p,t}$ represents the probability that by chance all strategies are in a high volatility state independently of the state in $t-1$.

Therefore, a large difference between $A_{p,t}$ and $J_{p,t}$ at any time t implies a commonality in the behavior of the idiosyncratic returns due to the presence of a common latent factor. As a result, $J_{p,t}$ is our indirect measure of a common latent factor exposure.

The presence of a common risk factor exposure in the residuals of hedge fund strategy returns means that the residuals are all related to the same source of risk, and thus are correlated. However, our $J_{p,t}$ measure is not able to capture the sign of that exposure. The sign of this exposure is related to the sign of $\mu_{1,i}$. If $\mu_{1,i}$ for all strategies has the same sign, idiosyncratic returns among hedge funds strategies are positively correlated during crisis periods. As a result this positive correlation among residuals greatly impedes diversification benefits among various hedge fund strategies.

4 Empirical Analysis

In this Section we conduct an empirical analysis of the impact of financial crises on hedge fund risk using data described in Section 4.1. In the next Section we shed light on the identification of common hedge fund risk exposures during financial crises. Common systematic risk exposures during crises are analyzed in Section 4.2. Increases in correlation and volatility of hedge fund returns during financial crises are thoroughly studied and decomposed in Section 4.3. The presence of a common latent factor exposure is investigated in Section 4.4.

4.1 Data

Our analysis is based on 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 in assets under management, a minimum one-year track record, and current audited financial statements. 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 eight strategies related to the equity market: directional strategies such as Dedicated Short Bias, 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. [5]

[INSERT Table (1) about here]

Categories differ greatly. For example, annualized mean of excess returns for the Dedicated Short Bias category is the lowest: -2.83%, and the annualized standard deviation is the highest at 16.95%. Long/Short Equity has the highest mean: 8.61% and a relatively high standard deviation: 10.51%. The lowest annualized standard deviation is reported for the Equity Market Neutral strategy at 2.83% with an annualized mean of 5.30%.[6]

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 Arbitrage all have negative skewness and high excess kurtosis. According to the Jarque-Bera test, which is a measure of departure from normality, based on the sample kurtosis and skewness, all hedge fund category returns are not normally distributed except for the Equity Market Neutral strategy.[7] For this strategy, normality of returns cannot be rejected. The S&P 500, is characterized by high annualized excess return of 4.86% and high standard deviation of 15.09% 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, covering stocks, bonds, currencies, commodities, momentum factor, and volatility. These factors are described below. They are also

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[5]One common risk factor considered in our analysis is the S&P 500; therefore, we concentrate only on hedge fund styles that either directly or indirectly have the S&P 500 exposure. For this reason, we take out Fixed Income Arbitrage and Managed Futures strategies.

[6]On November 2008 this strategy was largely affected by the Madoff fraud and the index was recorded to earn -40%. In order to make sure that our results are not driven by this event, we excluded all Madoff funds from the index. As a result, we replaced the -40% with -0.06% (provided by CSFB/Tremont after excluding all Madoff hedge funds).

[7]The Jarque-Bera (JB) test statistic is defined as $JB = \frac{n-q}{6}(SK^2 + \frac{(KU-3)^2}{4})$, where SK is the skewness, KU is the kurtosis, n is the number of observations, and q 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.

described by Chan, Getmansky, Haas, and Lo (2006) as relevant traded factors to be used for each hedge fund strategy:

- *S&P 500* is the monthly return of the S&P 500 index including dividends.

- *Large-Small* is the monthly return difference between Russell 1000 and Russell 2000 indexes.

- *Value-Growth* is the monthly return difference between Russell 1000 Value and Growth indexes.

- *USD* is the monthly return on Bank of England Trade Weighted Index.

- *Lehman Government Credit* is the monthly return of the Lehman U.S. Aggregated Government/Credit index.

- *Term Spread* is the difference between the 10-year Treasury Bond redemption yield and the 6-month LIBOR.

- *Change in VIX* is the monthly first-difference in the VIX implied volatility index based on the Chicago Board Options Exchange (CBOE)'s OEX options.

- *Credit Spread* is the difference between monthly seasoned BAA and AAA corporate bond yields provided by Moody's.

- *Momentum Factor* is the momentum factor based on six value-weighted portfolios formed using independent sorts on size and prior returns of NYSE, AMEX, and NAS-DAQ stocks.[8]

In all our analyses, hedge fund returns, S&P 500, USD, Lehman Government Credit are used in excess of three-month Treasury Bill rates.[9]

Another important element considered in our analysis is the identification of crisis periods. We provide two identifications methods for crisis periods. The exogenous definition is provided in this section. The endogenous specification is provided in Section 6.1.

For the exogenous definition of crisis periods, we create a dummy variable that is equal to one when we observe the Mexican (December 1994 - March 1995), Asian (June 1997 -

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[8]The momentum factor returns are downloaded from Ken French's website.

[9]We do not include emerging market risk factors used in Chan, Getmansky, Haas, and Lo (2006) because they are largely correlated with the S&P 500 during crises. Furthermore, we repeated our analysis including emerging market factors for bonds and stocks. The loadings on these factors are not significant for all strategies except for the Emerging Markets strategy. All main results about common systematic and idiosyncratic risk factors remain unchanged.

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, drying up of merger activities, increase in defaults, and WorldCom accounting problems crises (June 2002 - October 2002) (these crisis periods are identified by Rigobon (2003)), the 2007 subprime mortgage crisis (August 2007 - January 2008), and the 2008 Global financial crisis (September 2008 - November 2008) and zero otherwise.[10]

4.2 Analysis of Systematic Risk Exposures During Crises

For each hedge fund strategy we estimate a linear factor model with a crisis dummy as specified in Model (2) and the results are contained in Table 2.[11] As Table 2 shows, the crisis dummy variable is often significant for different risk factors. This confirms that during crisis periods risk exposures of hedge funds change. For example, during tranquil periods, the exposure of the Convertible Bond Arbitrage strategy to Credit Spread is -1.29. During a crisis period, the exposure doubles to -2.47. For the same strategy, the exposure to the S&P 500 is reduced by 0.14 during crisis periods.

[INSERT Table (2) about here]

Figure 1 depicts the number of strategies with significant factor exposures during tranquil and crisis periods. Compared to tranquil periods, more factors are common during crisis periods. Common risk exposures are observed for Credit Spread, change in VIX, Large-Small, and S&P 500 risk factors, suggesting that these factors are important in accessing systematic hedge fund risk, especially during crises.

[INSERT Figure (1) about here]

For most of the strategies, the 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

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[10]Statistics for all these risk factors and correlations of hedge fund returns and risk factors for the whole sample and during crisis periods are provided upon request.

[11]Similar to Chan, Getmansky, Haas, and Lo (2006), the step-wise linear approach was used to limit the final list of factors for the analysis.

time hedge market exposures, especially during financial crises. For example, the Long/Short Equity strategy has an exposure to the S&P 500 of 0.34 during the tranquil period, which is reduced to 0.06 (0.34+(-0.28)) during the crisis period.[12] This reduction in exposure can be also due to the decrease in leverage during crises.

We further study whether hedge fund managers are able to reduce hedge fund exposures to other risk factors during financial market distress. We find that Large-Small is a common factor during crises for five out of eight hedge fund strategies and for four out of eight it has the same sign. This result suggests that Large-Small variable may potentially capture a common factor in the hedge fund industry. Large-Small can serve as a market liquidity proxy (Amihud (2002) and Acharya and Pedersen (2005)). Small stocks have greater sensitivity to market illiquidity than large stocks, meaning that they have greater liquidity risk. We find that liquidity is highly relevant for hedge funds. This result is in line with the potential interpretation of Acharya and Schaefer (2006) that the "illiquidity" prices in capital markets exhibit different regimes. Specifically, in a tranquil regime, hedge funds are well capitalized and liquidity effects are minimal. However, in the "illiquidity" regime usually related to crises, hedge funds are close to their collateral constraints and there is "cash-in-the-market" pricing (Allen and Gale (1994, 1998)).

We also find that during tranquil times, Credit Spread exposure is negative and significant for only two strategies: Convertible Bond Arbitrage and Dedicated Short Bias. However, during crisis periods, the exposure to Credit Spread is negative and significant for seven out of eight strategies. As Table 2 shows, credit spread exposures double or triple during crisis periods. Credit Spread variable is a proxy for credit risk (Longstaff, Mithal, and Neis (2005)) and funding liquidity risk (Boyson, Stahel, and Stulz (2008) and Brunnermeier (2009)). In the times of uncertainty the rate on low-credit illiquid investments such as BAA corporate bonds increases. At the same time, the demand for high-credit liquid investments such as AAA corporate bonds increases, leading to the increase in credit spread. Adverse shocks to funding liquidity accompanied by an increase in credit spreads lead to an increase in margins, de-leveraging and margin calls, causing the unwinding of illiquid positions, generating further losses and margin calls, and finally culminating in hedge funds' collapse. During crisis periods, hedge funds are faced with sudden liquidation and margin calls (Khandani and Lo (2007)).

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 crisis periods, indicating

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[12]This is consistent with 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.

that returns of these strategies are reduced when volatility increases during crisis periods as showed by Bondarenko (2007).

Higher volatility is often associated with lower liquidity, higher credit spreads, higher correlations, and "flights to quality" (Bondarenko (2007) and Brunnermeier and Pedersen (2009)). After observing sharp price drops due to an increase in volatility, prime brokers are likely to increase margins and financiers might be reluctant to roll over short-term asset-backed commercial paper. Volatility also tends to "spill over" across assets and regions. During crisis periods, an increase in volatility is more likely to lead to hedge fund losses compared to other time periods (tranquil or up-market).

In terms of magnitudes, the effect of the credit spread is the strongest. For six strategies, hedge fund exposure to credit spread doubled, and in some cases tripled during crisis periods. Also, for many strategies risk exposure was absent (or exposure was positive) during tranquil times, but appeared during crisis periods, i.e, volatility risk exposure for Convertible Bond Arbitrage, Distressed, Emerging Markets, Event Driven Multi-Strategy, and Risk Arbitrage, and credit risk exposure for Equity Market Neutral, Emerging Markets, Long/Short Equity, Distressed, and Event Driven Multi-Strategy are negative and significant during crises.

In conclusion, during crisis periods the effects of liquidity, volatility, and credit risks on hedge funds are much higher compared to tranquil periods. Therefore, the exposures to Large-Small (market liquidity risk proxy), Credit Spread (credit risk and funding liquidity proxy), and change in VIX (volatility risk proxy) become more negative in crisis periods and are common across different hedge fund strategies.

4.3   Hedge Fund Risk and Correlation During Crises

We calculate correlation among hedge fund strategies considering a two-year rolling window, i.e. 24 observations. The average correlation among hedge fund strategies is plotted in Figure 2 Panel A from January 1994 through December 2008. This figure shows that correlation changes through time and greatly increases during financial crisis periods. Specifically, during August 1998 the correlation increased by 50% (from 0.21 to 0.31) and during September 2008 the correlation increased by 64% (from 0.32 to 0.52). The average correlation increase among hedge fund strategies during all financial crises is 33%.

Moreover, by splitting our sample into tranquil and crisis periods, we find that the average annualized volatility of hedge fund strategy returns jumped by 90% during crises (see Table 3), i.e. an increase of almost a factor of two. Crises affect hedge fund strategies differently. The effect ranges from a 38% increase in volatility for the Equity Market Neutral strategy to

176% for the Convertible Bond Arbitrage strategy.[13] However, in all cases, volatility greatly increased for hedge fund strategies during financial crisis periods.

[INSERT Figure (2) and Table (3) about here]

The increases in correlation and volatility can potentially be attributed to i) the increase in variance-covariance of classical systematic risk factors, ii) the increase in exposure to common systematic risk factors, and iii) the increase in idiosyncratic volatility and correlation of idiosyncratic returns during crisis periods.

In order to analyze characteristics of hedge fund risk during financial crises, for each strategy, we decompose the total change in variance in crisis periods into the change in monthly variance associated with an increase in variance-covariance of classical systematic risk factors, the change in variance associated with an increase in exposure to common systematic risk factors (i.e., an increase in factor loadings), and the increase in idiosyncratic variance during crisis periods.

To calculate the contribution of the variance-covariance component, for each strategy we compute the difference between the systematic variance during crisis periods, i.e. the variance generated by the exposure to classical systematic risk factors (assuming loadings on these factors are the same as loadings during tranquil periods) and systematic variance during tranquil periods:

$$\Delta\sigma^2_{VarCov}{}^{Crisis} = \beta^{Tranquil}VarCov^{Crisis}\beta^{Tranquil^T} - \beta^{Tranquil}VarCov^{Tranquil}\beta^{Tranquil^T} \quad (10)$$

where $\beta^{Tranquil}$ is the vector of factor loadings on classical systematic risk factors during tranquil periods and $\beta^{Tranquil^T}$ is its transpose. $VarCov^{Crisis}$ and $VarCov^{Tranquil}$ are variance-covariances of classical systematic risk factors in crisis and tranquil periods, respectively.

The contribution of the increase in common systematic risk factor exposures (i.e., an increase in betas) during crisis periods is the difference between the systematic variance during crisis periods where crisis loadings are considered and the systematic variance determined

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[13]This result is largely related to the exclusion of the Madoff effect.

considering the variance-covariance of risk factors during crisis periods and factor loadings of tranquil periods:

$$\Delta\sigma^2_{Beta}{}^{Crisis} = \beta^{Crisis}VarCov^{Crisis}\beta^{Crisis^T} - \beta^{Tranquil}VarCov^{Crisis}\beta^{Tranquil^T} \qquad (11)$$

where β^{Crisis} is the vector of factor loadings on classical systematic risk factors during crisis periods and β^{Crisis^T} is its transpose.

Finally, the increase in idiosyncratic variance of hedge fund returns during crisis periods is the difference between idiosyncratic variances in crisis and tranquil periods:

$$\Delta\sigma^2_{Idio}{}^{Crisis} = \sigma^2_{Idio}{}^{Crisis} - \sigma^2_{Idio}{}^{Tranquil} \qquad (12)$$

Table 3 provides results for these three separate contributions to the hedge fund risk during crises for each hedge fund strategy and an average of all of these strategies. In addition to the variance decomposition, we calculate percentage increases in variances in the crisis periods compared to the tranquil periods. On average, the increase in monthly variance during crisis periods, $\%\Delta\sigma^2 Crisis$, is 283%. Out of this, 42% is associated with an increase in variance-covariance of classical systematic risk factors ($\%\Delta\sigma^2_{VarCov}{}^{Crisis}$); 130% is due to the increase in exposure to common systematic risk factors ($\%\Delta\sigma^2_{Beta}{}^{Crisis}$), i.e., increase in factor loadings; and 111% is due to the increase in the idiosyncratic variance during crisis periods ($\%\Delta\sigma^2_{Idio}{}^{Crisis}$). In relative terms, 15% of the increase in total variance of hedge fund returns during crises comes from the increase in the variance-covariance of classical systematic risk factors, 46% is due to the increase in hedge fund exposures to common classical systematic risk factors, and the remaining 39% is due to the increase in the idiosyncratic variance during crisis periods.[14]

In order to explain the increase in correlations among hedge fund strategies during crisis periods, we investigate the behavior of the fitted returns generated by a linear model with and

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[14]The 46% relative increase in variance associated with the increase in hedge fund exposures to common classical systematic risk factors can potentially be explained by an increase in leverage during crises. However, on the contrary, we find that during crisis periods, the exposure to the S&P 500 is reduced. If leverage is proxied by a factor exposure to the S&P 500, then, during crisis periods leverage is actually decreased.

without the crisis dummy (see Model (2)). We calculate average two-year rolling correlations among hedge fund strategy fitted returns for these two models (see Figure 2 Panel B). The R^2 of the regression of the two-year rolling average correlation of hedge fund strategy returns (see Figure 2 Panel A) on the two-year rolling average correlation of fitted returns generated by a linear model without a crisis dummy (see Figure 2 Panel B) is 34%. Therefore, on average 34% of increase in correlation can be attributed to the change in variance-covariance of common classical systematic risk factors. The R^2 of the regression of the two-year rolling average correlation of hedge fund strategy returns (see Figure 2 Panel A) on the two-year rolling average correlation of fitted returns generated by a linear model with a crisis dummy (see Figure 2 Panel B) is 67%. Therefore, on average 33% (67%-34%) of the increase in correlation can be attributed to the increase in hedge fund exposures to common classical risk factors during crisis periods. The residual 33% is thus due to the increase in correlation of the idiosyncratic returns.[15]

In the next session we investigate whether the increase of correlation and volatility among idiosyncratic returns can be attributed to the presence of a common latent factor exposure.

4.4 Analysis of a Common Latent Factor Exposure During Crises

If all common hedge fund risk exposures are captured by the classical systematic hedge fund risk factors, then we should not observe a common latent factor exposure across all hedge fund strategies. In order to investigate this hypothesis we analyze the idiosyncratic returns of different hedge fund strategies. More specifically, for each hedge fund strategy, we calculate idiosyncratic returns using Equation (3) and estimate the model presented in Equation (5). The estimation of idiosyncratic mean and volatility conditional on the Markov chain $Z_{i,t}$ for each hedge fund strategy is provided in Table 4.

We find that the idiosyncratic volatility of hedge fund strategy returns, $\omega(Z_{i,t})$ is characterized by two different regimes with "high" (when $Z_{i,t}=1$) and "low" (when $Z_{i,t}=0$) volatilities.

[INSERT Table (4) about here]

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[15]The average correlation among hedge fund idiosyncratic returns during tranquil period is 0.15 and during crises period is 0.27, i.e. it increases by 84% during crisis periods. Correlations of hedge fund idiosyncratic returns for the whole sample and during tranquil and crisis periods are provided upon request.

For all strategies high idiosyncratic volatility (ω_1) is estimated to be at least twice the low volatility (ω_0) as depicted in Table 4. In particular, the idiosyncratic volatility for hedge fund returns in a high volatility regime is on average equal to 2.55% (8.83% annualized) which is more than two times larger than 1.11% (3.84% annualized) volatility in a low-volatility regime.

Moreover, when hedge fund strategies are in a high-volatility regime ($Z_{i,t}=1$), for seven out of eight strategies idiosyncratic returns on average are reduced by -0.88% (10.52% annualized), with the exception of the Dedicated Short Bias strategy.[16] For five strategies, the results are statistically significant.

As a result, for each strategy the latent factor contributes to an increase in idiosyncratic volatilities and reduction in idiosyncratic returns. Khandani and Lo (2007) find that forced liquidations, inability to maintain leverage and arbitrage positions, and margin calls are sources of increase in idiosyncratic volatility and reduction in idiosyncratic returns.

Using the model specification described in Equations (3) and (4), we estimate the dynamics of the probability of being in the high-volatility regime for each strategy. Results for all hedge fund strategies are shown in Figure 3.

[INSERT Figure (3) about here]

Figure 3 plots monthly probabilities from January 1994 to December 2008 for hedge fund indices facing the high volatility regime of idiosyncratic returns, 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 Bond 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 volatility dynamics.

We further explore the possibility of the presence of a common latent factor exposure across all hedge fund strategies. We introduce a novel methodology in which we identify the presence of a common latent (idiosyncratic) risk factor exposure across all hedge fund strategies. Our approach investigates the presence of a common latent factor exposure

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[16]However, the estimate for the Dedicated Short Bias strategy is not significant.

based on the determination of the joint probability that volatilities of idiosyncratic hedge fund returns for all hedge fund strategies are in a high volatility regime. The measure of the common latent factor exposure is given in Equation (8).

Specifically, we calculate the joint filtered probability of being in the high volatility regime for all hedge funds and plot it in Figure 4. We find that the joint filtered probability jumps from approximately 0% in May 1998 to 62.80% in August 1998, the month of the Long-Term Capital Management (LTCM) collapse, to 81.57% in September 1998. It started to subside in October 1998. The peak in the joint probability coincides with the liquidity crisis precipitated by the collapse of LTCM. Similar behavior is observed for the most recent September 2008 Global financial crisis. The joint probability that idiosyncratic volatilities of hedge fund returns for all eight strategies are in a high volatility state is 64.20% in September 2008 (Figure 4 Panel C), the month of the Lehman Brothers' bankruptcy. As a result, both LTCM and the September 2008 crisis exhibit similar patterns of behavior (see Figure 4 Panels B and C). Therefore, it is feasible that both these events were affected by similar shocks.

We check this result against the possibility that all eight strategies randomly exhibit a high-volatility regime. Using Equation (5), we calculate the theoretical probability of this event occurring, i.e. $A_{p,t}$. This probability is equal to 0.01%, i.e. out of 180 months in our sample, we should expect to see this happening for only 0.02 months. We find that for 5 months (i.e., 250 times larger than expected by chance), all strategies were in the high-volatility regime. Therefore, our result is not due to a chance, but due to the presence of a common latent factor exposure during LTCM and Global financial crises.

The presence of a common risk factor exposure in hedge fund idiosyncratic returns means that the residuals are all related to the same source of risk, and thus are correlated. Unfortunately, the joint increase in volatility is not able to indicate the sign of the correlation among hedge fund strategies. In order to uncover the sign of the correlation we analyze $\mu_{1,i}$ from Equation (5). We find that for seven out of eight strategies, $\mu_{1,i}$ is negative (five estimates are significantly different than zero). This means that the idiosyncratic risk negatively affects the returns of hedge fund idiosyncratic returns. As a result, the presence of the common risk factor leads to a positive correlation among residuals. Therefore, the presence of the common idiosyncratic risk factor exposure greatly limits diversification benefits among various hedge fund strategies.

In conclusion, both systematic and latent risk factor exposures contribute greatly to volatility and correlation of hedge fund strategy returns. As a result, it is essential to include both common systematic and latent factors in hedge fund risk modeling. Omitting the latent risk factor exposure significantly underestimates the impact of financial crises on

hedge fund risk and correlation among strategies.

[INSERT Figure (4) about here]

4.4.1 Discussion on Commonality Between 1998 and 2008 Crises

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 up of merger activities, increase in defaults, and WorldCom accounting problems), and the recent 2007 subprime mortgage crisis. Even though individual hedge fund strategies had specific latent factor exposures during these crises, the common latent factor exposure was absent for these crisis periods. Our results shed light on commonality between the 1998 and 2008 financial crises. Both of these crises were precipitated by the failure of two prominent financial institutions: Long-Term Capital Management (LTCM) in 1998 and Lehman Brothers in 2008.

LTCM was one of the largest hedge funds, and Lehman Brothers was one of the largest banks. Both of these institutions were counterparties for many derivatives and swaps agreements. Lehman Brothers was a counterparty to many hedge funds in derivatives contracts, swaps, and leverage; Lehman's bonds were also used as a collateral by hedge funds. The default of Lehman lead to the increase in counterparty risk, limitations for hedge funds to fund and maintain their arbitrage positions, and drying up of financial intermediation activities. Both LTCM and Lehman events lead to crippling of credit markets and more serious global impact. When Lehman Brothers declared bankruptcy, its prime brokerage in the U.K. went bankrupt. This lead to massive losses across many hedge funds as their securities that were posted as collateral disappeared in the system. Moreover, inter-bank markets froze as no bank trusted another's solvency and the entire financial intermediation activity was at risk of a complete collapse (see Acharya, Philippon, Richardson and Roubini (2009)).

Both LTCM and Lehman Brothers were not too big to fail contrary to popular opinions and market expectations.[17] As a result, the fragility of other financial institutions, especially

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[17]The default of LTCM created a large spillover effect so that the president of the New York Federal Reserve Bank summoned more than a dozen top executives of the firms which had loaned money to LTCM to an 8 p.m. meeting and warned them that the systemic risk posed by LTCM going into default was "very real"(Pacelle, Raghavan, and Siconolfi (1998)).

hedge funds, was exacerbated, which led to runs on hedge funds, massive redemptions, credit freeze, and subsequently poor performance and failure of many hedge funds.[18] Many hedge funds were faced with restrictions on short selling, increase in funding costs, redemptions, and inability to obtain leverage. As a result, they could not maintain their arbitrage positions and engage in eliminating price inefficiencies in the system.[19]

Therefore, margin spirals, runs on hedge funds, credit freeze, massive redemptions, and market-wide panic can be the sources of the common latent factor. In Sections 6 and 7 we try to uncover other potential sources of the latent risk factor by proposing alternative model specifications and additional liquidity and volatility traded and non-traded factors.

4.4.2   The 2007 Subprime Mortgage Crisis

We also investigate whether the 2007 subprime mortgage crisis impacted at least one subset of hedge fund strategies. During the subprime mortgage crisis Countrywide Financial (the largest U.S. home lender) almost went bankrupt due to an increase in subprime mortgage defaults, and had to be bailed out. Over 100 mortgage lending companies and the American Home Mortgage Investment Corp. went bankrupt as subprime mortgage-backed securities could no longer be sold to investors. The failure of two Bear Stearns funds and the sale of Sowood Capital Management's portfolio to Citadel foreshadowed larger problems in the hedge fund industry.

We find that the probability of being in a high idiosyncratic volatility regime for Distressed, Event Driven Multi-Strategy, Risk Arbitrage, Convertible Bond Arbitrage, and Equity Market Neutral strategies significantly increased during the subprime mortgage crisis of 2007. August 2007 corresponds to the peak of that crisis. Therefore, these strategies were affected by the crisis, even after taking into account systematic risk exposures. In contrast, Long/Short Equity experienced only a slight increase in the probability at the end of 2007. Similarly, Emerging Markets and Dedicated Short Bias categories had a zero probability of being in a high idiosyncratic volatility state during the 2007. As a result, the joint probability of a high idiosyncratic volatility state for all strategies, our measure for a common latent factor exposure, is zero during the subprime mortgage crisis of August 2007 - January 2008.

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[18]The theoretical explanation of runs on hedge funds and other financial institutions that use leverage based on short-term debt is provided by Acharya, Gale, and Yorulmazer (2009).

[19]In the second half of 2008, following steep equity price declines of financial issuers, the United States Securities and Exchange Commission (SEC) took steps to restrict short selling in these firms in an effort to stabilize these downward price movements. On July 15, 2009, the SEC issued an emergency order increasing restrictions on naked short selling in 19 financial stocks. On September 19, 2008, the SEC imposed much stronger restrictions and completely banned short selling in 799 stocks. This ban remained in effect through October 17, 2008.

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This means that the common latent factor exposure was not observed for the whole hedge fund industry during the crisis. Only a selected number of strategies was affected.

We further concentrate our analysis on the five strategies that were affected by the crisis: Distressed, Event Driven Multi-Strategy, Risk Arbitrage, Convertible Bond Arbitrage, and Equity Market Neutral and calculate the joint probability of the high volatility regime of the idiosyncratic returns. As expected, we find some evidence of co-movement of the idiosyncratic volatility for these strategies, as shown in Figure 5. However, the joint probability in August 2007 (the peak of the subprime mortgage crisis) is below 30%. Even though the majority (five out of eight)of hedge fund strategies were affected by the crisis as indicated by all five individual strategy latent factors being in a high volatility regime, the impact of this crisis on the sub-sample of strategies is much smaller than the impact of the LTCM and the recent Global financial crises on the whole hedge fund industry. The subprime mortgage problems spilled over to 2008 and amplified into a severe financial crisis (Brunnermeier (2009)). In the 2008 Global financial crisis the whole financial system approached meltdown. In early September of 2008 Fannie Mae and Freddie Mac, representing $5 trillion in mortgage obligations, were nationalized by the U.S. government. Lehman Brothers went bankrupt, and Washington Mutual and Wachovia became insolvent and were sold to stronger banks. In addition, AIG was 80% nationalized by the U.S. government. Therefore, the trigger for the Global financial crisis of 2008 was an increase in subprime mortgage defaults (Brunnermeier (2009)).

[INSERT Figure(5) about here]

In conclusion, the subprime mortgage crisis affected only a select number of strategies, in contrast to the LTCM and the Global financial crises which greatly affected the whole hedge fund industry.

5   Mutual Fund Indices

In this Section we investigate whether our finding of a common latent factor exposure across all different hedge fund strategies is unique to the hedge fund industry, or can be applicable to other classes of investments, such as 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, Small Value, Convertibles, Emerging Markets, Long/Short, and Bear Market. 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 Section 4.1, and results are described in Table 6. We find that all mutual fund indices exhibit positive exposure to the S&P 500 except the Bear Market strategy that profits from market downturns. The exposures to Large-Small are negative and significant for all strategies. The R^2 for all these strategies are very large. Therefore, the classical systematic risk factors largely explain the variability of these indices.

Next, we calculate residuals for all different indices and capture the dynamics of the idiosyncratic returns using Equation (4). Using the measure defined in Equation (8), we investigate the presence of the common latent factor exposure across all mutual fund strategies. We find no evidence of the idiosyncratic risk exposure across different mutual fund strategies.[20] This means that the presence of the common latent factor exposures during the LTCM and the 2008 Global financial crises is unique to the hedge fund industry which is characterized by arbitrage and leverage.

[INSERT Table (6) about here]

6   Alternative Model Specifications

Hedge funds often employ leverage; trade in options and other non-linear instruments; take state-dependent bets; 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 crisis dummy 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 misspecified. For these reasons we consider two different model specifications for capturing the exposure of hedge funds to

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[20]Results are provided upon request.

systematic risk factors and investigate the resulting behavior of the idiosyncratic returns. 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 (2002, 2004) that captures the non-linear exposure of hedge funds to systematic risk factors.

6.1 A Multi-Factor Regime-Switching Model

6.1.1 Theoretical Framework

Unlike linear models, multi-factor regime-switching models are able to analyze time-varying and state-dependent risk exposures. In this Section, consistent with the asset pricing perspective proposed by Bekaert and Harvey (1995), we analyze the exposure of hedge fund strategies with a multi-factor model based on regime-switching volatility, where non-linearity in the exposure is captured by factor loadings that are state-dependent. Moreover, unlike the exogenous definition of crises (as in the case of crisis dummies), this methodology allows for an endogenous identification of financial distress based on the distributional properties of the market factor (S&P 500).

More formally, the model could be represented as:

$$R_{i,t} = \alpha_i(Z_{i,t}) + \beta_i(S_t)I_t + \sum_{k=1}^{K} \theta_{i,k}(S_t)F_{k,t} + \omega_i(Z_{i,t})u_{i,t} \tag{13}$$

$$I_t = \mu(S_t) + \sigma(S_t)\epsilon_t \tag{14}$$

where $i = 1, ..., m$ is a hedge fund strategy, S_t and $Z_{i,t}$ are Markov chains with h_s and h_{zi} states respectively and transition probability matrices $\mathbf{P}_s$ and $\mathbf{P}_{zi}$, respectively; $u_{i,t}$ and ϵ_t are independent noise terms, normally distributed with zero mean and unit variance. 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 $Z_{i,t}$ characterizes the change in volatility of the idiosyncratic returns as well as extra returns captured by $\alpha_i(Z_{i,t})$. Hedge fund mean returns are related to the states of the market index I and the states of the idiosyncratic 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 returns $\omega_i(Z_{i,t})$. In both cases β_i and $\theta_{i,k}$ could be different conditional on the state of the market risk factor I.

For a three state Markov chain, $h_s = 3$ (state labels are denoted as 0, 1 or 2), β_i depends on the state variable S_t[21]:

$$\beta_i(S_t) = \begin{cases} \beta_{i,0} & \text{if } S_t = 0 \\ \beta_{i,1} & \text{if } S_t = 1 \\ \beta_{i,2} & \text{if } S_t = 2 \end{cases} \tag{15}$$

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

$$\mathbf{P}_s = \begin{bmatrix} p_{00} & p_{01} & p_{02} \\ p_{10} & p_{11} & p_{12} \\ p_{20} & p_{21} & p_{22} \end{bmatrix} \tag{16}$$

where p_{ij} is the transition probability of moving from regime i to regime j, $p_{02} = 1 - p_{00} - p_{01}$, $p_{12} = 1 - p_{10} - p_{11}$, 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.

6.1.2 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 Section 6.1.3, we estimate a multi-factor regime-switching model.

In order to determine the number of regimes 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 robustness analysis section we also describe the results for two regimes.

Using three regimes is also consistent with the literature that recognizes the presence of tranquil, up-market or down-market regions in equity market returns.[22] Moreover, the use

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[21]The same applies to $\theta_{i,k}$.

[22]Goetzmann, Ingersoll, Spiegel, and Welch (2007) show that an optimal strategy for hedge funds might be

of 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.[23]

[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 is not persistent (the probability of remaining in this regime in the following month is 32%). Regime 1 has a mean statistically different from zero and equal to 0.92% and a volatility of 2.30%, and we call it a tranquil 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 -1.62% and a volatility of 4.94%. The probability of remaining in this down-market regime is 83%.[24] Additional results about the dynamics of the S&P 500 in the sample are reported in Appendix A.

After having characterized the process for the S&P 500, we analyze the exposures of hedge fund strategies to different S&P 500 regimes and other risk factors. The use of a regime-switching model allows us to distinguish between dynamic exposures to systematic risk factors and idiosyncratic risk (latent) factors in different volatility regimes. We separately analyze these two components in the following Sections 6.1.3 and 6.1.4.

6.1.3 Dynamic Risk Exposures to Systematic Risk Factors

In this section, for each hedge fund strategy we estimate the multi-factor regime-switching model specified in Equation (13) and the results are contained in Table 8. Here, we are considering nonlinear exposures to systematic risk factors: S&P 500, Large-Small, Value-Growth, USD, Lehman Government Credit, Term Spread, change in VIX, Credit Spread, and Momentum factor. For each factor, we estimate three exposures: $\theta_{i,k,0}$ is a hedge fund strategy i exposure to a factor k when the $S\&P$ 500 is in the up-market; $\theta_{i,k,1}$ is a hedge

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selling out-of-the-money puts and calls, ensuring that during tranquil regimes, hedge fund managers obtain a positive cash flow, and have a large exposure in extreme events.

[23]All regime-switching models have been estimated by maximum likelihood using the Hamilton's filter (Hamilton, 1994).

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

fund strategy i exposure to a factor k when the $S\&P$ 500 is in the tranquil state; and $\theta_{i,k,2}$ is a hedge fund strategy i exposure to a factor k when the $S\&P$ 500 is in the down-market.

[INSERT Table (8) about here]

We find that in all cases hedge fund exposure to the S&P 500 in the down-market is smaller than in the tranquil or up-market states. This suggests that hedge fund managers are able to hedge market exposures, especially during financial crises. This result is in line with our main result found using the linear factor model with a crisis dummy variable and is consistent with the literature (Brunnermeier and Nagel (2004) and Chen and Liang (2007)).

We further study whether hedge fund managers are able to reduce hedge fund exposure to other risk factors during financial market distress. Our analysis of the dynamic exposures to 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 6 well highlights. This suggests 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.

These results are consistent with the previous results using a linear factor model with a crisis dummy variable. This indicates that allowing the data to endogenously identify crisis periods leads to similar results – the exposure to common systematic risk factors during crises is confirmed.

[INSERT Figure (6) about here]

In order to compare the goodness-of-fit between regime-switching and a linear model with a crisis dummy, we employ a Pseudo-R^2 analysis.[25] 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.[26]

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[25] $Pseudo - R^2 = 1 - \frac{logL_{UR}}{logL_R}$ 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.

[26] The Pseudo-R^2 for the linear factor model with a crisis dummy for each strategy is the following: Convertible Bond Arb 0.09, Dedicated Short Bias 0.17, Emerging Markets 0.06, Equity Market Neutral 0.07, Long/Short Equity 0.04, Distressed 0.13, Event Driven MS 0.10, and Risk Arbitrage 0.13.

6.1.4   Analysis of a Common Latent Factor Exposure During Crises

We further test whether the presence of a common latent factor exposure across all hedge fund strategies is due to the misspecification of a linear model with a crisis dummy and can be explained by time-varying and state-dependent risk exposures. In order to answer this question, we investigate the dynamics of the idiosyncratic returns for each hedge fund strategy using the multi-factor regime-switching model specified in Equation (13). We find that the dynamics are very similar to those already estimated for the linear factor model with a crisis dummy.

We further analyze the presence of a common latent factor exposure across all hedge fund strategies. Specifically, we calculate the joint filtered probability that idiosyncratic volatilities of hedge fund returns for all hedge fund strategies are in a high volatility state and plot it in Figure 7. As before, we found the presence of the common latent factor exposure across all hedge fund strategies that manifested in 1998 and 2008.

[INSERT Figure(7) about here]

6.2   Option-Based Factor Model

Hedge fund managers often use options to implement their strategies. For this reason an option-based factor model was originally proposed by Fung and Hsieh (2002, 2004) to explain hedge fund returns. We compare estimates from the Fung and Hsieh's model to the linear model with a crisis dummy. Results are presented in Table 9. Similar to the linear model with a crisis dummy, the option-based factor model shows evidence of the presence of common exposures to the SP(market) and SC-LC (liquidity) factors.

Moreover, we observe that the linear model with a crisis dummy fits the data better than the option-based model. In fact, for all styles, the adjusted-R^2 for the linear model with a crisis dummy is larger than the one for the option-based model (the only exception is the Emerging Markets strategy). Therefore, adjusting for crisis periods is important in capturing hedge fund risk exposures.

[INSERT Table (9) about here]

We also analyze the residuals of the option-based model and estimate the latent factor exposure. The dynamics of idiosyncratic returns and latent factor exposure are again similar to the ones found using the linear model with a crisis dummy.[27] Therefore, the presence of a common latent factor exposure across all hedge fund strategies is not explained by omission of option-based factors (Fung and Hsieh (2002, 2004)).

7   Robustness Analysis

In this section we investigate the robustness of our results to the presence of common classical systematic and latent factor exposures for hedge fund strategies. First, we investigate additional model specifications that allow for time-varying risk exposures. Second, as 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. We investigate whether smoothing and illiquidity are the sources of the common latent factor exposure we observe. Third, the current financial crisis highlighted the fact that hedge funds are greatly exposed to liquidity and volatility risks. In addition to including Large-Small, change in VIX, and Credit Spread, we include other liquidity and volatility variables. Finally, we concentrate on individual hedge funds and investigate whether our index-based results are consistent with those observed for individual hedge funds.

7.1   Two S&P 500 Regimes

For completeness we re-estimate regime-switching models with only two regimes (instead of three). We find that Credit Spread, Large-Small, and Change in VIX are still common risk factors, but for a lower number of strategies. The presence of the common latent factor exposure across all hedge fund strategies is confirmed in the 1998 (LTCM) and the 2008 crisis periods.[28]

7.2   Different Risk Factor Regimes

We also estimate different Markov chains for change in VIX, Large-Small, and Credit Spread, and allow hedge fund strategy exposures to change conditional on the properties of each of

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[27]Results are available upon request.
[28]Results are available upon request.

these Markov chains. We still observe the presence of a common latent factor exposure in 1998 and 2008.[29]

7.3 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 $R_{i,t}$ the true economic returns of a hedge fund strategy i in period t, and let $R_{i,t}$ satisfy the following single linear factor model:

$$R_{i,t} \;=\; \mu_i \;+\; \beta_i \Lambda_t \;+\; \epsilon_{i,t} \;\;,\;\; \mathrm{E}[\Lambda_t] = \mathrm{E}[\epsilon_{i,t}] = 0 \;\;,\;\; \epsilon_{i,t} \,,\, \Lambda_t \;\sim\; \mathrm{IID} \qquad (17a)$$

$$\mathrm{Var}[R_{i,t}] \;\equiv\; \sigma_i^2 \;. \qquad (17b)$$

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, $R_{i,t}^o$ denotes the reported or observed return in period t, and let

$$R_{i,t}^o \;=\; \theta_{i,0}\, R_{i,t} \;+\; \theta_{i,1}\, R_{i,t-1} \;+\; \cdots \;+\; \theta_{i,l}\, R_{i,t-l} \qquad (18)$$

$$\theta_{i,j} \;\in\; [0,1] \;\;,\;\; j = 0,\ldots,l \qquad (19)$$

$$1 \;=\; \theta_{i,0} \;+\; \theta_{i,1} \;+\; \cdots \;+\; \theta_{i,l} \qquad (20)$$

which is a weighted average of the fund's true returns over the most recent $l+1$ periods, including the current period.

In line with this approach we determine $R_{i,t}^o$, i.e., "real returns" and estimate our models on the real returns. 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.

Moreover, the dynamics of the volatility of the idiosyncratic returns factor are not affected by data smoothing or illiquidity; and the result of the presence of a common latent factor exposure across all hedge fund strategies in 1998 and 2008 is confirmed.[30]

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[29]Results are available upon request.

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

7.4 Additional Liquidity and Volatility Factors

The common latent factor can potentially be captured by some traded and non-traded systematic factors not yet identified in our analysis. The most plausible source of this common latent factor is liquidity risk. In fact, liquidity is very important to hedge funds, especially during crisis periods. Both LTCM and 2008 crises were liquidity events that lead to dislocations in the hedge fund industry. So far, in our analysis we used the following established liquidity proxies: Large-Small, change in VIX, and the illiquidity measure of Getmansky *et al.* (2004). Here we consider six additional traded liquidity proxies: Bank Index used in Adrian and Brunnermeier (2008), the Datastream Bank index, the spread between the US 3 month Interbank rate and the 3 month T bill (Libor-T Bill), the spread between the US 3 month Interbank rate and the UK 3 month Interbank rate (Libor US-Libor UK), the Prime Broker Index (PBI), the spread between the U.S. Treasury reverse repo overnight and the 3 month T bill (RepoRe-T Bill). Moreover, as in Adrian and Brunnermeier (2008) we consider two additional traded volatility factors that capture the implied future volatility in the stock market (Straddle) and the variance risk premium (Variance Swap). For detailed descriptions of these variables see Appendix B.

These liquidity and volatility variables are largely correlated with classical risk factors considered in our analysis. For example, Bank index, Datastream bank index, and the Prime broker index are highly correlated with the S&P 500 with 0.80, 0.68, and 0.83 correlation coefficients, respectively. The Bank index, the Prime broker index, the straddle, and the variance swap have a correlation of -0.60, -0.58, 0.77, and 0.59, respectively, with the change in VIX. Also, the variance swap is highly correlated with credit spread (0.55).

These liquidity variables are also correlated with each other. The Bank index and the Datastream bank index have a correlation of 0.64. PBI and the Bank index have a correlation of 0.94, and Libor-T Bill is significantly correlated with the variance swap (0.53). These correlations are even larger during crisis periods.[31]

As a result, most of these liquidity variables are redundant and could create collinearity problems if all are added in the main analysis. We performed an analysis where all eight liquidity and volatility proxies are added one by one and the presence of a common latent factor exposure among the different hedge fund strategies during the LTCM and the recent Global financial crises is confirmed.[32]

We also investigate four other non-traded liquidity factors: the Pastor and Stambaugh level of aggregate liquidity, Pastor and Stambaugh innovations in aggregate liquidity, Sadka

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[31]Correlations are provided upon request.

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

transitory fixed liquidity, and Sadka permanent variable liquidity factors.[33] Again, the presence of a common latent factor exposure during these two crises is confirmed. This means that all these risk factors are not sources of the common latent (idiosyncratic) risk factor.

7.5 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. Using the TASS database we randomly select different hedge funds and repeat the analysis described in the paper. Results show that exposures of single hedge funds to various factors are in line with index exposures.[34]

8 Conclusion

In this paper we study the effects of financial crises on hedge fund risk. During crises average volatility and correlation of hedge fund strategy returns increases. We investigate how the presence of common hedge fund exposures to classical (systematic) and latent (idiosyncratic) risk factors contributes to these increases.

We find that liquidity, credit, and volatility risks are common systematic risk factors for hedge funds. Moreover, we find that hedge fund exposures to the S&P 500 during crisis periods are smaller or negative compared to tranquil periods. This suggests that hedge fund managers reduce market exposures during the periods of high volatility.

We introduce a novel methodology that identifies the presence of a common latent (idiosyncratic) factor exposure for hedge funds. We find that all hedge fund strategies are exposed to the common latent factor during the LTCM/Russian crisis (August-October 1998) and during the recent Global financial crisis (August-September 2008). During the subprime mortgage crisis of 2007 only a sub-sample (five out of eight) hedge fund strategies had a common latent factor exposure. This is consistent with the subprime mortgage crisis being a pre-cursor to financial dislocations that amplified into a severe financial crisis of 2008. Moreover, we find that this common latent factor exposure is unique to the hedge fund in-

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[33]Data for all these variables is available till December 2006. We thank Ronnie Sadka for providing this data.

[34]Summary results for individual hedge funds in each category are available upon request. We consider Convertible Bond Arbitrage, Dedicated Short Bias, Emerging Markets, Equity Market Neutral, Long/Short Equity, and Event Driven strategies. Distressed and Risk Arbitrage strategies are a sub-set of the Event Driven strategy in the TASS individual hedge fund database.

dustry which is characterized by arbitrage and leverage. Even after controlling for additional twelve observable risk factors related to liquidity and volatility risk, we still find a strong evidence for the presence of the common latent factor. This common latent factor can potentially be related to margin spirals, runs on hedge funds, massive redemptions, credit freezes, market-wide panic, and interconnectedness between financial institutions. Identification of proxies for these relationships is a fruitful ground for further research.

Moreover, if changes in hedge fund risk exposures during crises and the common latent risk factor are omitted in risk modeling, the resulting effect of financial crises on hedge fund risk is greatly underestimated and diversification benefits are overestimated. Therefore, in order to fully capture the effects of financial crises on hedge fund risk, both common systematic and latent factor exposures should be modeled.

Appendix A: S&P 500 Dynamics

Using the methodology developed in Section 6.1.1, allows us to infer when the S&P 500 was in one of the three regimes for each date of the sample.[35]

We observe that in the first part of the sample, the S&P 500 returns are frequently characterized by the tranquil regime 1, in particular from July 1994 to December 1996 (91.7% of time in tranquil 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 tranquil regime 1 (100%). Finally, in August 2007 the S&P 500 returns are again almost exclusively in regime 2 (89.7% of time in the down-market and 6.9% in tranquil regime). This clearly captures the effects of the subprime crisis and the beginning of the current economic downturn. It is important to note that the three-regime approach does not simply imply 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.[36]

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 (8) about here]

Figure 8 depicts unconditional distributions of the S&P 500 overall, in down-market, tranquil, and up-market regimes. First, during the time period analyzed in this paper, the market clearly experienced three distinct regimes: up-market, tranquil, and down-market. Moreover, the total distribution is skewed, and distribution of being in a down-market state is characterized by fat tails. Figure 8 also depicts conditional distributions of different regimes, conditional on starting in regime 2, a down-market regime. The resulting total distribution

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[35]For the estimation, the Hamilton's filter and smoothing algorithms (Hamilton, 1994) are used.

[36]The regime-switching approach allows us to endogenously determine changes in market return distributions without exogenously splitting the data into positive and negative returns.

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 (83%), and both conditional regime 2 and total distributions are fat-tailed.

The possibility of characterizing the distribution of the S&P 500 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 (9) about here]

Our analysis also allows us to analyze the distribution of the S&P 500 returns and derive hedge funds risk exposures in the other two regimes.

Figure 9 shows conditional distributions of the S&P 500 overall, in down-market, tranquil, and up-market regimes first conditional on an up-market regime and second conditional on a tranquil 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 tranquil regime, the total distribution is almost identical to the conditional probability of a tranquil regime. Therefore, if a market is in the tranquil regime, it is more likely to be persistent (98%). The conditional distributions for all regimes are very close to tranquil 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 measure 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 8 and 9, it is clear that not accounting for three separate regimes and only concentrating on a tranquil regime will underestimate the left tail of the distribution and thus bias hedge fund market risk exposure during market financial distress.

Appendix B: Liquidity and Volatility Variables

Bank Index This index corresponds to the one used in Adrian and Brunnermeier (2008), and consists of weighted average of the stock returns, for the period for which they are available, of the following investment banks: Morgan Stanley, Merrill Lynch, Goldman Sachs, Bear Stearns, and Lehman Brothers. The weights are proportional to the total market capitalization, in USD, of each bank.

Datastream Bank Index The Datastream bank stock index, is an equally weighted index of the stock returns of national commercial and regional banks provided by Datastream.

Prime Broker Index (PBI) The Prime Broker Index is an equally weighted index of the stock returns of 11 prime brokerage firms, for the periods for which the stock prices are available. The brokerage firms included in the index are: Goldman Sachs, Morgan Stanley, Bear Stearns, UBS AG, Bank of America, Citigroup, Merrill Lynch, Lehman Brothers, Credit Suisse, Deutsche Bank, and Bank of New York Mellon. The only common components to both the Datastream Bank index and the PBI are Bank of America and Citigroup.

Libor-T bill This index is constructed as the difference of the 3 month USD Libor rate (obtained from Datastream), and the market yield on U.S. Treasury securities at 3-month (T-bill) constant maturity (obtained from the Federal Reserve website).

Libor US-Libor UK This index is constructed as the difference of the 3 month USD Libor rate and the 3 month Sterling Libor rate (both rates are obtained from Datastream).

RepoRe-T bill This index is constructed as the difference of the interest rate on a U.S. Treasury reverse repo overnight contract quoted by Bloomberg and the market yield on U.S. Treasury securities at 3-month (T-bill) constant maturity (obtained from the Federal Reserve website).

Straddle This variable, used in Adrian and Brunnermeier (2008), is the return difference between a hypothetical at-the-money straddle position, based on the VIX implied volatility and the 3 month T-bill rate. The returns of this strategy are computed as the difference of the Black and Scholes price at the beginning of the month of a long put and a long call S&P500 option contract with a 3-month maturity, and the price of the same position at the end of the month. The volatility used to compute these prices is the one implied by the VIX index.

Variance Swap A Variance Swap contract captures the associated risk premium for risky shifts in volatility (Adrian and Brunnermeier (2008)). The variance swap contract pays off the difference between the realized variance over the coming months and its delivery price at the beginning of the month.

Pastor and Stambaugh Level of Aggregate Liquidity This non-traded liquidity factor is constructed by Pastor and Stambaugh (2003). This liquidity factor is associated with temporary price fluctuations induced by order flow. The monthly aggregate liquidity measure is a cross-sectional average of individual-stock liquidity measures. Each stock's liquidity in a given month, estimated using that stock's within-month daily returns and volume, represents the average effect that a given volume on day d has on the return for day $d + 1$, when the volume is given the same sign as the return on day d.

Pastor and Stambaugh Innovations of Aggregate Liquidity This non-traded liquidity factor constructed by Pastor and Stambaugh (2003) is a measure of innovations in the level of the aggregate liquidity factor.

Sadka Transitory Fixed Liquidity This non-traded liquidity factor is constructed by Sadka (2006) and is computed as a shock to the fitted time series of aggregate transitory fixed component of the Glosten and Harris (1988) model. The liquidity measure is estimated per firm and per month.

Sadka Permanent Variable Liquidity This non-traded liquidity factor is constructed by Sadka (2006) and is computed as a shock to the fitted time series of aggregate permanent variable component of the Glosten and Harris (1988) model. The liquidity measure is estimated per firm and per month.

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Table 1: **Summary Statistics**

This table presents summary statistics for monthly CSFB/Tremont hedge fund index excess returns and the S&P 500 excess 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 Return is annualized mean return, and Ann. SD is annualized standard deviation. Min. Return, Med. Return, and Max. Return are minimum, median, and maximum monthly returns, respectively. The returns are in percentage terms. Skew measures skewness and Kurt measures excess kurtosis. JB p-value is p-value of the Jarque-Bera test. The JB 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. In the Equity Market Neutral category all Madoff funds are excluded.

Strategy	N	$\beta_{S\&P500}$	Ann. Mean Return (%)	Ann. SD (%)	Min. Return (%)	Med. Return (%)	Max. Return (%)	Skew	Kurt	JB p-value
Convertible Bond Arbitrage	180	0.16	1.81	6.70	-12.65	0.59	3.10	-3.57	19.20	0.00
Dedicated Short Bias	180	-0.84	-2.83	16.95	-9.11	-0.58	22.30	0.75	1.58	0.00
Emerging Markets	180	0.55	4.04	15.86	-23.44	1.08	16.05	-0.76	4.49	0.00
Equity Market Neutral	180	0.08	5.30	2.83	-1.89	0.41	2.84	0.06	0.67	0.22
Long/Short Equity	180	0.18	8.61	10.51	-11.88	0.80	10.15	-0.09	2.93	0.00
Distressed	180	0.27	6.68	6.67	-12.86	0.81	3.81	-2.43	12.86	0.00
Event Driven MS	180	0.24	5.31	6.43	-11.93	0.59	4.23	-2.13	11.04	0.00
Risk Arbitrage	180	0.14	3.18	4.21	-6.56	0.21	3.39	-1.15	5.47	0.00
S&P 500	180	1.00	4.86	15.09	-16.69	0.95	9.37	-0.75	1.25	0.00

Table 2: **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, Large-Small, Value-Growth, USD, Lehman Government Credit, Term Spread, Change in VIX, Credit Spread, and Momentum Factor, 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 and zero otherwise. 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: $R_{i,t} = \alpha_i + \sum_{k=0}^K \beta_{i,k}F_{k,t} + \sum_{k=0}^K \beta_{i,D,k}D_t F_{k,t} + \omega_i u_t$. F_{kt} represents all risk factors, D_t is a crisis dummy, and ω is idiosyncratic volatility. Parameters that are significant at the 10% level are shown in bold type.

	Convertible Bond Arb		Dedicated Short Bias		Emerging Markets		Equity Market Neutral		Long/Short Equity		Distressed		Event Driven Multi-Strategy		Risk Arb	
	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat
α	**1.40**	**4.18**	**1.50**	**2.59**	-0.88	-1.07	**0.52**	**3.18**	0.62	1.00	**0.99**	**3.37**	**0.60**	**2.06**	0.12	0.63
β_0 (S&P 500)	0.07	1.46	**-1.01**	**-12.46**	**0.61**	**5.59**	**0.06**	**2.63**	**0.34**	**3.81**	**0.24**	**5.79**	**0.19**	**4.85**	**0.12**	**4.23**
β_1 (Large-Small)	**-0.12**	**-2.93**	**0.61**	**8.41**					0.01	0.14	**-0.15**	**-3.94**	**-0.16**	**-4.32**	**-0.12**	**-4.88**
β_2 (Value-Growth)	0.04	1.09	**0.14**	**2.00**					0.08	0.99	**0.09**	**2.45**			0.04	1.52
β_3 (USD)			0.07	0.60	0.00	0.00							-0.04	-0.65		
β_4 (Lehman Gov. Credit)	**0.21**	**2.04**					**-0.15**	**-2.79**	-0.19	-0.96	0.15	1.64				
β_5 (Term Spread)							-0.00	-0.07	0.05	0.55						
β_6 (Change in VIX)	0.02	0.35	**-0.24**	**-2.65**	**0.23**	**1.76**	0.17	0.88	0.28	0.39	**0.08**	**1.65**	**0.09**	**1.96**	0.05	1.53
β_7 (Credit Spread)	**-1.29**	**-3.40**	**-1.14**	**-1.73**	**1.76**	**1.89**					-0.35	-1.06	-0.03	-0.10	0.20	0.89
β_8 (Momentum Factor)							0.05	1.41	**0.13**	**2.69**						
β_0 (S&P 500) dummy	**-0.14**	**-1.77**	0.00	-0.01	**-0.38**	**-2.02**			**-0.28**	**-1.90**	-0.02	-0.24	0.02	0.30	-0.03	-0.60
β_1 (Large-Small) dummy	**0.22**	**2.85**	**-0.23**	**-1.71**					0.01	0.06	0.02	0.29	0.02	0.23	0.01	0.32
β_2 (Value-Growth) dummy	0.03	0.36	0.05	0.37					**0.35**	**2.04**	**-0.13**	**-1.77**			0.06	1.15
β_3 (USD) dummy			-0.22	-0.91	0.32	0.94							**0.47**	**3.92**		
β_4 (Leh. Gov. Credit) dummy	**0.39**	**2.02**					**0.28**	**1.83**	0.91	1.54	-0.26	-1.52				
β_5 (Term Spread) dummy							0.02	0.50	-0.21	-1.57						
β_6 (Change in VIX) dummy	**-0.23**	**-3.13**	0.09	0.69	**-0.60**	**-3.31**	**-0.48**	**-2.07**	**-2.25**	**-2.39**	**-0.16**	**-2.40**	**-0.24**	**-3.62**	**-0.18**	**-4.13**
β_7 (Credit Spread) dummy	**-1.18**	**-3.72**	**-1.10**	**-2.05**	**-2.25**	**-3.20**			**-2.25**	**-2.39**	**-0.72**	**-2.57**	**-0.48**	**-1.76**	-0.22	-1.25
β_8 (Mom. Factor) dummy									**0.28**	**2.39**						
ω	**1.47**	**6.42**	**2.53**	**3.83**	**3.64**	**1.82**	**0.73**	**6.67**	**2.67**	**3.50**	**1.28**	**6.75**	**1.29**	**6.74**	**0.88**	**6.92**
Adj. R^2	0.39		0.71		0.34		0.37		0.20		0.56		0.52		0.47	

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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 during tranquil and crisis periods. The linear factor model with a crisis dummy is analyzed. The following factors are considered: S&P 500, Large-Small, Value-Growth, USD, Lehman Government Credit, Term Spread, Change in VIX, Credit Spread, and Momentum Factor. Eight is the maximum number of strategies.
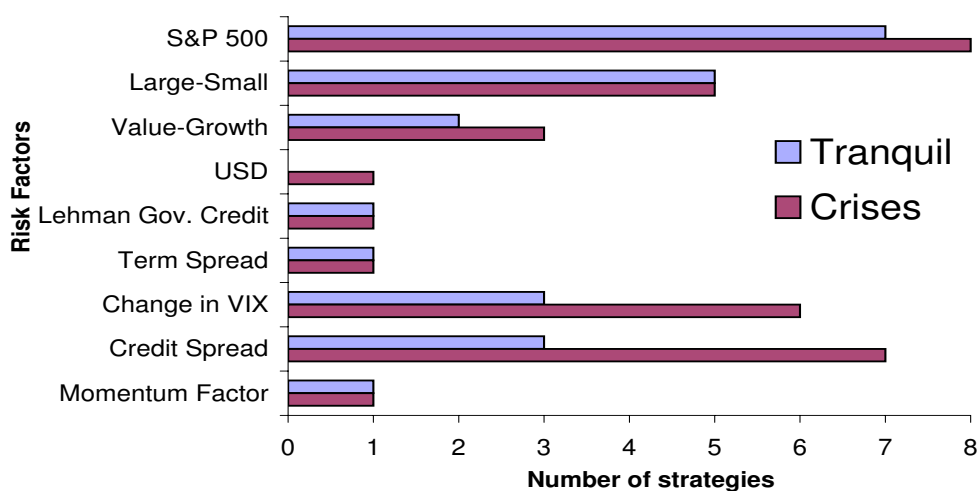
Figure 2: **Rolling Correlation Among Hedge Fund Strategies**

Panel A depicts a two-year rolling window average correlation among hedge fund strategy returns. Panel B shows a two-year rolling window average correlation among hedge fund strategy fitted returns generated by a linear model with and without a crisis dummy. Convertible Bond Arbitrage, Equity Market Neutral, Long/Short Equity, Dedicated Short Bias, Emerging Markets, Distressed, Event Driven Multi-Strategy, and Risk Arbitrage strategies are analyzed.

Panel A   Average Rolling Correlation Among Hedge Fund Strategy Returns
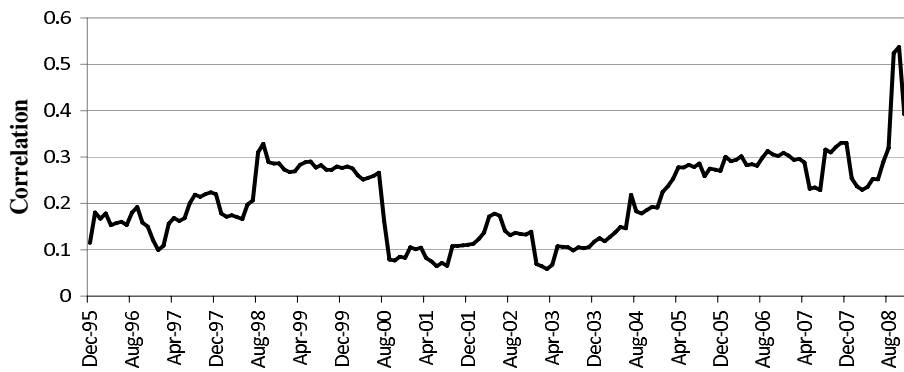
Panel B   Average Rolling Correlation Among Hedge Fund Strategy Fitted Returns
Generated By A Linear Model With and Without A Crisis Dummy

- - - Fitted returns without a crisis dummy   ▲ Fitted returns with a crisis dummy
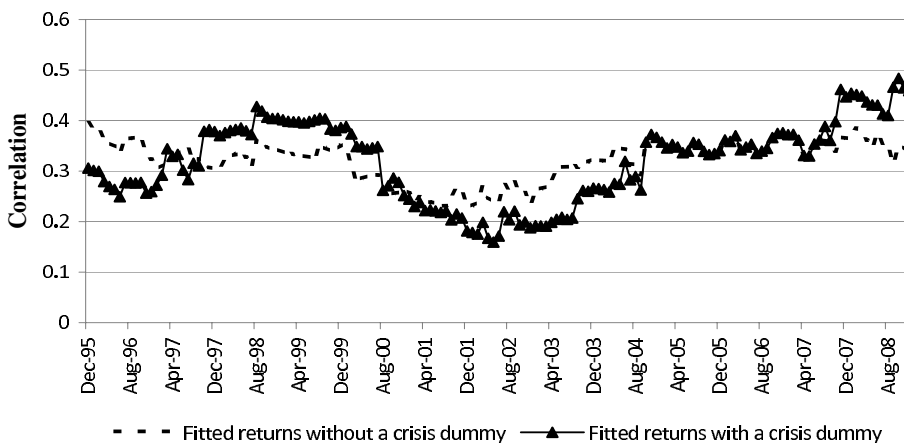
Table 3: **Variance Decomposition**

This table presents variance decomposition during tranquil and crisis periods for all hedge fund strategies and the average of all these strategies. $Ann.\sigma^{Tranquil}$ and $Ann.\sigma^{Crisis}$ are annualized hedge fund strategy volatilities during tranquil and crisis periods, respectively. The percentage change in this volatility is given by $Ann.\%\Delta\sigma^{Crisis}$. $\sigma^2 Tranquil$ and $\sigma^2 Crisis$ are hedge fund strategy monthly variances during tranquil and crisis periods, respectively. The percentage change in this variance is given by $\%\Delta\sigma^2 Crisis$. $\%\Delta\sigma^2 Crisis$ is decomposed into $\%\Delta\sigma^2_{VarCov}{}^{Crisis}$, $\%\Delta\sigma^2_{Beta}{}^{Crisis}$, and $\%\Delta\sigma^2_{Idio}{}^{Crisis}$, which are percentage changes in variance associated with an increase in variance-covariance of classical systematic risk factors, an increase in exposure to common risk factors, and the increase in idiosyncratic variance during crisis periods, respectively. $\sigma^2_{Beta^{Tranquil}VarCov^{Tranquil}}$ is the systematic hedge fund strategy variance during tranquil periods. $\sigma^2_{Beta^{Tranquil}VarCov^{Crisis}}$ is the systematic variance during crisis periods (assuming loadings on these factors are the same as loadings during tranquil periods). $\sigma^2_{Beta^{Crisisl}VarCov^{Crisis}}$ is the systematic variance during crisis periods when crisis loadings are considered. $\sigma^2_{Idio}{}^{Tranquil}$ and $\sigma^2_{Idio}{}^{Crisis}$ are idiosyncratic hedge fund strategy variances during tranquil and crisis periods, respectively. Convertible Bond Arbitrage, Dedicated Short Bias, Emerging Markets, Equity Market Neutral, Long/Short Equity, Distressed, Event Driven Multi-Strategy, and Risk Arbitrage strategies are analyzed.

	Convert Bond Arb	Ded Short Bias	Emerging Markets	Equity Market Neutral	Long Short Equity	Distress	Event Driven MS	Risk Arbitrage	Average
$Ann.\ \sigma^{Tranquil}$	4.24	15.12	12.83	2.60	9.23	4.46	4.43	3.22	7.01
$Ann.\ \sigma^{Crisis}$	11.70	21.92	20.45	3.58	14.17	10.33	9.81	6.33	12.29
$Ann.\ \Delta\sigma^{Crisis}$	7.46	6.80	7.62	0.98	4.94	5.88	5.38	3.11	5.27
$Ann.\ \%\Delta\sigma^{Crisis}$	**176%**	**45%**	**59%**	**38%**	**54%**	**132%**	**121%**	**97%**	**90%**
$\sigma^{2Tranquil}$	1.50	19.04	13.73	0.56	7.09	1.66	1.63	0.86	5.76
$\sigma^{2Crisis}$	11.41	40.05	34.86	1.07	16.73	8.90	8.01	3.34	15.55
$\Delta\sigma^{2Crisis}$	9.91	21.00	21.13	0.50	9.63	7.24	6.38	2.48	9.79
$\%\Delta\sigma^{2Crisis}$	**662%**	**110%**	**154%**	**90%**	**136%**	**437%**	**391%**	**287%**	**283%**
$\sigma^2_{Beta}{}^{Tranquil}{}_{VarCov}{}^{Tranquil}$	0.29	14.52	3.24	0.07	1.14	0.58	0.49	0.21	2.57
$\sigma^2_{Beta}{}^{Tranquil}{}_{VarCov}{}^{Crisis}$	1.42	28.73	6.34	0.16	2.98	1.82	0.99	0.36	5.35
$\Delta\sigma^2_{VarCov}{}^{Crisis}$	1.13	14.21	3.10	0.09	1.84	1.24	0.49	0.15	2.78
$\%\Delta\sigma^2_{VarCov}{}^{Crisis}$	**75%**	**75%**	**23%**	**16%**	**26%**	**75%**	**30%**	**18%**	**42%**
$\sigma^2_{Beta}{}^{Tranquil}{}_{VarCov}{}^{Crisis}$	1.42	28.73	6.34	0.16	2.98	1.82	0.99	0.36	5.35
$\sigma^2_{Beta}{}^{Crisis}{}_{VarCov}{}^{Crisis}$	5.44	27.30	14.46	0.47	4.74	5.34	4.53	2.16	8.06
$\Delta\sigma^2_{Beta}{}^{Crisis}$	4.03	-1.43	8.11	0.30	1.77	3.53	3.54	1.79	2.71
$\%\Delta\sigma^2_{Beta}{}^{Crisis}$	**269%**	**-7%**	**59%**	**54%**	**25%**	**213%**	**217%**	**208%**	**130%**
$\sigma^2_{Idio}{}^{Tranquil}$	1.21	4.53	10.49	0.49	5.96	1.07	1.14	0.65	3.19
$\sigma^2_{Idio}{}^{Crisis}$	5.97	12.74	20.40	0.60	11.98	3.55	3.48	1.18	7.49
$\Delta\sigma^2_{Idio}{}^{Crisis}$	4.75	8.22	9.92	0.11	6.02	2.48	2.34	0.53	4.30
$\%\Delta\sigma^2_{Idio}{}^{Crisis}$	**317%**	**43%**	**72%**	**19%**	**85%**	**150%**	**143%**	**62%**	**111%**

This table provides estimation of idiosyncratic mean and volatility for eight hedge fund strategies. Idiosyncratic returns are 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 classical systematic risk factors, and D_t is a crisis dummy. The idiosyncratic returns are characterized by a switching mean μ_i and a switching volatility ω_i: $r_{i,t} = \mu_i(Z_{i,t}) + \omega_i(Z_{i,t}) u_{i,t}$. $Z_{i,t}$ is a Markov chain with 2 states (0 = low idiosyncratic volatility state and 1 = high idiosyncratic volatility state) and a transition probability matrix $\mathbf{P}_{z,i}$. $u_{i,t}$ is IID. μ and ω are provided for each state of the idiosyncratic volatility. P_{00}^z (P_{11}^z) is the transition probability of staying in the low (high)-idiosyncratic volatility state. Parameters that are significant at the 10% level are shown in bold type.

Panel A

Variable	Convertible Bond Arb		Dedicated Short Bias		Emerging Markets		Equity Market neutral	
	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat
μ_0	**0.33**	**4.77**	-0.02	-0.09	**0.39**	**1.77**	**0.23**	**3.18**
μ_1	**-0.71**	**-2.90**	0.23	0.18	-0.69	-1.37	**-0.43**	**-3.10**
ω_0	**0.54**	**7.46**	**2.33**	**17.68**	**1.87**	**8.68**	**0.54**	**10.44**
ω_1	**1.99**	**11.25**	**4.31**	**4.85**	**4.53**	**13.43**	**0.81**	**12.35**
P_{00}^Z	**0.87**		**0.99**		**0.98**		**0.96**	
P_{11}^Z	**0.86**		**0.92**		**0.99**		**0.97**	

Panel B

Variable	Long/Short Equity		Distressed		Event Driven MS		Risk Arb	
	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat
μ_0	0.08	0.54	0.10	1.16	**0.23**	**3.09**	0.11	1.18
μ_1	-0.07	-0.18	**-3.14**	**-1.66**	**-0.77**	**-2.12**	**-0.33**	**-2.70**
ω_0	**1.23**	**9.43**	**1.08**	**16.04**	**0.73**	**9.06**	**0.55**	**8.71**
ω_1	**3.33**	**13.33**	**2.45**	**2.79**	**1.96**	**7.93**	**0.98**	**14.67**
P_{00}^Z	**0.98**		**0.98**		**0.89**		**0.98**	
P_{11}^Z	**0.99**		**0.45**		**0.76**		**0.99**	

Figure 3: **Dynamics of Latent Factor Exposures for Individual Hedge Fund Strategies**

These figures depict the probability of idiosyncratic volatility being in a high-volatility state for Convertible Bond Arbitrage, Dedicated Short Bias, Emerging Markets, Equity Market Neutral, Long/Short Equity, Distressed, Event Driven Multi-Strategy, and Risk Arbitrage strategies from January 1994 to December 2008.

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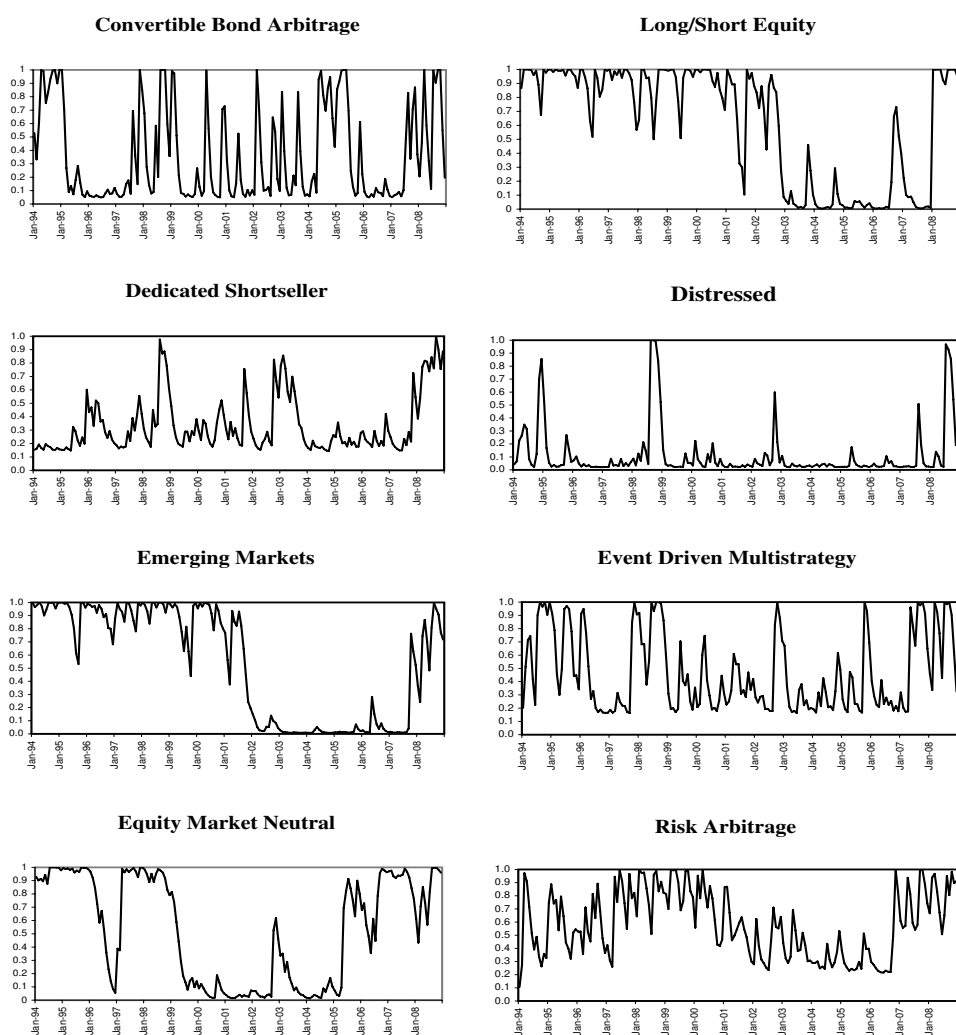
Figure 4: **Common Exposure to a Latent Factor for All Hedge Fund Strategies**
Panel A presents the joint probability of a high idiosyncratic volatility regime for all CSFB/Tremont hedge fund index strategies from January 1994 to December 2008. Panel B concentrates on the joint probability of a high idiosyncratic volatility regime 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 Idiosyncratic Volatility Regime
           for All Hedge Fund Strategies: January 1994 - December 2008
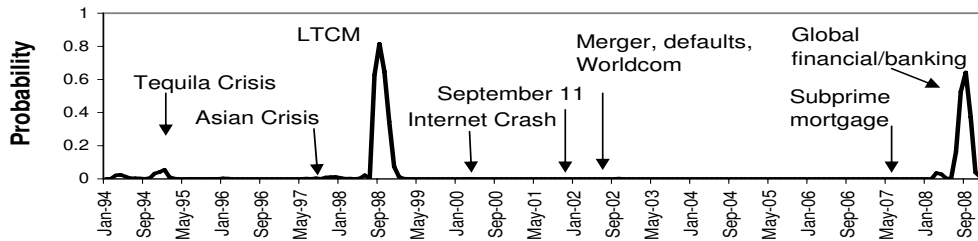
Panel B   The Joint Probability of High Idiosyncratic Volatility Regime
           for All Hedge Fund Strategies: LTCM crisis of 1998
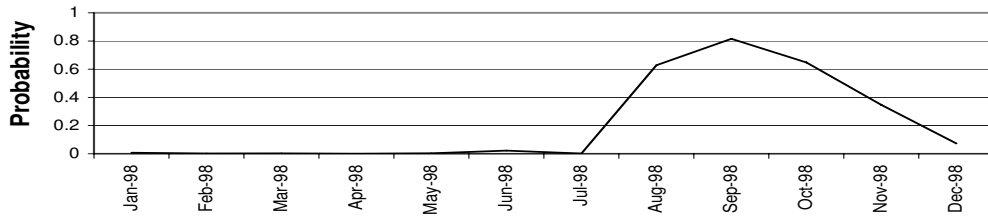
Panel C   The Joint Probability of High Idiosyncratic Volatility Regime
           for All Hedge Fund Strategies: Global Financial Crisis of 2008

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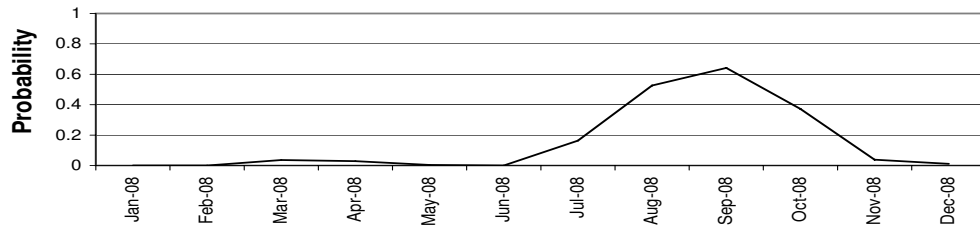
Figure 5: **Common Exposure to a Latent Factor for Five Hedge Fund Strategies During the 2007 Subprime Mortgage Crisis**

This figure presents the joint probability of a high idiosyncratic volatility regime for Distressed, Event Driven Multi-Strategy, Risk Arbitrage, Convertible Bond Arbitrage, and Equity Market Neutral strategies for the year 2007. August 2007 marks the peak of the subprime mortgage financial crisis.
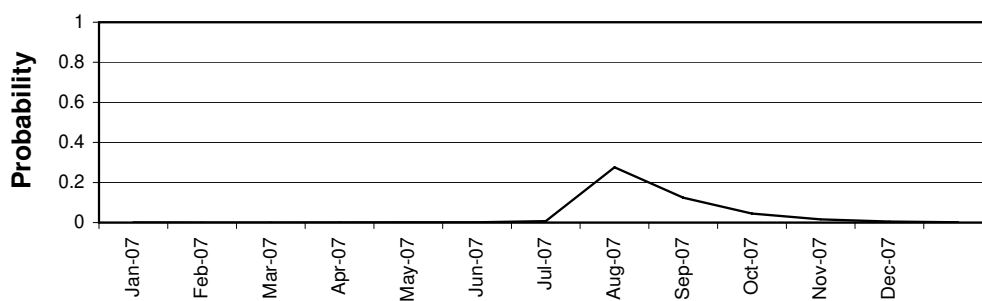
Table 5: **Mutual Fund Summary Statistics**

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 Return is annualized mean return, and Ann. SD is annualized standard deviation. Min, Med, and Max are minimum, median, and maximum monthly returns, respectively. The returns are in percentage terms. Skew measures skewness and Kurt measures excess kurtosis. JB p-value is p-value of the Jarque-Bera test.

Strategy	N	$\beta_{S\&P500}$	Ann. Mean Return (%)	Ann. SD (%)	Min. Return (%)	Med. Return (%)	Max. Return (%)	Skew	Kurt	JB p-value
Large Blend	180	0.95	1.67	14.50	-17.54	0.91	7.64	-0.96	1.85	0.00
Large Growth	180	1.10	1.53	17.48	-17.76	0.54	11.52	-0.73	1.03	0.00
Large Value	180	0.84	2.26	13.60	-17.32	0.70	9.70	-0.96	2.52	0.00
Mid-Cap Blend	180	0.96	3.74	15.79	-21.28	0.75	8.04	-1.19	3.09	0.00
Mid-Cap Growth	180	1.16	3.35	20.87	-20.61	0.73	19.65	-0.49	1.53	0.00
Mid-Cap Value	180	0.85	3.91	14.55	-20.91	0.88	10.27	-1.23	4.06	0.00
Small Blend	180	0.94	4.36	17.51	-21.43	0.85	10.11	-1.02	2.45	0.00
Small Growth	180	1.15	4.13	22.71	-22.41	0.90	23.82	-0.30	1.45	0.00
Small Value	180	0.80	4.61	15.53	-20.19	0.76	9.13	-1.17	3.29	0.00
Convertibles	180	0.65	1.51	11.80	-18.55	0.50	8.99	-1.38	5.63	0.00
Emerging Markets	180	1.13	1.89	23.39	-28.45	0.97	16.77	-0.98	2.38	0.00
Long/Short	180	0.18	0.68	4.37	-6.89	0.29	2.84	-1.59	5.79	0.00
Bear Market	180	-1.31	-8.64	19.41	-13.66	-1.19	20.64	1.15	2.68	0.00

Table 6: Mutual Fund Analysis

This table presents results for the regression of Morningstar open-ended US mutual fund index returns on S&P 500, Large-Small, Value-Growth, USD, Lehman Government Credit, Term Spread, Change in VIX, Credit Spread, and Momentum Factor. Large Blend, Large Growth, Large Value, Mid-Cap Blend, Small Blend, Small Growth, Small Value, Mid-Cap Growth, Mid-Cap Value, Convertibles, Emerging Markets, Long/Short, and Bear Market 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 is idiosyncratic volatility. Parameters that are significant at the 10% level are shown in bold type.

Panel A

	Large Blend		Large Growth		Large Value		Mid-Cap Blend		Small Blend		Small Growth		Small Value	
	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat
α	**-0.15**	**-1.73**	-0.21	-1.38	-0.01	-0.10	0.23	1.17	0.22	1.15	0.03	0.10	0.19	0.82
β_0 (S&P 500)	**0.93**	**79.16**	**1.02**	**49.85**	**0.90**	**62.85**	**0.94**	**35.19**	**0.95**	**36.61**	**1.11**	**30.05**	**0.88**	**28.61**
β_1 (Large-Small)	**-0.08**	**-8.60**	**-0.20**	**-11.62**	**-0.09**	**-7.77**	**-0.43**	**-19.53**	**-0.83**	**-38.43**	**-1.04**	**-34.03**	**-0.72**	**-28.24**
β_2 (Value-Growth)	0.00	0.31	**-0.33**	**-18.38**	**0.36**	**28.82**	**0.09**	**3.68**	**0.13**	**5.46**	**-0.36**	**-11.25**	**0.37**	**13.76**
β_3 (USD)	**-0.06**	**-3.57**	-0.04	-1.40	**-0.05**	**-2.25**	**-0.11**	**-2.73**	**-0.08**	**-2.08**	**-0.13**	**-2.31**	-0.05	-1.01
β_4 (Lehman Gov)	-0.02	-0.76	**-0.08**	**-1.83**	0.00	0.00	0.01	0.21	-0.04	-0.76	**-0.15**	**-1.89**	-0.02	-0.29
β_5 (Term Spread)	-0.01	-0.35	**-0.08**	**-1.75**	-0.02	-0.64	0.03	0.59	0.05	0.96	-0.11	-1.43	**0.12**	**1.92**
β_6 (Change in VIX)	**-0.02**	**-2.35**	-0.01	-0.29	**-0.03**	**-2.65**	**-0.06**	**-2.47**	-0.03	-1.19	0.02	0.60	-0.02	-0.60
β_7 (Credit Spread)	-0.06	-0.68	-0.01	-0.04	-0.09	-0.82	**-0.38**	**-1.89**	-0.32	-1.64	-0.12	-0.44	-0.25	-1.07
β_9 (Mom Factor)	-0.01	-1.06	**0.06**	**4.88**	**-0.07**	**-8.03**	0.00	-0.09	-0.01	-0.68	**0.11**	**5.25**	**-0.07**	**-3.89**
ω	**0.42**		**0.72**		**0.51**		**0.94**		**0.92**		**1.30**		**1.08**	
Adj. R²	0.99		0.98		0.98		0.96		0.97		0.96		0.94	

Panel B

	Mid-Cap Growth		Mid-Cap Value		Convertibles		Emerging Markets		Long/Short		Bear Market	
	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat
α	0.16	0.57	0.26	1.23	0.48	1.91	-0.72	-0.82	**0.66**	**4.00**	0.58	1.38
β_0 (S&P 500)	**1.07**	**27.38**	**0.87**	**30.30**	**0.56**	**16.53**	**0.98**	**8.32**	**0.17**	**7.56**	**-0.85**	**-15.05**
β_1 (Large-Small)	**-0.67**	**-20.76**	**-0.31**	**-13.01**	**-0.35**	**-12.40**	**-0.49**	**-4.96**	**-0.11**	**-6.10**	**0.12**	**2.66**
β_2 (Value-Growth)	**-0.41**	**-11.92**	**0.40**	**15.83**	**-0.09**	**-2.97**	0.01	0.13	**0.08**	**4.07**	**0.42**	**8.44**
β_3 (USD)	**-0.10**	**-1.74**	**-0.08**	**-1.77**	**-0.12**	**-2.31**	**-0.37**	**-2.12**	-0.03	-0.97	0.08	0.97
β_4 (Lehman Gov)	-0.09	-1.04	0.03	0.54	**0.28**	**3.91**	-0.20	-0.79	**0.14**	**2.93**	**0.25**	**2.07**
β_5 (Term Spread)	-0.12	-1.41	0.03	0.45	0.03	0.47	0.19	0.76	0.06	1.23	0.15	1.23
β_6 (Change in VIX)	-0.01	-0.22	**-0.08**	**-3.25**	**-0.09**	**-2.84**	**-0.22**	**-2.12**	-0.03	-1.61	**0.22**	**4.32**
β_7 (Credit Spread)	-0.32	-1.09	-0.28	-1.31	**-0.80**	**-3.14**	0.23	0.26	**-0.90**	**-5.40**	**-1.50**	**-3.54**
β_9 (Mom Factor)	**0.12**	**5.15**	**-0.08**	**-4.77**	**0.05**	**2.33**	0.03	0.45	**0.05**	**4.16**	**0.17**	**5.21**
ω	**1.39**		**1.02**		**1.20**		**4.18**		**0.79**		**2.00**	
Adj. R²	0.95		0.94		0.88		0.62		0.61		0.88	

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

This table presents results for the regime-switching model for the market risk factor, S&P 500, labeled as I. S&P 500 returns are in excess of three-month Treasury Bill rates. The following model is estimated: $I_t = \mu(S_t) + \sigma(S_t)\epsilon_t$. The state of the market index I is described by the Markov chain S_t. Each state of the market index has its own mean $\mu(S_t)$ and standard deviation $\sigma(S_t)$. There are three regimes that are estimated: regime 0 (up-market), regime 1 (tranquil), 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 μ (%)

Regime 0 (Up-Market) μ_0		Regime 1 (Tranquil) μ_1		Regime 2 (Down-Market) 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 σ (%)

Regime 0 (Up-Market) σ_0		Regime 1 (Tranquil) σ_1		Regime 2 (Down-Market) 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&P 500 regimes from 1994-2008 (%)

Regime 0 (Up-Market)	Regime 1 (Tranquil)	Regime 2 (Down-Market)
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, Large-Small, Value-Growth, USD, Lehman Government Credit, Term Spread, Change in VIX, Credit Spread, and Momentum Factor for different S&P 500 regimes. The following model is estimated: $R_{i,t} = \alpha_i(Z_t) + \beta_i(S_t)I_t + \sum_{k=1}^{K}\theta_{ik}(S_t)F_{kt} + \omega_i(Z_{i,t})u_{i,t}$. I_t is the market factor, S&P 500, F_{kt} are other risk factors, and $\omega_i(Z_{i,t})$ is the volatility of the idiosyncratic risk factor. $Z_{i,t}$ is a Markov chain with 2 states (0 = low idiosyncratic volatility state and 1 = high idiosyncratic volatility state. Regime 0: up-market, regime 1: tranquil, and regime 2: down-market. Parameters that are significant at the 10% level are shown in bold type.

	Convertible Arbitrage		Dedicated Short Bias		Emerging Markets		Equity Market Neutral		Long/Short Equity		Distressed		Event Driven Multi-Strategy		Risk Arb	
	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat
α_0	**2.13**	**8.68**	**1.90**	**2.62**	0.26	0.28	**0.87**	**4.33**	**1.41**	**2.29**	**1.61**	**5.34**	**1.05**	**3.99**	**0.56**	**2.20**
α_1	**0.89**	**2.37**	**3.94**	**1.98**	-1.11	-1.20	0.37	1.53	0.16	0.23	**1.16**	**4.25**	-0.25	-0.48	0.29	1.10
β_0 (S&P 500)	-0.12	-1.07	**-1.42**	**-3.67**	0.55	1.10	**0.32**	**3.06**	**1.24**	**2.78**	0.12	0.54	**0.29**	**2.23**	0.20	1.24
β_1 (S&P 500)	0.04	1.11	**-1.13**	**-8.20**	**0.38**	**2.43**	**0.09**	**2.19**	**0.29**	**3.28**	**0.24**	**5.21**	**0.25**	**3.70**	**0.18**	**4.48**
β_2 (S&P 500)	**-0.09**	**-2.83**	**-0.78**	**-6.11**	**0.34**	**2.61**	0.02	0.74	-0.10	-1.22	**0.19**	**3.01**	**0.15**	**3.31**	0.02	0.40
θ_{1_0} (Large-Small)	0.02	0.36	-0.31	-1.50					-0.09	-0.44	**-0.32**	**-3.32**	**-0.20**	**-2.61**	-0.09	-1.13
θ_{1_1} (Large-Small)	0.04	0.92	**-0.73**	**-6.60**					0.09	1.21	**-0.14**	**-3.80**	**-0.12**	**-2.47**	**-0.10**	**-3.08**
θ_{1_2} (Large-Small)	**0.11**	**5.62**	**-0.37**	**-4.76**					-0.04	-0.67	-0.06	-1.44	**-0.14**	**-4.61**	**-0.16**	**-5.13**
θ_{2_0} (Value-Growth)	**0.13**	**1.63**	-0.11	-0.50					**0.46**	**2.29**	0.17	1.26			**0.21**	**2.12**
θ_{2_1} (Value-Growth)	0.05	0.82	**0.35**	**2.27**					**0.16**	**1.78**	**0.11**	**2.30**			-0.02	-0.32
θ_{2_2} (Value-Growth)	**0.06**	**3.47**	**0.29**	**4.25**					0.00	-0.07	0.03	0.86			**0.06**	**2.00**
θ_{3_0} (USD)			0.53	1.63	0.51	0.98							0.20	1.49		
θ_{3_1} (USD)			**0.24**	**1.63**	**-0.36**	**-2.39**							-0.03	-0.47		
θ_{3_2} (USD)			-0.20	-1.22	0.11	0.62							-0.01	-0.13		
θ_{4_0} (Leh Gov. Credit)	-0.09	-0.57					-0.18	-0.87			0.12	0.34				
θ_{4_1} (Leh Gov. Credit)	-0.02	-0.28					-0.04	-0.67			-0.08	-1.19				
θ_{4_2} (Leh Gov. Credit)	**0.37**	**5.14**					-0.01	-0.11			-0.02	-0.12				
θ_{5_0} (Term Spread)									**1.88**	**1.90**						
θ_{5_1} (Term Spread)									-0.08	-0.75						
θ_{5_2} (Term Spread)									-0.18	-0.69						
θ_{6_0} (Change in VIX)	0.10	1.62	-0.24	-1.13	0.46	1.58	0.10	1.56	**1.08**	**5.01**	0.08	0.66	**0.25**	**3.18**	0.05	0.61
θ_{6_1} (Change in VIX)	-0.01	-0.29	-0.08	-0.61	-0.02	-0.12	0.05	1.39	**0.15**	**1.83**	**0.09**	**1.98**	0.06	0.82	**0.08**	**1.93**
θ_{6_2} (Change in VIX)	**-0.20**	**-4.98**	-0.11	-0.98	**-0.30**	**-2.38**	-0.05	-1.62	**-0.19**	**-2.54**	**-0.12**	**-2.67**	-0.04	-1.12	**-0.14**	**-3.79**
θ_{7_0} (Credit Spread)	0.61	0.82	1.62	0.62	0.58	0.19	**-1.42**	**-1.87**	**-4.22**	**-1.65**	-0.36	-0.23	-0.40	-0.41	-0.22	-0.23
θ_{7_1} (Credit Spread)	**-1.78**	**-5.74**	-1.46	-1.54	0.67	0.60	**-0.54**	**-2.15**	-1.07	-1.51	**-0.57**	**-1.70**	-0.34	-0.92	-0.20	-0.59
θ_{7_2} (Credit Spread)	**-1.74**	**-6.70**	**-2.47**	**-3.03**	0.93	1.16	-0.22	-0.96	0.22	0.31	**-1.35**	**-4.66**	**-0.54**	**-2.11**	**-0.43**	**-2.02**
θ_{8_0} (Momentum Factor)									**0.31**	**2.65**						
θ_{8_1} (Momentum Factor)									**0.23**	**3.62**						
θ_{8_2} (Momentum Factor)									-0.02	-0.62						
ω_0	**0.41**	**9.92**	**2.05**	**17.33**	**1.66**	**10.74**	**0.54**	**14.37**	**0.92**	**10.81**	**0.47**	**9.51**	**0.80**	**13.58**	**0.54**	**9.23**
ω_1	**1.99**	**11.18**	**5.02**	**5.07**	**4.98**	**12.52**	**0.95**	**8.61**	**3.40**	**11.81**	**1.63**	**14.16**	**2.20**	**8.37**	**1.10**	**10.98**
p^{L}_{00}	**0.87**		**0.99**		**0.98**		**0.98**		**0.98**		**0.94**		**0.97**		**0.97**	
p^{L}_{11}	**0.84**		**0.86**		**0.99**		**0.96**		**0.99**		**0.98**		**0.89**		**0.98**	
PseudoR^2	0.21		0.19		0.11		0.10		0.14		0.16		0.15		0.15	

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Figure 6: **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 tranquil, up, and down states. The following factors are considered: S&P 500, Large-Small, Value-Growth, USD, Lehman Government Credit, Term Spread, Change in VIX, Credit Spread, and Momentum Factor. Eight is the maximum number of strategies.
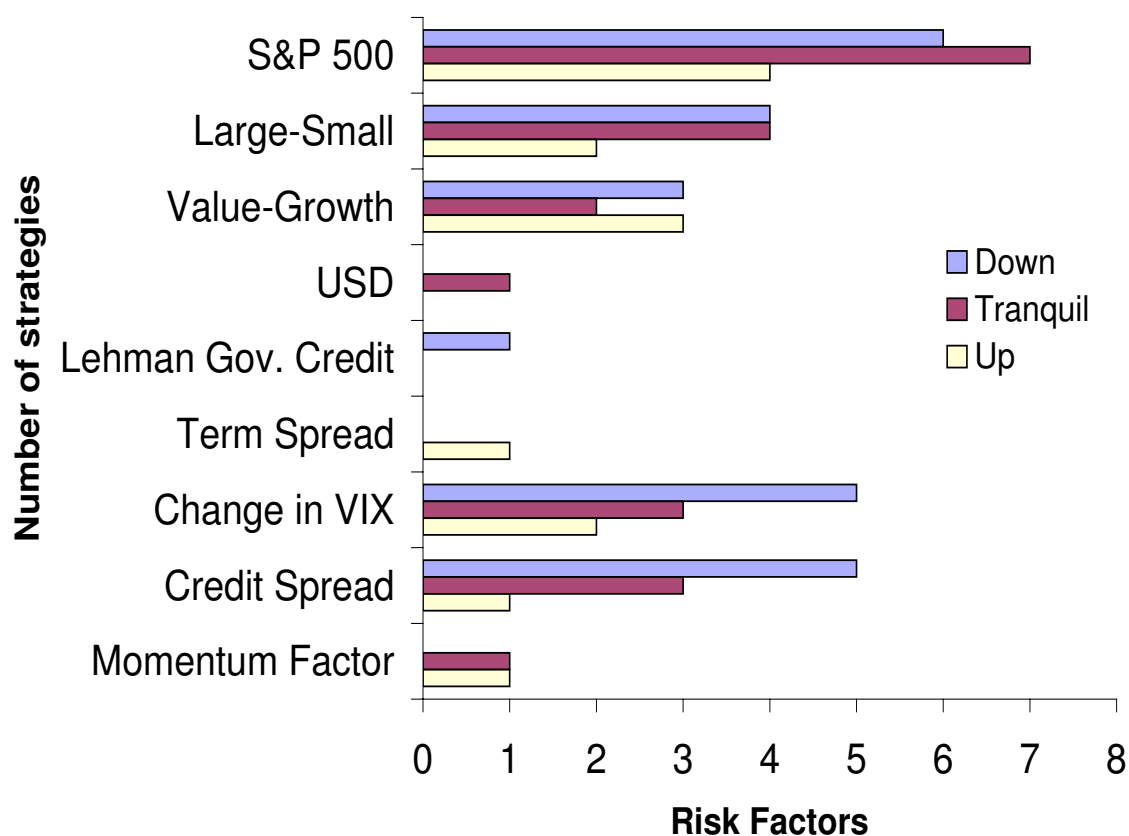
Figure 7: **Common Exposure to a Latent Factor for All Hedge Fund Strategies: Multi-Factor Regime-Switching Model**

This figure presents the joint probability of high idiosyncratic volatility regime for all CSFB/Tremont hedge fund index strategies from January 1994 to December 2008 using the multi-factor regime-switching model.

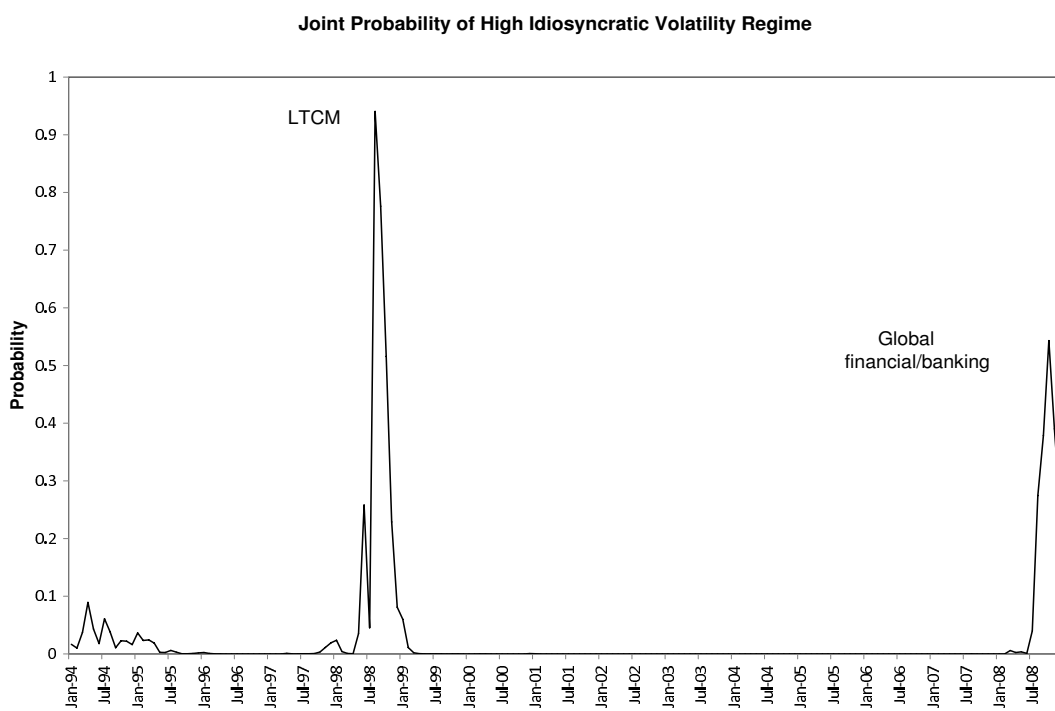**Joint Probability of High Idiosyncratic Volatility Regime**

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 is idiosyncratic volatility. Parameters that are significant at the 10% level are shown in bold type.

	Convertible Bond Arb		Dedicated Short Bias		Emerging Markets		Equity Market Neutral		Long/Short Equity		Distressed		Event Driven Multi-Strategy		Risk Arb	
	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat
α	**1.51**	**4.62**	**1.41**	**2.67**	-0.03	-0.12	**0.41**	**7.41**	**0.59**	**2.29**	**1.15**	**4.26**	**0.29**	**2.76**	**0.20**	**2.79**
$\beta 1$ (SP)	**0.10**	**3.46**	**-0.90**	**-18.39**	**0.57**	**8.70**	**0.08**	**6.21**	**0.22**	**4.45**	**0.23**	**9.37**	**0.23**	**9.02**	**0.13**	**7.83**
$\beta 2$ (SC-LC)	**0.09**	**2.32**	**-0.48**	**-7.92**	**0.30**	**3.67**					**0.14**	**4.75**	**0.14**	**4.60**	**0.12**	**5.59**
$\beta 3$ (10Y)	**-1.56**	**-4.65**	**-1.42**	**-2.63**							**-0.79**	**-2.88**				
$\beta 4$ (CS)					**0.11**	**2.04**			**0.15**	**3.50**			0.04	1.71		
$\beta 5$ (Bd Opt)					**-0.04**	**-2.33**					**-0.02**	**-3.38**	**-0.03**	**-3.82**	**-0.02**	**-3.09**
$\beta 6$ (FX Opt)	-0.01	-1.81					0.01	1.60								
$\beta 7$ (Com Opt)			**-0.03**	**-2.00**												
ω	**1.66**	**5.98**	**2.71**	**3.42**	**3.62**	**1.84**	**0.74**	**6.69**	**2.83**	**3.16**	**1.37**	**6.60**	**1.40**	**6.56**	**0.95**	**6.97**
Adj. R^2	0.25		0.68		0.36		0.36		0.16		0.52		0.45		0.40	
Pseudo R^2	0.05		0.15		0.06		0.06		0.02		0.11		0.08		0.10	

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Figure 8: **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 tranquil 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 tranquil regime, and regime 2 is a down-market regime.

Expected Distribution

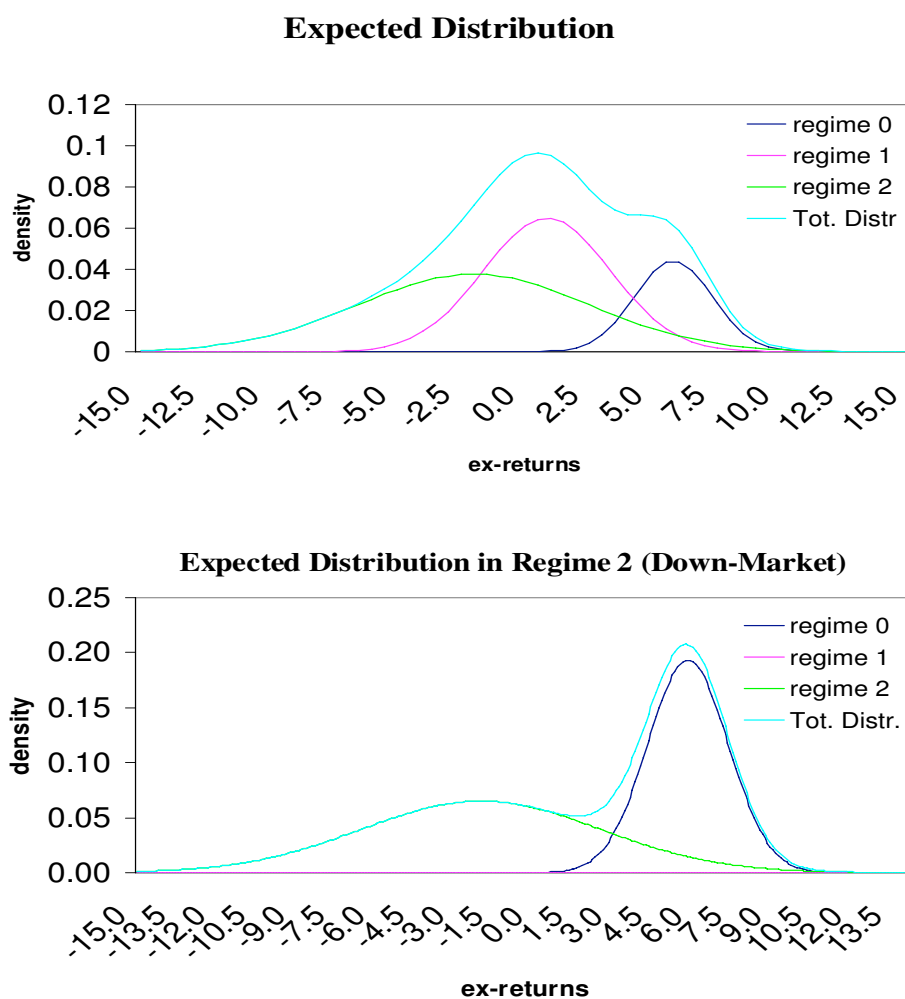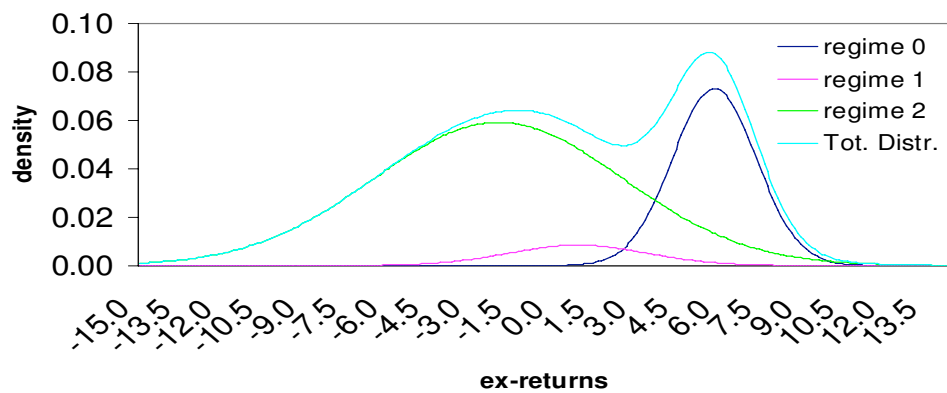**Expected Distribution in Regime 2 (Down-Market)**

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Figure 9: **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 tranquil regime. There are 3 states of the market: regime 0 is an up-market regime, regime 1 is a tranquil regime, and regime 2 is a down-market regime.

Expected Distribution in Regime 0 (Tranquil)

Expected Distribution in Regime 1 (Up-Market)