OFFICE OF FINANCIAL RESEARCH
U.S. DEPARTMENT OF THE TREASURY

Office of Financial Research
Working Paper #0006
March 13, 2013

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Hedge Fund Contagion and Risk-adjusted Returns: A Markov-switching Dynamic Factor Approach*

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March 2013

Forthcoming in the Journal of Empirical Finance

Abstract

We provide an empirical analysis of two important phenomena influencing the hedge fund industry - contagion and time variation in risk-adjusted return (alpha) - in a flexible unified framework. After accounting for standard hedge fund pricing factors, we quantify the common latent factor in hedge fund style index returns and model its time-varying behavior using a dynamic factor framework featuring Markov regime-switching. We find that three regimes - crash, low mean, and high mean - are necessary to provide a complete description of joint hedge fund return dynamics. We also document significant time variation in the alpha-generating ability of all hedge fund investment styles. The period following the stock market crash of 2000 is dominated by the persistent low-return state, while the long bull market of the 1990s is associated with the strongest performance of the industry generating high positive returns. We also investigate drivers of the regime shifts in the common latent pricing factor and find that both flight to safety and large funding liquidity shocks play important roles in explaining the abrupt shift of the common factor to the crash state.

Keywords: Hedge fund, Contagion, Risk-adjusted return, Dynamic factor models, Markov-switching, Funding liquidity, Flight to safety

JEL codes: G01, C32, C58

* We would like to thank participants at the 19th Annual Symposium of the Society for Nonlinear Dynamics and Econometrics, the 17th International Conference on Computing in Economics and Finance, and the 2011 Financial Management Association Annual Meeting. We also thank an anonymous referee whose constructive comments have greatly improved this manuscript. The views expressed in this paper are solely the responsibility of the authors and should not be interpreted as reflecting the views of the Board of Governors of the Federal Reserve System, the Office of Financial Research, the Treasury Department, or their respective staff members. Correspondence: Ozzy.Akay@treasury.gov, Zeynep.Senyuz@frb.gov, Emre.Yoldas@frb.gov.

1. Introduction

Hedge funds have become an increasingly important part of the finance industry in the last two decades. Although the financial crisis of 2008 had a negative impact on the performance and assets under management, the industry still manages around $2.13 trillion as of the first quarter of 2012, according to a press release by Hedge Fund Research, Inc.[1]

One of the reasons behind the growth of the hedge fund industry is that hedge fund managers follow an absolute-return strategy, promising a positive return independent of market conditions. To achieve this, they can pursue highly complex investment strategies that are not available to others in the investment management industry due to regulatory constraints. Therefore, one would expect a low correlation between hedge fund returns and returns on broad based portfolios, as well as among different hedge fund investment styles, because they invest in different sets of assets and follow different strategies. However, recent financial crises demonstrated that the returns of different hedge fund styles might be more correlated than anticipated during times of distress, indicating a systemic risk in the industry.

Chan et al. (2006) define systemic risk as "*the possibility of a series of correlated defaults among financial institutions – typically banks – that occur over a short period of time, often caused by a single major event*." Systemic risk is important in analyzing hedge funds because it impedes the benefits of diversification to hedge fund investors, especially in down market conditions. Moreover, as pointed out by Bernanke (2006), among others, it may affect the broader financial market through asset price changes, liquidity spirals, and increased uncertainty in financial markets. Khandani and Lo (2007) illustrate how these forces increased systemic risk in the hedge fund industry in 2007.

[1] Report available at https://www.hedgefundresearch.com/pdf/pr_20120419.pdf

In a related context, hedge fund contagion is defined as the dependence that resides after systematic risk factors are accounted for. Boyson et al. (2010) and Dudley and Nimalendran (2011) study residuals obtained from a standard asset pricing model to identify the dependence that cannot be explained by exposure to economic fundamentals. Although they use different methodologies, both studies conclude that funding liquidity is a crucial channel leading to increased dependence among hedge fund returns during times of distress. Boyson et al. (2010) emphasize money market distress reflected in the form of a higher spread over the risk-free borrowing rate, while Dudley and Nimalendran (2011) focus on the impact of changing margin requirements on speculators' capital and provision of liquidity. Billio et al. (2010) also analyze hedge fund style index returns and conclude that there is a common latent pricing factor, after accounting for observable pricing factors. This factor potentially affects all hedge fund styles during times of extreme turmoil, such as those followed by the LTCM failure and the Lehman Brothers bankruptcy. However, they do not quantify this latent factor or make direct inference on its state-dependent behavior.

Another interesting phenomenon regarding hedge funds that has been documented recently is the existence of a downward trend in their risk-adjusted returns. Fung et al. (2008) and Naik et al. (2007) show that hedge fund alpha has been declining since 2000. Both papers argue that this trend is mainly driven by the equilibrium arguments presented in Berk and Green (2004), namely, decreasing returns to scale and higher fees charged by absolute return generating managers.

In this paper we study these two important phenomena influencing the hedge fund industry - contagion and time-varying alpha - in a unified framework. Our paper contributes to the literature on several grounds. First, we use a novel approach to quantify the common latent factor in hedge fund style index returns and identify its regime-dependent dynamics. Instead of relying on exogenous classifications, our dynamic factor Markov-switching framework endogenously determines crises and other distinct periods. Our analysis reveals that a three-regime specification adequately describes the dynamics of the latent pricing factor. The three regimes are, (1) an unusual crash state with large negative mean return and very high volatility, (2) a low mean/high volatility state, and (3) a high mean state with minimal volatility in the common latent factor. Second, we provide evidence of declining hedge fund alpha in the context of endogenously determined regimes. Probabilistic inference from our model suggests that the latent pricing factor has been in the low mean/high volatility state during most of the last decade. Third, we show that co-movement in hedge fund style returns is not restricted to times of extreme financial turmoil, although these are the periods during which strongest dependence is observed. Finally, we link funding liquidity and flight to safety (or panic) to the probability of observing the crash state. Our estimates imply that abrupt increases in the TED spread, the margin requirement on the S&P 500 contract, and the VIX index result in a statistically significant elevation in the crash-state probability. Our results emphasize the role of panic and funding liquidity in creating a state of contagion in hedge fund returns.

We show that our results are robust to time variation in exposure to standard risk factors, as well as exclusion of the subprime-led crisis from the estimation sample. We also find that the distinct periods observed in the median risk-adjusted return obtained from individual fund level analysis are in line with the regime classification from our three-state model. Average individual fund exposure, after accounting for standard risk factors, is also in line with our finding based on style indices.

The rest of the paper is organized as follows: We introduce the data and summarize the statistical methodology in Section 2, present our findings in Section 3, and consider extensions and robustness analyses in Section 4. We conclude in Section 5.

2. Data and Methodology

2.1 Data

We use hedge fund index returns from the Dow Jones Credit Suisse Hedge Fund Indexes database from January 1994 to December 2010. Specifically, we consider Convertible Arbitrage, Dedicated Short Bias, Emerging Markets, Equity Market Neutral, Event-Driven Distressed, Event-Driven Multi Strategy, Event-Driven Risk Arbitrage, and Long/Short Equity styles to make our findings comparable to the existing research.[2]

Summary statistics for the returns on monthly hedge fund style indices are provided in Table 1 (Panel A). We see that all hedge fund indices have positive average returns in the sample with the exception of Dedicated Short Bias, which has a slightly negative average return. The highest average monthly return is provided by the Event-Driven Distressed strategy (0.90 percent) followed by the Long/Short equity style (0.86 percent). Dedicated Short and Emerging Markets strategies exhibit the most variability. All hedge fund styles have positive first order autocorrelation. Convertible Arbitrage and Distressed Securities display the highest persistence, which is most likely due to these styles' investments in illiquid securities, as discussed in Getmansky et al. (2004). In general, hedge fund returns are left skewed with the exception of Dedicated Short, which is slightly right skewed, and Long/Short Equity, which is essentially

[2] A detailed description of the indices and construction methodology are publicly available at Dow Jones Credit Suisse website www.hedgeindex.com.

symmetric. Returns on non-directional strategies such as Convertible Arbitrage and Event-Driven style have the fattest tails, evidenced by large kurtosis estimates.

We consider the observable risk factors described in Fung and Hsieh (2001, 2002, 2004): the primitive trend-following strategies approximated by the returns on lookback straddles on bonds, currencies, and commodities; the S&P 500 index monthly total return as the equity market factor; the size spread measured as the difference between Russell 2000 and S&P 500 returns; the bond market factor approximated by the change in the 10-year T-bond yield; the change in the spread between Moody's Baa and 10-year T-bond as a proxy for default risk; and the return on the MSCI emerging market stock index. We also provide summary statistics of the pricing factors in Panel B of Table 1. The trend-following factors are more volatile than the other risk factors, while the credit factor and the size spread have fatter tails.

2.2 Methodology

We estimate the latent factor based on a two-step procedure. First, we run the following regression for all of the index style returns and retrieve the residuals:

$$(1) \qquad r_{i,t} = \alpha_i + \rho_i r_{i,t-1} + \boldsymbol{\beta}_i' \mathbf{x}_t + u_{i,t}, \;\; i \; = \; 1, \dots, 8,$$

where $r_{i,t}$ is the return on the i^{th} hedge fund style index in month t, $\mathbf{x}_t$ is a vector that contains the observable hedge-fund pricing factors, and $u_{i,t}$ is a possibly heteroskedastic error term such that $E[u_{i,t}] = 0$, and $Corr(u_{i,t}, u_{i,t-j}) = 0 \; \forall \, j \neq 0$. Note that in Section 4.1, we will relax the assumption of constant betas and use a model that incorporates time variation in risk exposures.

Next, we incorporate the residuals from the above model into a dynamic factor framework featuring Markov regime-switching. Our goal is to identify the latent hedge fund pricing factor and model its asymmetric behavior over the phases of hedge fund industry cycles.[3] The first equation of the model is the measurement equation, which links the residuals from Equation (1) to the latent pricing factor that represents the co-movement of the underlying hedge-fund returns beyond the standard pricing factors:

(2) $$y_{i,t} = \theta_i F_t + \epsilon_{i,t}, \quad \epsilon_{i,t} \sim NID(0, \sigma_i^2), \quad i = 1, \dots, 8,$$

where $y_{i,t}$ is the i^{th} residual from Equation (1), F_t is the common latent pricing factor, θ_i is the factor loading of the i^{th} series that represents its exposure to the common factor, and $\epsilon_{i,t}$ is the white noise idiosyncratic term. The second equation is the transition equation that describes dynamics of the latent factor:

(3) $$F_t = \nu_{s_t} + \phi F_{t-1} + \eta_t, \qquad \eta_t \sim ND\left(0, \tau_{s_t}^2\right),$$

where s_t is the unobservable state variable that drives dynamics of the latent hedge-fund pricing factor. The drift term and the volatility are both subject to regime shifts driven by $s_t \in \{1, \dots, M\}$. This specification captures both time variation in expected returns and heteroskedasticity, two well known stylized facts of financial returns. The model is completed by specifying dynamics of the unobservable state variable, s_t. This state variable evolves according to a first order M-state Markov process, with transition probabilities given by $p_{ij} = \Pr\left(s_t = j | s_{t-1} = i\right)$ where $i, j \in \{1, \dots, M\}$. The transition probabilities are collected in a $M \times M$ matrix, say $\boldsymbol{P}$, given by

(4) $$\boldsymbol{P} = \begin{bmatrix} p_{11} & p_{21} & \cdots & p_{M1} \\ p_{12} & p_{22} & \cdots & p_{M2} \\ \vdots & \vdots & \ddots & \vdots \\ p_{1M} & p_{2M} & \cdots & p_{MM} \end{bmatrix},$$

such that $p_{iM} = 1 - p_{i1} - \cdots - p_{i,M-1}$ for $i = 1, \dots, M$.

[3] See Kim (1994), Chauvet (1998), Chauvet (1998/1999), and Chauvet and Potter (2000) among others for applications of dynamic factor models with Markov-switching asymmetry in macroeconomics and finance. See Kim and Nelson (1999) for a comprehensive survey and numerous illustrations of this approach using maximum likelihood and Gibbs-sampling.

The latent factor is assumed to be uncorrelated with the idiosyncratic terms at all leads and lags, which guarantees identification. Since the extracted factor summarizes information common to all residual series and it is not observable, we need to define a scale for its interpretation. Therefore, we normalize the first factor loading to unity, i.e. $\theta_1 = 1$. Note that this has no effect on the dynamic properties of the extracted factor or the regime classification.

For model estimation we combine a nonlinear discrete version of the Kalman filter with Hamilton's (1989) filter using Kim's (1994) approximate maximum likelihood method. The filter estimates the latent factor and the probabilities associated with the Markov-state variable using available data. Based on information available at time t, the algorithm produces the prediction of the latent factor and probabilities of the Markov states.

After estimating the model parameters, we make inference about the unobserved states using filtered and smoothed probabilities. Filtered probabilities use information available up to time t, $P(S_t = j|\Omega_t)$, whereas smoothed probabilities are based on the entire sample, $P(S_t = j|\Omega_T)$, where Ω_t denotes information set available as of time t.[4]

3. Empirical Results

3.1 Markov-switching Dynamic Factor Models

We start our analysis by running the regression model specified in Equation (1) for each of the eight hedge fund indices. Table 2 summarizes the estimation results. The eight risk factors are explaining between 28 percent and 71 percent of the variation in hedge fund index returns, and thus are appropriate for our empirical design. Note that the goodness of fit measures in our regressions are comparable to those presented in related research, e.g. Billio et al. (2010) and

[4] For a detailed discussion of the filter and smoother algorithms, see Hamilton (1994) and Kim and Nelson (1999).

Boyson et al. (2010). All styles produce a positive and significant alpha with the exception of Emerging Markets. We will provide insights into time variation in risk-adjusted returns when we analyze these residuals in the Markov-switching dynamic factor framework. The autoregressive component is significant for all of the hedge fund indices, pointing out to serial correlation due to illiquid asset holdings as argued by Getmansky et al. (2004). The significance and sign of the factors change across hedge fund indices as different investment styles are associated with different strategies. The equity market factor, the emerging market factor, and the primitive trend-following strategy based on bonds are significant for most of the indices. The currency trend-following factor is significant for only the Equity Market Neutral style, while the commodity trend-following factor is not significant for any of the style indices considered. Residuals from these regressions are shown in Figure 1.

Next, we estimate Markov-switching dynamic factor models for the residuals from the pricing regressions. We consider two specifications that incorporate two and three distinct states, respectively. The two-state model corresponds to the conventional bull/bear taxonomy of the financial markets, while the three-state model introduces an additional state to provide a more realistic approximation to the true underlying data generating process.

To determine the optimal number of regimes, we follow Guidolin and Timmermann (2006) and use the Davies (1987) procedure to calculate the upper bound for the p-value of the likelihood ratio test statistic, and also compare the two specifications with respect to the Hannan-Quinn information criterion. We find that the Davies p-value is zero up to six digits, strongly favoring the three-regime specification. The Hannan-Quinn criterion also selects the three-regime specification with a calculated value of 12.52, as opposed to 12.58 for the two-state specification.

Table 3 presents maximum likelihood estimates of the selected Markov-switching dynamic factor specification. The first state can be regarded as a crash state with large negative returns accompanied by extreme volatility. Specifically, this regime is characterized by a drift of -0.88, which implies an annualized return of about -8 percent given the estimate for the autoregressive parameter (-0.3). Annualized volatility in this regime is about 6 percent. State 2 is also a negative mean regime but it is substantially milder than the first one with an implied mean estimate of -2.6 percent per annum. Volatility, at 1.8 percent, is also significantly dampened compared to State 1. In the third state, the latent factor takes a positive annualized mean value of 5.5 percent. This is also the state that exhibits minimum volatility with an annualized point estimate of 1.2 percent.

Estimated factor loadings suggest that all series are positively significantly correlated with the latent factor with the exception of the Dedicated Short Bias strategy. Therefore, although they have reportedly distinct investment strategies, almost all hedge-fund investment styles have exposure to a common latent factor. After accounting for each style's exposure to the latent factor, we observe that Dedicated Short and Emerging Markets strategies have the most volatile idiosyncratic components.[5]

The extracted latent factor is plotted in Panel A of Figure 2. The factor displays a smoother behavior compared to the individual hedge fund residuals, as it captures their co-movement. At first glance, two episodes during which the latent factor takes large negative values are discernable. The first one takes place in August 1998, associated with the Russian default and the failure of LTCM. The Lehman Brothers bankruptcy gives rise to the second one

[5] The style indices are calculated based on information reported by hedge funds, so they are subject to the effects of style drift. Hence, the style specific results such as factor loadings and idiosyncratic volatilities should be interpreted accordingly. We thank the referee for pointing this out.

in September 2008. The factor mostly takes positive values in the first half of the sample, whereas it is usually negative since 2001.

Panels B through D in Figure 2 show the filtered and the smoothed probabilities of the three states respectively. Based on the smoothed probabilities, the crash state (State 1) captures the LTCM crisis (August 1998 to October 1998) and the subprime-led financial crisis of 2008 (June 2008 to April 2009). Hence, the factor stays in the crash state for 14 months out of 204 in the sample. In light of the existing literature, this state can also be regarded as a state of contagion, in which there is very strong left-tail dependence among hedge funds that cannot be explained by standard observable risk factors. State 2 prevails early in the sample (February 1994 to March 1995) and during most of the post tech-bubble era (November 2001 to December 2010), with the exception of the subprime crisis period. The rest of the sample is dominated by State 3, which has the positive mean and minimal volatility. Among the three states, State 1 has the shortest expected duration with six months. The expected durations of low mean/high volatility (State 2) and high mean/low volatility (State 3) states are about 45 and 27 months, respectively, implying higher persistence in the former state.[6]

3.2 Time-variation in Risk-Adjusted Returns

Next, we analyze risk-adjusted returns, or alpha, of hedge fund styles in our three distinct regimes. Table 5 reports exposures to the latent factor, unconditional alphas, and alphas in three states implied by the latent factor exposures. Our estimates imply that the average annual risk-adjusted return across the hedge fund styles, excluding the Dedicated Short strategy that has an

[6] Bollen and Whaley (2009) conduct structural break tests with respect to factor exposures and alpha using individual fund data from January 1994 to December 2005. When we compare their switching frequencies for funds of funds to our regime classification, we observe that the transition period from a high to a low risk-adjusted return state is associated with relatively large fractions of funds experiencing switches in their risk exposures and alpha.

insignificant exposure to the latent factor, goes down by about 7.2 percent and becomes -2.7 percent in the crash state. The average risk-adjusted return is about 2.2 percent in State 2 while it is 9.4 percent in State 3. Equity Market Neutral and Risk Arbitrage Strategies experience the minimum expected risk-adjusted return change due to their relatively low factor loadings but they are not immune to the abrupt shifts in the drift term of the common factor.

These findings, combined with the estimates of regime probabilities, suggest that hedge fund industry has been in a prolonged low-return state, on a risk-adjusted basis, since late 2001, which was amplified during the financial crisis of 2008. Fung et al. (2008) argued that alpha mostly disappeared after March 2000 using funds of funds data.[7] Using more recent data, we confirm this conjecture for almost all investment strategies with respect to endogenously determined regimes and the associated probabilistic inference from our flexible framework.

We do not attempt to empirically identify the underlying factors behind this finding as it is not the focus of our study. However, a possible explanation is that the capacity constraints in the hedge fund industry might hinder the ability to generate alpha, in line with the arguments developed in Berk and Green (2004). As noted by Fung and Hsieh (2004), the search for alternative investments in the aftermath of the tech-bubble led to increasing cash flows to hedge funds. Increased investor interest, and thus cash flows, may cause hedge funds to operate above their optimal size. This eventually cripples their capacity to generate significant risk-adjusted returns. Another channel is the higher fees charged by absolute return generating hedge fund managers. Therefore, persistent dominance of the low mean state in the last decade can be explained by increasing evidence for capacity constraints and the upward trend in management fees.

[7] Naik et al. (2007) also show that alpha decreases from 2000 to the end of 2004 using individual fund data. See Ramadoari (2012), Weidenmüller and Verbeek (2009), and Zhong (2008) for further evidence.

3.3 The Role of Funding Liquidity and Flight to Safety in Contagion

Liquidity has a substantial impact on hedge fund returns, even after controlling for systematic hedge fund risk factors. Sadka (2010) shows that funds that are highly sensitive to an aggregate market liquidity factor carry, on average, a 6 percent annual return premium over those funds that exhibit less sensitivity. He argues that although liquidity shocks are rare, they create notable differences in the cross-section of hedge funds returns due to their nature. Teo (2011) shows that even liquid hedge funds, those with monthly redemption terms or better, have significant exposures to liquidity risk. Kessler and Scherer (2011) develop a market-wide latent liquidity factor by using a dynamic state space model and show that this factor is negatively related to the hedge fund index returns.

Related to the extant literature on hedge fund returns and liquidity, it has been suggested that a major channel through which hedge fund returns exhibit co-movement beyond that implied by the hedge fund pricing factors is market and funding liquidity, see Boyson et al. (2010) and Dudley and Nimalendran (2011). The theoretical framework for using the funding liquidity variables in explaining hedge fund contagion is provided by Brunnermeier and Pedersen (2009). In their model, funding liquidity constraints, in the form of margin requirements, might trigger a market wide selloff, which might impede asset liquidity and cause liquidity spirals that adversely affect the prices of all financial assets. Since hedge funds use leverage extensively, it is of interest to analyze the relationship between our extracted latent hedge fund pricing factor and proxies for funding liquidity risk.

Motivated by these previous findings we consider two funding liquidity measures as potential channels of contagion: the margin requirement on S&P500 futures relative to the level of the index, and the TED spread.[8] To shed light on the potential role of panic in leading to a crash (or contagion) state, we also consider the CBOE's popular implied volatility index, VIX as a proxy.[9] We first construct a binary variable based on the estimated smoothed probabilities of the crash state. Specifically, this variable equals one when the smoothed probability of crash state is greater than 0.5 and 0 otherwise. We then estimate probit regressions, in which the dependent variable is the constructed dummy that reflects the regime classification from the dynamic factor model.

The results are presented in Table 6. VIX and margin requirement are in logarithms and all right-hand-side variables are standardized by subtracting their sample mean and dividing by standard deviation to facilitate comparison. When considered in isolation, an increase in VIX predicts a significant rise in the probability of the crash state. Specifically, a jump in the VIX from its sample average to its 99th percentile value causes the probability of the crash state to increase from 0.01 to 0.8. This counterfactual is actually in line with what happened during the LTCM crisis and late 2008 following the Lehman bankruptcy. A similar extreme jump in the TED spread brings the probability of crash from approximately 0.03 to 0.84 and from 0.02 to 0.46 in case of the margin requirement. Among the three variables, VIX has the highest explanatory power as measured by MacFadden pseudo R^2. When we consider these variables jointly, we find that all are individually significant, and the pseudo R^2 becomes an impressive 68

[8] We are grateful to Markus K. Brunnermeier for providing the margin requirements data on S&P 500 futures contracts.

[9] Coates and Hebert (2008) find significant correlation between a trader's cortisol, which plays a role in responding to stress and uncertainty, and market volatility. We acknowledge that VIX is an imperfect proxy for isolating the impact of panic among investors as significant reductions in market and funding liquidity may result in deviations from fundamentals and create high levels of asset price volatility. By including direct measures of liquidity alongside VIX we aim to isolate the panic effect in creating contagion.

percent. According to our estimates, when these three variables jointly move from their respective means to the 90th percentile, the probability of observing a crash state in hedge fund styles increases from 0 to 0.5. A simultaneous jump in these variables to 99th percentile values predicts that the crash state will take place with certainty. Note that we also considered direct measures of market liquidity in the probit regression, such as the innovations in aggregate liquidity proposed by Pastor and Stambaugh (2003), and found that they have no additional explanatory power for the crash state once we take into account VIX, TED spread, and the margin requirement.

Our results reinforce the results of Boyson et al. (2010) regarding importance of money market distress in the form of increased TED spread as a potential contagion channel. However, even after controlling for the TED spread, the margin requirement, emphasized by Dudley and Nimalendran (2011), has additional explanatory power along with our panic measure, VIX. Therefore, even though funding liquidity is a very important factor in leading to contagion in hedge fund returns by creating liquidity spirals à la Brunnermeier and Pedersen (2009), panic (or flight to safety) also plays an important, and possibly more dominant, role.

4. Robustness and Extensions

4.1 Time-variation in Risk Exposures

In this section we relax the assumption of constant risk exposures in Equation (1), as hedge funds typically follow dynamic investment strategies that might change sensitivity of returns to risk factors. Moreover, if this assumption is not warranted by the data, then the results from our Markov-switching dynamic factor model may be biased due to the inherent non-linearity in the first stage. Therefore, in order to address this issue, we now relax the assumption of constant risk exposures and use a more flexible framework to allow for time variation. In particular, we consider the framework first proposed by Ferson and Schadt (1996) for mutual funds and extended by Patton and Ramadorai (2011) to the case of hedge funds. Formally, we have,

$$(5) \qquad r_{i,t} = \alpha_i + \rho_i r_{i,t-1} + \boldsymbol{\beta}'_{i,t}\mathbf{x}_t + u_{i,t},$$

$$(6) \qquad \boldsymbol{\beta}_{i,t} = \boldsymbol{\beta}_i + \gamma_i Z_{t-1},$$

where Z_t is the variable that drives variation in risk exposures over time, and it is normalized to have a zero-mean so that $\boldsymbol{\beta}_i$ represents the average exposure. Substituting Equation (6) in (5) yields a simple regression that allows for time-variation in betas, but can be estimated by least squares. Following Patton and Ramadorai (2011) we consider four alternatives as the driver of time-varying betas: change in the three-month T-bill rate, the TED spread, volatility as measured by the VIX index, and the return on S&P500 index. Since the TED spread and VIX are highly persistent, we use their de-trended versions after applying an exponentially weighted moving average filter estimated by nonlinear least squares, as in Patton and Ramadorai (2011).

We find that the results are qualitatively very similar across the four variables considered. Hence, we present the results using the first principal component, which explains 45 percent of the total variation in the four series.[10] As in the case of constant betas, both the Davies procedure and the Hannan-Quinn criterion favor the three-state model. In the interest of space, we do not report all parameter estimates as they are mostly very close to the ones obtained under constant betas. The only notable change is that allowing time variation in betas reduces markedly volatility of the crash state while the mean changes only slightly.

The extracted factor is presented in Panel A of Figure 3 and the regime probabilities are shown in Panels B through D. It is clear that the latent factor is very similar to the one obtained

[10] All additional results are collected in a supplemental appendix, which is available from the authors upon request.

under constant betas. In fact, the correlation coefficient between the two factors is about 0.97. Similar conclusions apply to the filtered and smoothed regime probabilities, which are only slightly different from the baseline case that assumes constant betas. The dates when the regime switches around the LTCM crisis is unchanged, while the crash state associated with the subprime crisis now prevails from July 2008 to June 2009, instead of June 2008 to April 2009, according to the smoothed probabilities. The regime classifications for States 2 and 3 are almost identical to those from the baseline model. Overall, we conclude that time-variation in risk exposures, although empirically relevant, does not change our key findings.

4.2 Sub-sample Analysis

The most recent financial crisis has been unprecedented in so many ways that it is worthwhile to explore the robustness of our findings when we exclude this period from our sample. To check robustness of our results we re-estimate the models using data only up to December 2006 under both constant and time-varying risk exposure assumptions. Regime probabilities are presented in Figure 4. Panel A shows that the three-month period surrounding the LTCM crisis (August 1998 to October 1998) is identified as the only episode during which there was a crash in hedge-fund strategy returns under both constant and time-varying risk exposure assumptions. This regime classification is in complete agreement with the results from the full-sample for the corresponding period. Regarding states 2 and 3, the chronologies obtained under constant beta assumption are identical to those from the full sample, while allowing for time-varying risk exposure results in a somewhat different classification. The period from July 2002 to March 2003 is identified as belonging to the high mean state under time-varying risk exposures.

Parameter estimates, not reported to save space, are generally close to their full-sample counterparts in both cases. A noteworthy change is that the crash state is associated with a much lower mean since it is now identified as an even more extreme event. In addition, as one would expect, latent factor volatility goes down in all states with exclusion of the subprime crisis from the sample.

4.3 Evidence from Individual Fund Data

Our framework is not suitable to work with individual funds, as cross sectional dimension of such data makes estimation of the Markov-switching dynamic factor model practically impossible. Moreover, we require a large number of time series observations to accurately identify cyclical dynamics while individual fund data fails to satisfy this requirement on a consistent basis.

However, we can still reconcile our findings from style indices with the information content of individual fund data. For that purpose, we retrieve individual hedge fund data from Morningstar Direct. We eliminate fund-of-funds and funds with less than $5 million in assets under management and identify 5,868 unique hedge funds for which at least 24 consecutive months of return and size data are available. Starting from January 1996, for each month in the sample, we use the past 24 months of return data in a rolling regression framework and estimate the risk-adjusted returns (alpha) for individual hedge funds after accounting for the eight standard hedge-fund risk factors described above. We estimate cross-sectional average risk-adjusted return for each month by taking the median alpha across individual funds. Other outlier robust measures such as trimmed mean provide identical results. This procedure yields a time-series of risk-adjusted return across funds from January 1996 to December 2010.

The risk-adjusted return, along with smoothed regime probabilities from our baseline model, are plotted in Figure 5. Turning points of all three states from our dynamic factor model are associated with distinct patterns in the median risk-adjusted return. In Panel A, we observe sizable drops in the median risk-adjusted return following the two crash states in 1998 and in 2008-2009. The median risk-adjusted return responds to switches in regime with a lag of about six months, due to using a rolling estimation scheme. In Panel B, we see that switch to the low mean state marks the beginning of a period during which the median alpha consistently declines and stabilizes around a much lower value until the next regime change. Finally, in line with these observations, Panel C shows that the high mean state from our model is accompanied by relatively much higher alpha values.

To explore hedge funds' exposure to the latent factor, we estimate a nine-factor pricing regression by adding our extracted factor to the set of eight risk factors. Using the rolling regression methodology described above, we estimate the factor exposures for 24-month periods for each fund in our sample. The average latent factor exposure is significant and fluctuates around 0.7. This average point estimate is very close in magnitude to the average exposure implied by the style indices. Then, we form decile portfolios with respect to size, and compute the median exposure for each portfolio. We find that there is a statistically significant spread of about 0.1 between the latent factor exposures of the largest and the smallest deciles. We attribute this finding to the strong correlation between our extracted factor and funding liquidity proxies, as large funds will typically have more access to external funding and hence will possibly be more exposed to large funding shocks. Note also that this spread is almost twice as large in the first half of the sample during which State 3 prevails.

5. Concluding Remarks

The hedge fund industry has become an increasingly important part of the financial markets in the last two decades. There is evidence that hedge fund returns may exhibit strong co-movement in times of financial distress, above and beyond what would be justifiable by economic fundamentals, and that average risk-adjusted return has been in decline. Motivated by these findings, we apply a novel methodology to extract the latent common pricing factor in hedge fund returns and find that a three-regime specification is necessary to capture its dynamics. The first regime is a crash state with large negative mean and extreme volatility, the second regime is a low mean/high volatility state, and the third regime is a high mean state with minimal volatility. We also provide evidence for a decline in risk-adjusted returns for most investment strategies through probabilistic inference on endogenously determined regimes.

Our findings show that co-movement in hedge fund returns, after accounting for common risk factors, is not restricted to times of extreme financial turmoil, although these are the periods during which the strongest dependence is observed. Finally, we link the probability of observing the crash state to liquidity proxies (measured by the TED spread and the margin requirement on the S&P 500 contract) and panic or flight to safety (measured by the VIX index), and find that both play a significant role in leading to contagion.

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Table 1: Descriptive Statistics

Panel A: Hedge Fund Returns

	CA	DS	EM	EN	EDST	EMS	ERA	L/S
Mean	0.65	-0.20	0.76	0.66	0.90	0.82	0.58	0.86
Minimum	-12.59	-11.28	-23.03	-5.61	-12.45	-11.52	-6.15	-11.43
Maximum	5.81	22.71	16.42	3.66	4.15	4.78	3.81	13.01
Std. Dev.	2.04	4.92	4.39	1.09	1.91	1.89	1.21	2.88
Autocorrelation	0.57	0.10	0.32	0.18	0.40	0.31	0.29	0.21
Skewness	-2.76	0.70	-0.78	-1.14	-2.29	-1.84	-1.08	-0.01
Kurtosis	16.17	1.52	5.03	6.11	12.04	9.41	5.09	3.46

Notes: Descriptive statistics of the returns on the following hedge-fund investment style indices: Convertible Arbitrage (CA), Dedicated Short-bias (DS), Emerging Markets (EM), Equity Neutral (EN), Event Driven Distressed (EDST), Event Driven Multi-strategy (EMS), Event-Driven Risk Arbitrage (ERA), and Long-short Equity (L/S). AR(1) denotes first order autocorrelation. Sample period is from Jan 1994 to December 2010.

Panel B: Pricing Factors

	PTFSBD	PTFSFX	PTFSCOM	EM	SIZE	BOND	CRDT	EMG
Mean	-1.45	0.00	-0.38	0.75	0.08	-0.01	0.00	0.63
Minimum	-25.36	-30.13	-23.04	-16.79	-16.38	-1.08	-0.79	-29.29
Maximum	68.86	90.27	64.75	9.78	18.41	0.95	1.53	16.66
Std. Dev.	14.97	19.41	13.77	4.54	3.51	0.28	0.23	7.07
Skewness	1.44	1.41	1.27	-0.71	0.27	0.02	1.38	-0.78
Kurtosis	2.89	2.92	2.63	0.97	4.71	1.06	11.08	1.96

Notes: Descriptive statistics of the following hedge-fund pricing factors: Primitive trend following strategies on bonds, currencies, and commodities (PTFSBD, PTFSCOM, PTFSCOM respectively), the equity market factor (EM), the size spread (SIZE), the bond market factor (BOND), the credit spread (CRDT), and the emerging market factor (EM). See the main text for detailed descriptions of the empirical proxies for these factors. Sample period is from Jan 1994 to December 2010.

Table 2: Pricing Regression Results

	CA	DS	EM	EN	EDST	EMS	ERA	**L/S**
Constant	**0.370**	**0.477**	0.203	**0.449**	**0.440**	**0.430**	**0.359**	**0.384**
	(2.87)	(2.16)	(1.14)	(5.35)	(3.93)	(3.85)	(4.42)	(3.05)
AR1	**0.366**	**0.080**	**0.241**	**0.204**	**0.300**	**0.270**	**0.211**	**0.163**
	(4.21)	(1.76)	(4.29)	(3.53)	(5.74)	(4.87)	(3.82)	(2.44)
PTFSBD	-0.010	0.003	**-0.029**	0.001	**-0.020**	**-0.021**	**-0.010**	-0.013
	(-1.64)	(0.21)	(-1.90)	(0.27)	(-1.74)	(-2.38)	(-1.66)	(-1.30)
PTFSFX	-0.002	0.000	-0.009	**0.007**	0.003	0.005	0.002	0.003
	(-0.50)	(-0.01)	(-0.91)	(2.01)	(0.63)	(0.85)	(0.45)	(0.39)
PTFSCOM	-0.005	-0.021	0.019	0.006	0.009	0.004	-0.001	0.014
	(-0.56)	(-1.19)	(1.60)	(1.42)	(1.38)	(0.64)	(-0.20)	(1.56)
EM	-0.001	**-0.788**	-0.070	**0.099**	**0.142**	**0.078**	**0.048**	**0.276**
	(-0.03)	(-9.85)	(-1.20)	(2.84)	(5.05)	(2.83)	(2.37)	(5.37)
SIZE	-0.001	**-0.481**	0.022	-0.018	**0.065**	**0.064**	**0.070**	**0.285**
	(-0.03)	(-7.35)	(0.39)	(-0.89)	(2.74)	(2.17)	(3.19)	(4.55)
BOND	**-1.753**	-0.946	**-1.164**	-0.057	-0.502	-0.145	-0.430	**-1.402**
	(-3.04)	(-1.10)	(-1.84)	(-0.24)	(-1.31)	(-0.35)	(-1.58)	(-2.71)
CRDT	**-4.435**	**-3.051**	0.844	-0.020	-1.079	-1.005	-0.016	0.395
	(-4.24)	(-1.94)	(0.77)	(-0.05)	(-1.57)	(-1.30)	(-0.04)	(0.37)
EMG	**0.048**	-0.064	**0.517**	0.025	**0.070**	**0.112**	**0.061**	**0.120**
	(2.34)	(-1.33)	(11.13)	(1.62)	(2.81)	(4.96)	(3.67)	(3.75)
$\bar{R}^2$	0.56	0.69	0.71	0.28	0.59	0.59	0.41	0.63

Notes: Results of the first stage pricing regressions of hedge-fund style index returns on risk factors. See the notes to Table 1 for abbreviations of investment styles and pricing factors. Each column provides the regression coefficient estimates and asymptotic t-ratios (in parenthesis) for the corresponding style index return. Heteroskedasticity robust standard errors are used to calculate t-ratios. Coefficient estimates reported in bold indicate significance at 10 percent level. Sample period is from Jan 1994 to December 2010.

Table 3: Maximum Likelihood Estimates of the Markov-Switching Dynamic Factor Model

Parameter	Estimate (t-ratio)	Parameter	Estimate (t-ratio)
$\boldsymbol{v_1}$	-0.882	θ_3	1.135
	(-1.81)		(4.71)
$\boldsymbol{v_2}$	-0.278	θ_4	0.339
	(-3.16)		(3.79)
$\boldsymbol{v_3}$	0.598	θ_5	0.943
	(5.50)		(6.92)
$\boldsymbol{\phi}$	-0.306	θ_6	1.152
	(2.89)		(7.73)
$\boldsymbol{\tau_1}$	1.718	θ_7	0.483
	(4.48)		(5.11)
$\boldsymbol{\tau_2}$	0.527	θ_8	1.153
	(6.11)		(6.10)
$\boldsymbol{\tau_3}$	0.348	σ_1	1.069
	(4.61)		(17.12)
$\boldsymbol{p_{11}}$	0.836	σ_2	2.662
	(7.88)		(20.12)
$\boldsymbol{p_{12}}$	0.097	σ_3	2.115
	(1.27)		(19.39)
$\boldsymbol{p_{21}}$	0.012	σ_4	0.860
	(2.09)		(19.65)
$\boldsymbol{p_{22}}$	0.978	σ_5	0.925
	(55.96)		(17.38)
$\boldsymbol{p_{31}}$	0.020	σ_6	0.745
	(0.92)		(12.73)
$\boldsymbol{p_{32}}$	0.018	σ_7	0.821
	(0.89)		(19.26)
$\boldsymbol{\theta_2}$	-0.279	σ_8	1.435
	(-1.33)		(18.55)

Notes: Maximum likelihood estimates and asymptotic t-ratios (in parenthesis) of the Markov-switching dynamic factor model given in equations (2) - (4) with $M = 3$. Sample period is from Jan 1994 to December 2010.

Table 5: Time Variation in Risk-adjusted Returns

	CA	DS	EM	EN	EDST	EMS	ERA	L/S
Latent Factor Exposure	1.00	-0.28	1.13	0.34	0.94	1.15	0.48	1.15
Unconditional RAR	4.44	5.73	2.43	5.39	5.28	5.16	4.31	4.61
RAR in State 1	-3.67	7.99	-6.76	2.64	-2.37	-4.19	0.39	-4.74
RAR in State 2	1.88	6.44	-0.47	4.53	2.86	2.21	3.07	1.66
RAR in State 3	9.93	4.20	8.67	7.26	10.46	11.49	6.96	10.94

Notes: RAR denotes risk-adjusted return. State dependent RARs are calculated in relation to the latent factor exposures. All return related figures are reported on an annualized basis. Sample period is from Jan 1994 to December 2010.

Table 6: Crash State, and the Effects of Volatility and Liquidity

Constant	VIX	TED	MRGN	MacFadden R^2
-2.543	1.408			0.49
(-6.01)	(4.79)			
-1.915		0.802		0.36
(-12.26)		(5.69)		
-1.972			0.943	0.24
(-7.27)			(3.78)	
-3.312	1.487	0.885	0.490	0.68
(-6.02)	(3.22)	(5.30)	(2.18)	

Notes: Probit regression results when the crash dummy is regressed on volatility and liquidity proxies. VIX is the natural logarithm of the CBOE Volatility Index, MRGN is the natural log of margin requirement on S&P500 futures relative to the level of the index, and TED is the spread between three month T-Bill and Libor rates. Sample period is from Jan 1994 to December 2010.

Figure 1: Residuals of First Stage Pricing Regressions

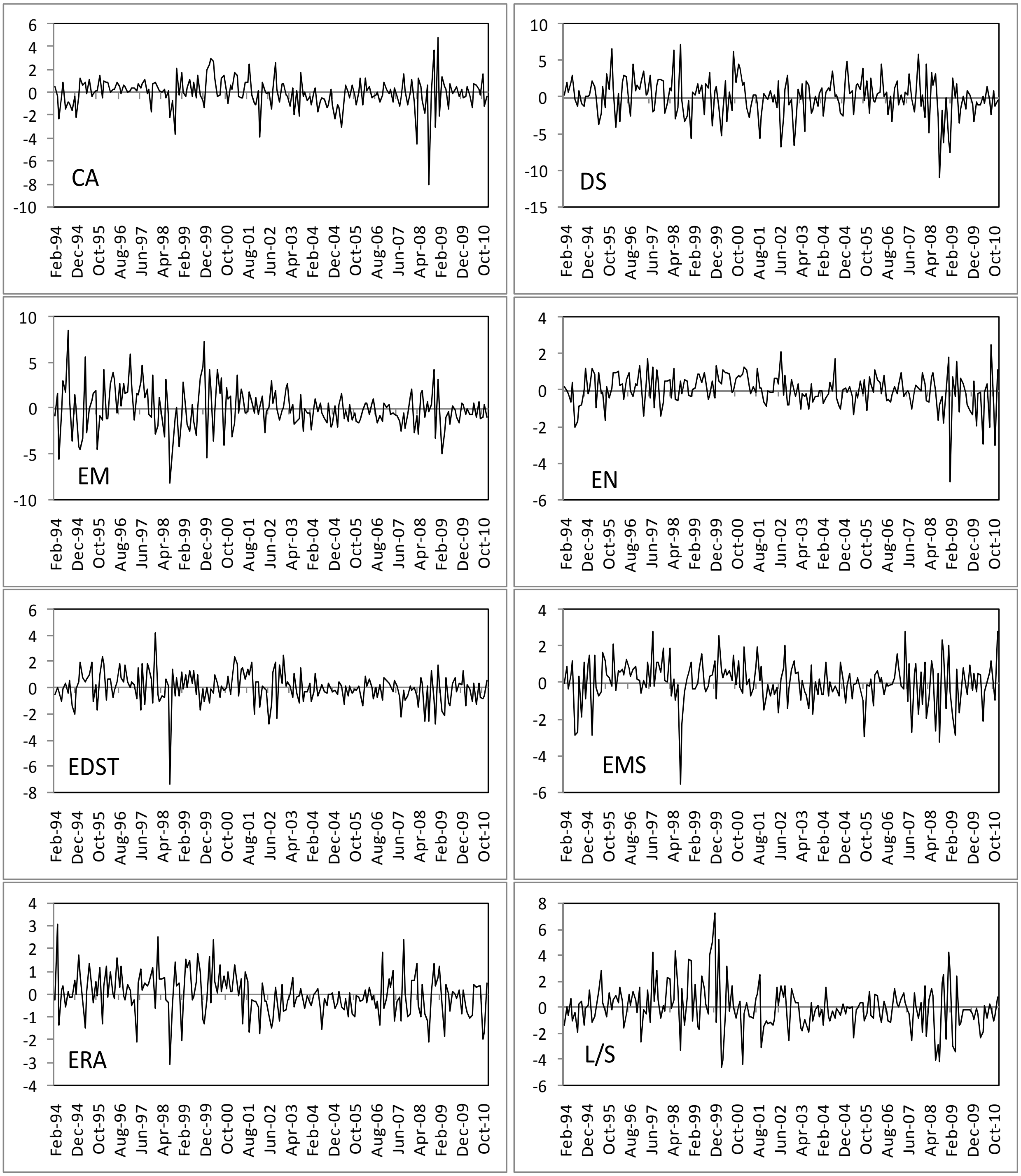
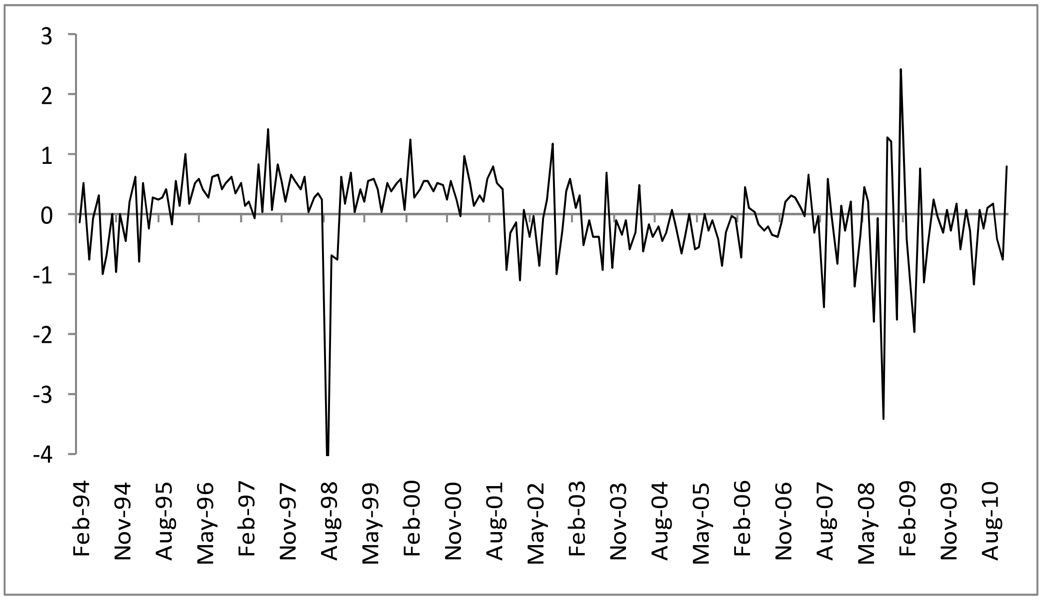


Figure 2: Latent Factor and Regime Probabilities from the Markov-Switching Dynamic Factor Model

Panel A: Latent factor



Panel B: Probability of the Crash State

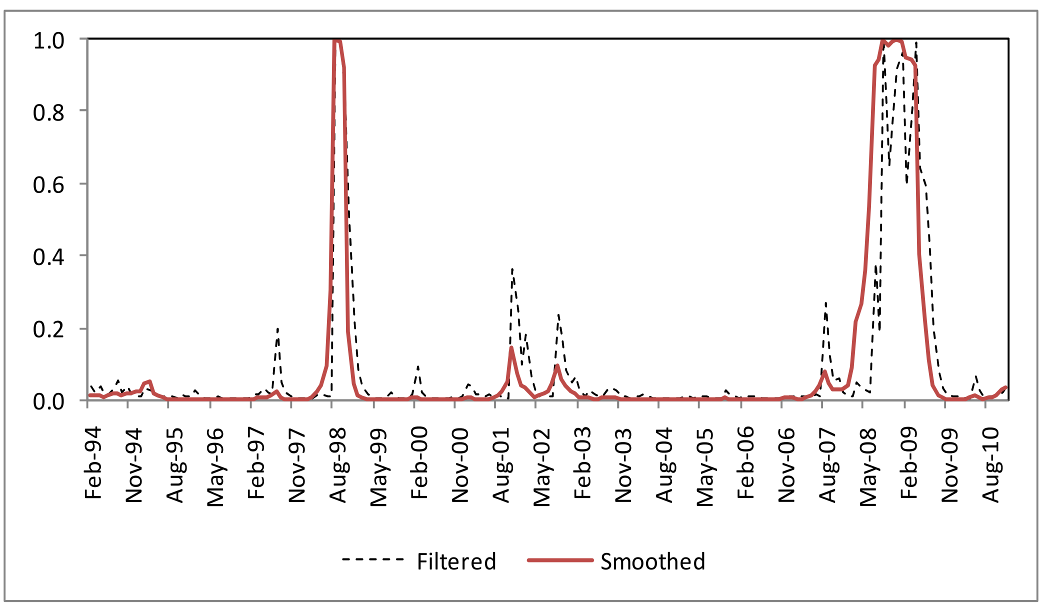
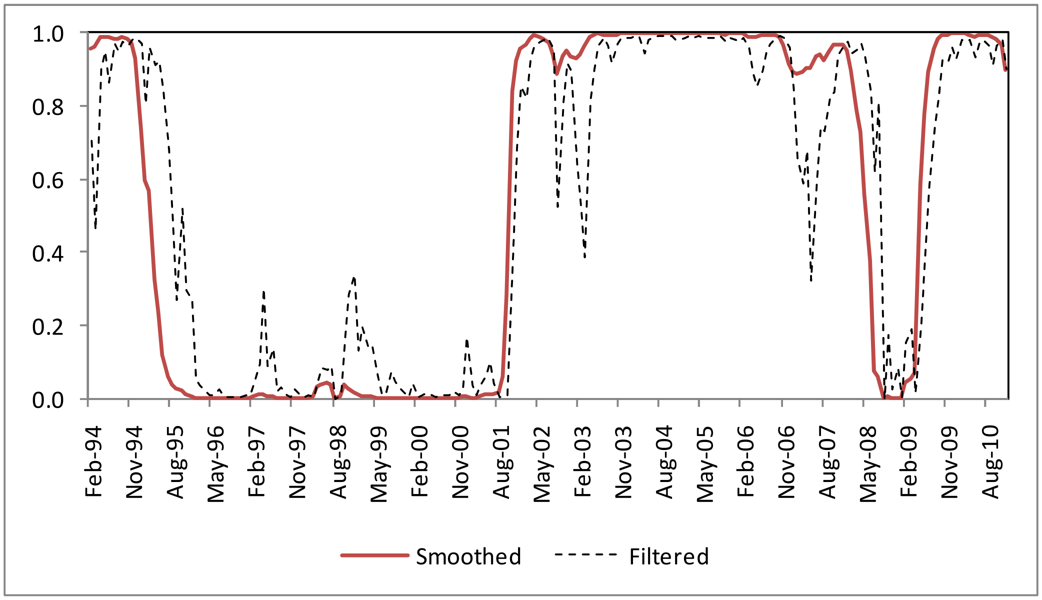


Figure 2 (cont'd)

Panel C: Probability of the Low-mean State



Panel D: Probability of the High-mean State

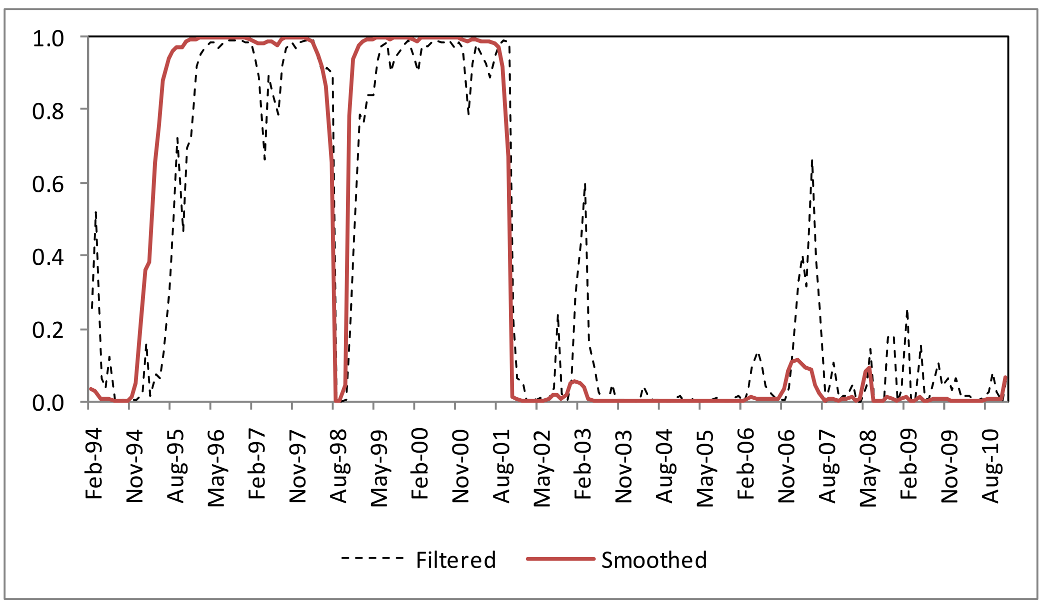
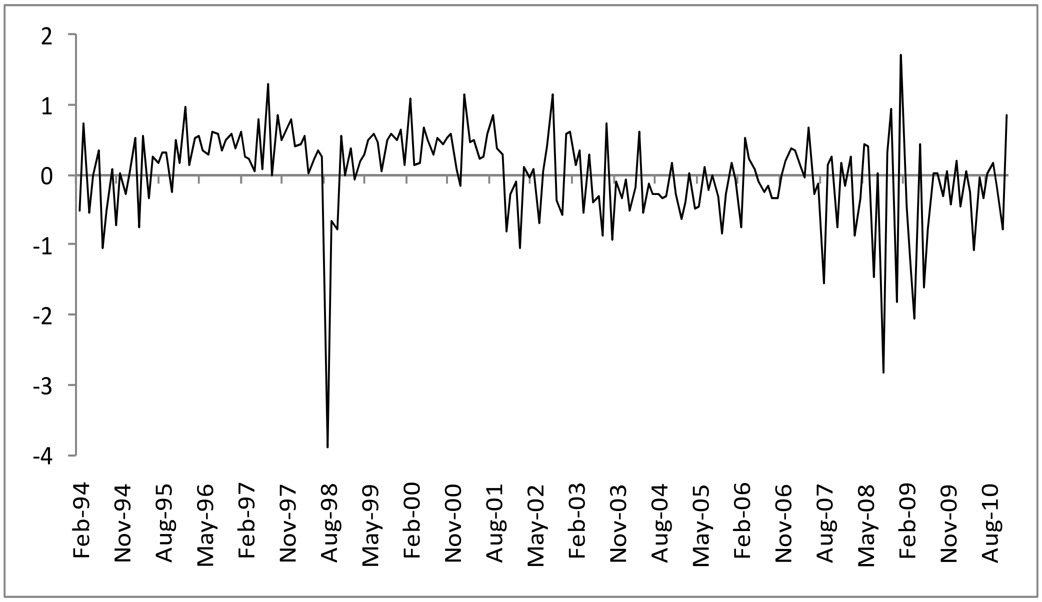


Figure 3: Latent Factor and Regime Probabilities from the Markov-Switching Dynamic Factor Model with Time-varying Risk Exposures in the First Stage Regression

Panel A: Latent factor



Panel B: Probability of the Crash State

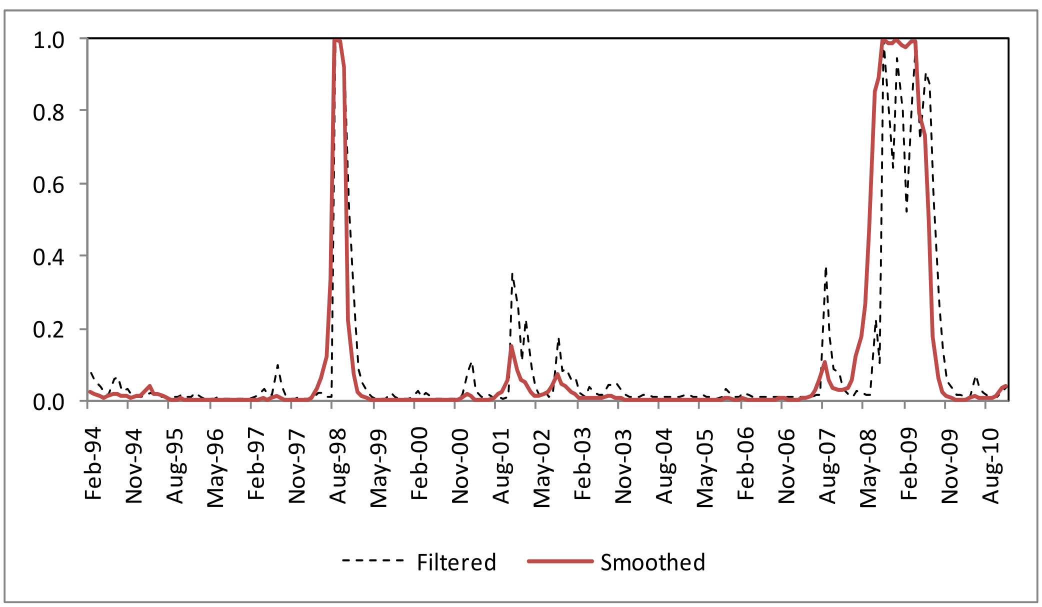
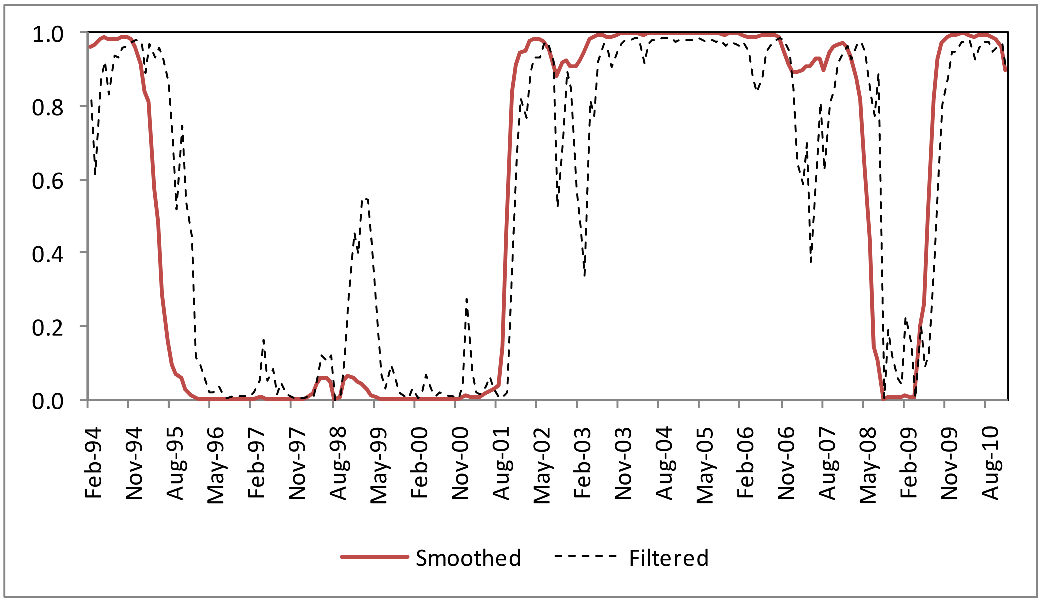


Figure 3 (Cont'd)

Panel C: Probability of the Low-mean State



Panel D: Probability of the High-mean State

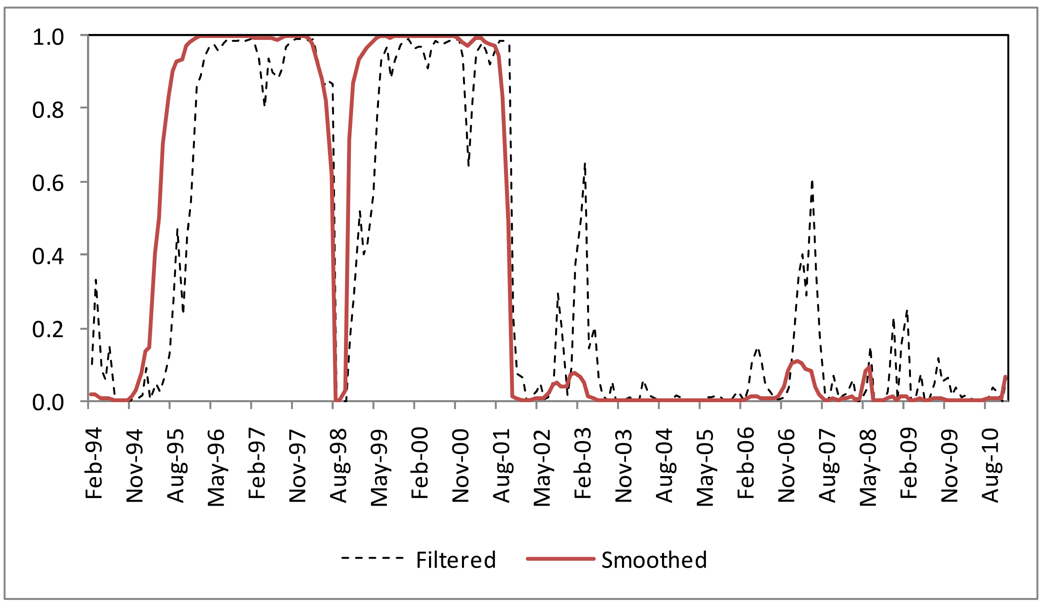
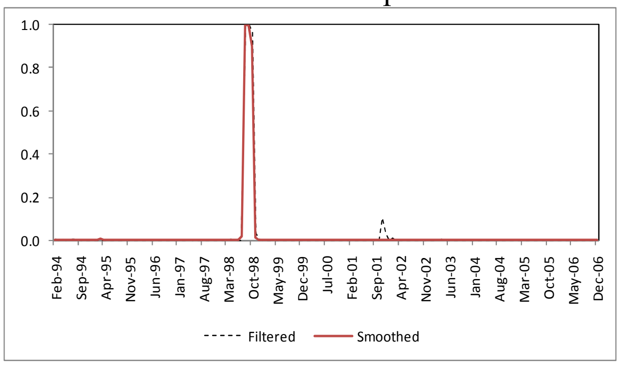


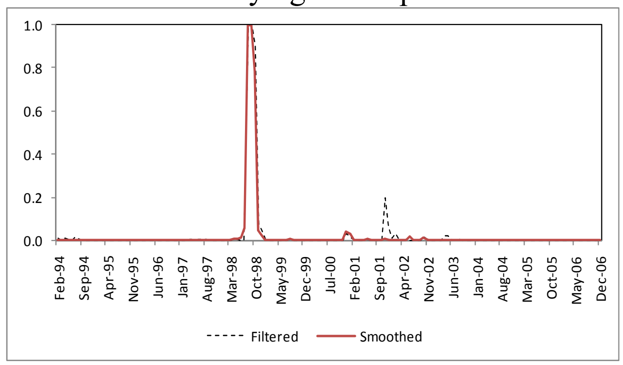
Figure 4: Sub-sample Results

Panel A: Probability of Crash State

Constant risk exposures

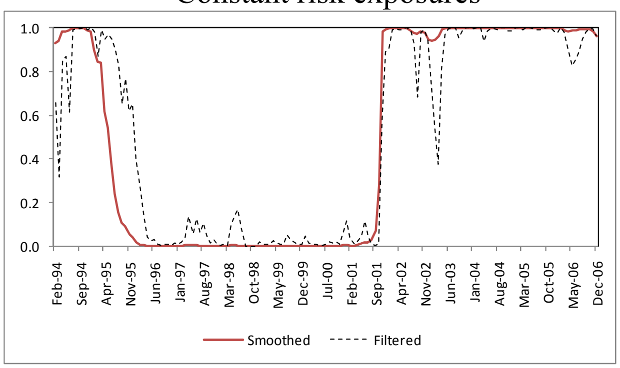


Time-varying risk exposures

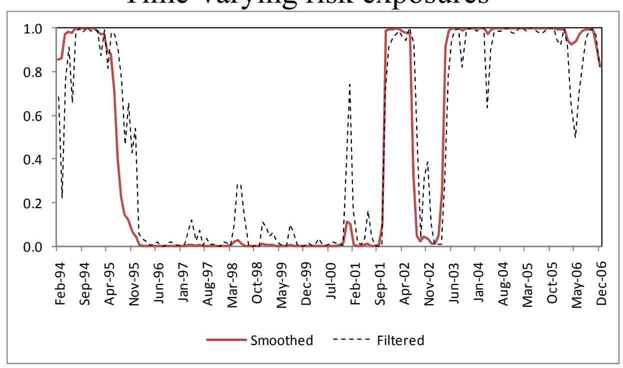


Panel B: Probability of Low-mean State

Constant risk exposures

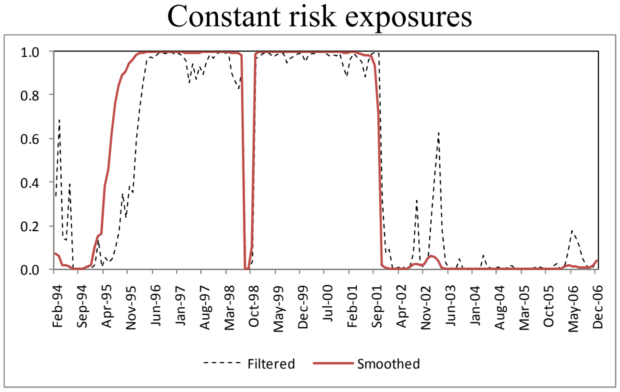


Time-varying risk exposures



Panel C: Probability of High-mean State

Constant risk exposures



Time-varying risk exposures

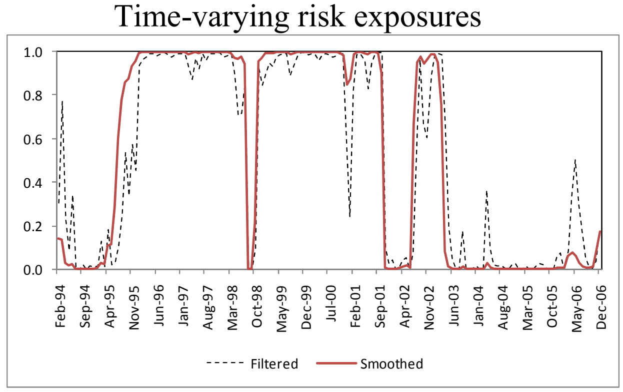
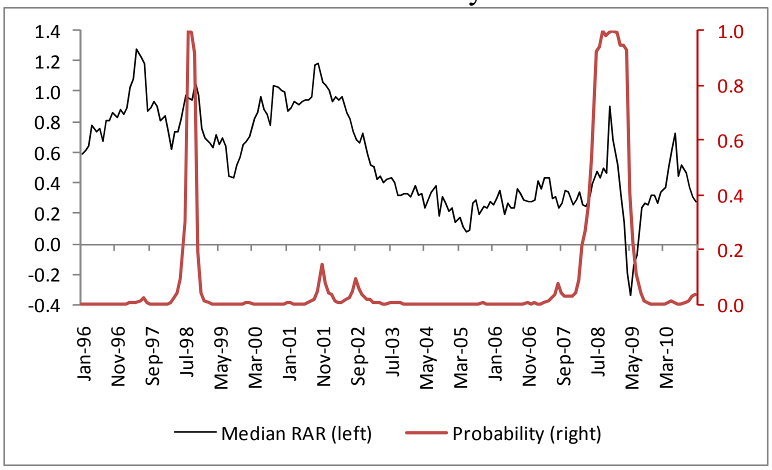
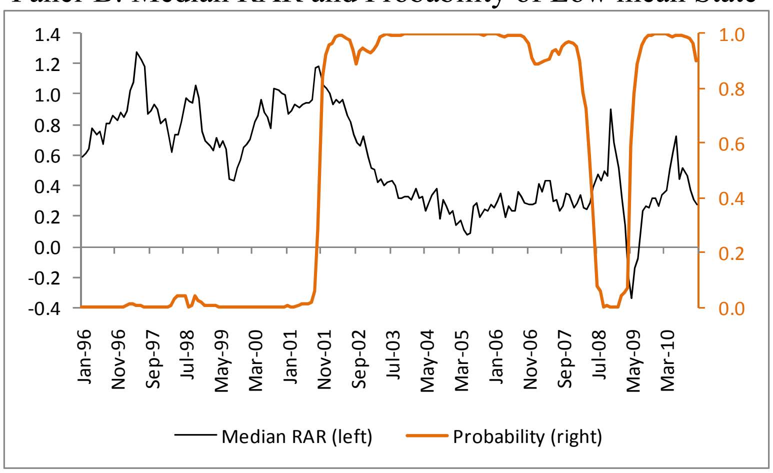


Figure 5: Median Risk-adjusted Return (RAR) across Individual Hedge Funds and Smoothed Regime Probabilities

Panel A: RAR and Probability of Crash State



Panel-B: Median RAR and Probability of Low mean State



Panel-C: Median RAR and Probability of High mean State