Hedge Fund Systemic Risk Signals

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Abstract

In this paper we realize an early warning system for hedge funds based on specific red flags that help to detect symptoms of impending extreme negative returns and contagion effect. To do this we rely on regression trees analysis identifying a series of splitting rules which act as risk signals. The empirical findings prove that contagion, crowded-trade, leverage commonality and liquidity concerns are the leading indicators to be used to predict worst returns. We do not only provide a variable selection among potential predictors, but we also assign the values for such predictors that should be considered as excessively risky. Out-of-sample analysis documents that such an approach would have been able to predict more than 90 per cent of the total worst returns occurred over the period 2007-2008. Yet, an in depth analysis of contagion reveals a changing and complex nature of hedge fund systemic risk which reflects on poor forecasting ability.

Keywords: Hedge Funds; Dynamic Conditional Correlations; Time-varying beta; Regression Trees.

JEL codes: C11; C13 ; G12 ; G13.

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I. Introduction

In June 2006 the European Central Bank issued a warning on the risk posed by hedge fund industry for financial stability arguing that "... the increasingly similar positioning of individual hedge funds within broad hedge fund investment strategies is another major risk for financial stability … . Some believe that broad hedge fund investment strategies have also become *increasingly correlated*, thereby further increasing the potential adverse effects of disorderly exits from crowded trades." The events of 2007-2009 confirmed how this warning was so timely highlighting the importance of monitoring the comovements of hedge fund strategies over time.

In a retrospective view, the sub-prime crisis goes back to August 1998, when LTCM collapsed because Russia defaulted on its GKO government bonds. In both cases, credit spreads widened then generating a "margin call spiral", which in turn sparked extreme losses due to illiquid portfolio positions. However, this is an analogy on the crisis effects and not on their inner causes. On this point, Khandani and Lo (2007) note that "In contrast to August 2007 … the well-documented demand for liquidity in the fixed-income arbitrage space of August 1998 had no discernible impact on the very same strategy."

While LTCM and the sub-prime crises are two cases in which hedge funds have been clearly associated with systemic risk (Brown, et al., 2009), the difference between the two events is the way through which the risk propagated among fund managers. In 1998, the default was on the LTCM proprietary strategy, while August 2007 was a fund strategy failure as a whole, showing how the systemic risk induced by increasingly commonality in hedge fund strategies has become predominant within the industry. In such a new context, where complex and highly dynamic financial ramifications form intricate connections among institutions and markets, understanding and preventing systemic risk within hedge fund industry are of primary importance. The purpose of this paper is to consider both issues.

How can we define systemic risk whithin hedge fund industry? While a clear definition is controversial among academics and policymakers, a possible generalization of the concept bringing back its multiple facets is: the risk that an economic shock or institutional failure, i.e. a systemic event, causes a chain of bad economic consequences, such as contagion, spillover effects or, less dramatically, significant losses to financial institutions or substantial financial-market price volatility. This definition not only emphasizes the concept of a broad-based risk in the financial system, but also impliedly delineates a "pivotal" notion of systemic risk since it focuses on one financial sector to lever on the other interconnected sectors. For hedge funds, this signifies that exploring the risk of the industry as a whole is the first step to understand the potential destabilizing contribution of the hedge funds for the entire financial system.

The economic mechanism by which systemic risk originates and propagates among hedge funds can be explained with Stein (2009), who argues that sophisticated investors, "in the process of pursuing a given trading strategy, … inflict negative externalities on one another" through crowded-trade and leverage effects. This is because if traders follow the same set of signals to buy the same stocks using leverage, a negative shock could force to liquidate common portfolio assets to meet margin calls, then reflecting on negative price pressures which in turn translate on negative returns of the traders.

Ephasizing the role of comovements induced by both crowded-trade and leverage effects, Stein (2009) suggests a way to explore the systemic risk which is economically consistent with the new literature on liquidity spirals (Brunnermeier and Pedersen, 2009) and the studies on leveraged arbitrageurs (Shleifer and Vishny, 1997; Kyle and Xiong, 2001; Morris and Shin, 2004). Furthermore, the economic setting assumes a *stylised* world where sophisticated arbitrageurs have rational expectations making optimizing leverage decisions, which is consistent with the *real* world of hedge funds. Following this line of reasoning, many papers empirically explore how hedge funds comove together especially in times of stress. Billio et al. (2010) look at correlation to capture the degree of connectivity among financial institutions and its impact in terms of contagion, spillover effects and joint crashes. Boyson et al. (2010) focus on clustering of worst returns and using the arguments developed in Bakaert et al. (2005) they define hedge fund contagion as the "correlation over and above what one would expect from economic fundamentals". In their view, the clustering of worst returns is conceived as a form of excess correlation, which in turns reflects on contagion or interdependencies (Forbes and Rigobon, 2002)[1]. Adrian (2007) relies on hedge fund return correlation to proxy the degree of similarities of hedge fund strategies which is assumed to be a key determinant of the risk of the entire hedge fund industry.

Using data from the CSFB/Tremont indices over the period from January 1994 to September 2008 our work looks at excess correlation as a symptom of contagion, which is proxied by the number of the other hedge fund styles that have a worst return in the same month[2] as in Boyson et al. (2010). We follow Boyson et al. (2010) also to define hedge fund tail event, which is identified by returns that fall in the bottom 10% of a hedge fund style's monthly returns, and to compute correlations using filtered returns (asset pricing model residuals), in order to better circumscribe the risk induced by commonality in proprietary trading strategies then giving the proxy for crowded-trade. Correlations are also computed for systematic risk exposure estimates (proxy for leverage commonality) and common risk factors (proxy for risk factor commonality), since we conjecture that contagion could be connected also to commonalities in beta dynamics and cross-market comovements.

The first question we address in this paper is about the value of the proxies for commonality in (i) trading strategies, (ii) leverage dynamics and (iii) risk factors we have to consider as alarm thresholds for hedge fund worst returns. We try to answer this question taking into account also the proxy for contagion as well as other potential predictors for excess negative returns.

A second and related question we face concerns the contagion. Are we able to predict the number/proportion of hedge funds which will experience a worst return? In answering this second

[1] Forbes and Rigobon (2002) define significant increases in cross-market comovements as *contagion*, while continued high levels of correlations are defined as *interdependence*.

[2] Such a definition of contagion derives from the literature on sovereign defaults. In Eichengreen et al. (1996) contagion is indeed defined as a case where knowing that there is a crisis elsewhere increases the probability of a crisis at home, even after taking into account for country's fundamentals.

question we give a measure for systemic risk since we provide a probability estimate of hedge fund styles that could be subject to extreme negative returns.

To do this we proceed in three methodological steps.

In the first, we use a Bayesian time-varying CAPM-based beta model (Amisano and Savona, 2008; Savona, 2009) to estimate filtered returns and time-varying betas.

In the second, we measure the dynamic conditional correlations using the model introduced in Alexander (2002) based on GARCH volatilities of the first few principal components of a specific system of covariates.

In the third and final step, we realize an early warning system (EWS) using regression trees analysis. This is a nonparametric statistical technique, introduced in Breiman, et al. (1984), through which the predictor space is recursively partitioned into subsets in which the distribution of Y is successively more homogeneous. The structure of regression trees is based on some splitting rules, namely a series of threshold values associated with selected input variables in order to get the best nonlinear predictor (in a mean squared error sense) of the dependent variable of interest. Using regression trees analysis we develop a monitoring risk system for hedge funds in the spirit of the signal approach (Kaminsky et al. 1998; Manasse and Roubini, 2009) based on specific "red flags" that help to detect symptoms of impending hedge fund worst returns and contagion effect.

In our empirical analysis we prove that contagion and leverage commonality play the role of leading indicators in signaling potential worst returns. Furthermore, market and funding liquidity concerns lead together to increase the risk for hedge funds, since risky clusters are signaled when credit spread widens and funds tend to de-leverage. A clinical study about the reasons of LTCM and sub-prime crises in terms of worst returns suffered by hedge funds suggests that, on the one hand, LTCM collapse was mainly due to extreme commonality in leverage dynamics and higher leverage level, on the other, the main reasons of sub-prime crisis were the crowded-trade together with substantial drop in leverage commonality due to strong de-leveraging.

By inspecting the contagion effect we found a more stronger changing nature of their inner mechanisms. In August-October 1998 extreme interconnectedness in leverage dynamics together with illiquidity shocks were the reasons for contagion; interestingly, crowded-trade effects were virtually absent. The story was different for the sub-prime crisis, when the transmission channels changed significantly. We indeed ascribed the quant crisis (August 2007) to dramatic de-leveraging and de-correlations in leverage dynamics together with strong crowded-trade. While the huge systematic volatility of hedge fund risk factors exploded with the Lehman crash (September 2008) was the culprit of the higher negative impact over the entire hedge fund industry ever.

The paper is organized as follows. Section II describes how filtered returns and time-varying betas are estimated. Section III discusses the methodology used to estimate dynamic conditional correlations, while Section IV presents the regression trees approach we follow to realize the early warning system. The dataset used in the paper is discussed in Section V and Section VI reports the empirical result. Finally, Section VII concludes.

II. Filtered Returns and Time-Varying Betas

Hedge fund returns and time-varying betas are estimated using the 3-equation system implemented in Savona (2009), which is a model developed within a Bayesian framework in which fund returns are modelled by imposing a pseudo-stochastic process on the path of a CAPM-based beta. The econometric procedure is as follows[3]:

- First, a multi-beta structural model with the 7+1 risk factors proposed in Fung and Hsieh (2004, 2007a,b) (FH) is estimated using the expectations net of the risk-free rate as a fund-specific style benchmark, $r_{b,i,t} = E(R_{i,t}) - r_{f,t}$ with $R_{i,t} = A_i + \sum_{k=1}^{8} B_{i,k} F_{k,t} + E_{i,t}$ ($r_{f,t}$ is the risk-free rate, $R_{i,t}$ is the return of the hedge fund index *i*, A_i is a constant, $B_{i,k}$ is the beta on factor *k*, $F_{k,t}$ is the return of factor *k* and $E_{i,t}$ is the error term).

[3] See Savona (2009) and Amisano and Savona (2008) for technical details.

- Second, within a Bayesian framework a 3-equation system is estimated where:
    (i) the first equation describes the excess return behavior using a CAPM-based model expressed as $r_{p,t} = \alpha_p + \beta_{p,t} r_{b,t} + \varepsilon_{p,t}$ (α_p is a constant, $\beta_{p,t}$ is the time-varying beta, $r_{b,t}$ is the excess benchmark return, and $\varepsilon_{p,t}$ is error term, i.e. the "filtered return");
    (ii) the second equation is the single beta relative to the regression-based style benchmark which is assumed to follow the process $\beta_{p,t} = \mu + \phi(\beta_{p,t-1} - \mu) + \Gamma' \mathbf{z}_t + \eta_{p,t}$ (ϕ is the persistence beta parameter, μ the unconditional mean-reverting beta term, Γ' the transposed vector of sensitivities towards $\mathbf{z}_t$, which is the vector of some contemporaneous observable covariates, and $\eta_{p,t}$ is the stochastic component);
    (iii) the third equation is the fund-specific style benchmark excess return which is modeled using the same set of covariates used to describe the beta evolution and expressed as $r_{b,t} = \Lambda' \mathbf{z}_t + u_{b,t}$ (Λ' is the transposed vector of sensitivities towards $\mathbf{z}_t$ and $u_{b,t}$ is the unexpected benchmark return).

The hypothesis underlying this model is that some exogenous variables ($\mathbf{z}_t$) act as "primitive risk signals" (PRS) that hedge fund managers use in changing their trading strategies. For this reason these covariates enter into the beta process. In such a setting, the systematic risk exposure may be modified in response to changes in PRSs and risk factors themselves (the style benchmark). The model also imposes a non-negative covariance matrix in the system innovation, developing a framework that could help to explain how expected and unexpected hedge fund returns, i.e. the filtered returns, are correlated with systematic risk factors through the beta dynamics[4].

[4] As discussed in Savona (2009), by imposing such a non-negative covariance matrix we do not try to remove the stochastic inaccessibility inherent the price process, but, rather, we offer a possibility to tame it. In a sense, where the PRSs fail to explain the beta dynamics, the innovations try to measure what is, generally, unobservable, namely the measurement error of observable PRSs.

III. Time-Varying Correlations

Since our objective is to scrutinize the time evolution of crowdedness in trading strategies, together with leverage commonality and risk factor commonality, we rely on dynamic conditional correlation estimators which allow to compute potentially very large correlation matrices with clear computational advantages, since they are parameterized directly.

We followed Alexander (2002) whose method is based on GARCH volatilities of the first few principal components of a specific system of factors then using the corresponding factor weights for generating correlations of the original system.

III.1. Principal Components and Covariances

One starts with a $T \times k$ matrix $\boldsymbol{Y}$ of asset or risk factor returns extracting uncorrelated r principal components with $r < k$, each component being a linear combination of the original data with weights the eigenvectors of the correlation matrix of $\boldsymbol{Y}$ and variances the corresponding eigenvalues. Letting $\boldsymbol{W}$ be the matrix of eigenvectors we have:

$$\boldsymbol{P} = \boldsymbol{XW} , \tag{1}$$

where $\boldsymbol{P}$ is the $T \times r$ matrix of principal components and $\boldsymbol{X}$ the normalized (each column has zero mean and variance one) matrix of $\boldsymbol{Y}$. Since $\boldsymbol{W}$ is orthogonal, then

$$\boldsymbol{X} = \boldsymbol{PW}' + \boldsymbol{E} , \tag{2}$$

in which $\boldsymbol{E}$ is the $T \times (k - r)$ matrix of error terms, since we use the first $r < k$ principal components. Having r orthogonalized components, their covariance matrix $\boldsymbol{D}$ will be diagonal and taking variances of $\boldsymbol{Y}$ gives

(3) $$\boldsymbol{V} = \boldsymbol{ADA}' + \boldsymbol{V_e},$$

where $\boldsymbol{A}$ is the $k \times r$ matrix of normalized factor weights, $\boldsymbol{D} = \mathrm{diag}\left(\boldsymbol{V}\left(\boldsymbol{p}_1\right) + \ldots + \boldsymbol{V}\left(\boldsymbol{p}_r\right)\right)$ is the covariance matrix of the principal components and $\boldsymbol{V_e}$ is the covariance matrix of the errors. Choosing r so as to make $\boldsymbol{E}$ negligible, we can ignore $\boldsymbol{V_e}$, giving the approximation

(4) $$\boldsymbol{V} \approx \boldsymbol{ADA}',$$

which leads to significant computational efficiency since we need to estimate only the r variances instead of the $k(k+1)/2$ variances and covariances of the matrix $\boldsymbol{Y}$.

III.2. Dynamic Conditional Correlations

Having discussed the relation between a generic dataset and the corresponding principal components, the computation of dynamic conditional correlations is now simple to understand. The procedure is as follows:

- First, extract the first r principal components from the original matrix data $\boldsymbol{Y}$ so as to achieve a cumulative explained variance in order to make the residual variance as smaller as possible.
- Second, for each component, estimate the conditional time-varying variance using the univariate GARCH(1,1):

(5) $$\sigma_t^2 = \varpi + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2$$

  with $\varpi > 0, \alpha, \beta \geq 0$ and where α measures the response to lagged innovation ε_{t-1}^2 and β the persistence in volatility.
- Third, over the period of interest compute the pairwise correlations for all $i \neq j$ in $\boldsymbol{Y}$ as

(6) $$\rho_{i,j,t} = \frac{a_i' d_t a_j}{\left[\left(a_i' d_t a_i\right)^{0.5}\right]\left[\left(a_j' d_t a_j\right)^{0.5}\right]}$$

where a is the $r \times 1$ vector of normalized factor weights for i and j, and d_t is the $r \times 1$ vector of the conditional variances in t for the first r principal components.

III.3. Aggregating Dynamic Conditional Correlations

In order to aggregate pairwise correlations in hedge fund filtered returns and time varying betas we looked at the hedge fund industry as a single portfolio, as recently suggested by Lo (2008) to inspect the systemic risk. First, we estimate all pairwise correlations between each index and all other ones, next computing the cross-sectional median of the estimated dynamic correlations relative to each index. Second, we compute the value-weighted average of cross-sectional median correlations using the monthly proportion of AUM for the hedge fund indices. Mathematically,

(7) $$\Omega_t = \sum_i w_{i,t} M_{i,t}\left(\rho_{i,j,t}\right),$$

where $M_i\left(\rho_{i,j,t}\right)$ is the cross-sectional median of all the pairwise correlations between the index i and all the remaining indices j with $i \neq j$ in the period t; $w_{i,t}$ are simply the proportion of assets under management for index i at time t, namely $w_{i,t} = \frac{\text{AUM}_{i,t}}{\sum_{j=1}^{N} \text{AUM}_{j,t}}$ with N denoting the number of indices.

We run equation (7) for hedge fund filtered returns (crowded-trade) and corresponding time-varying betas (leverage commonality), while for correlations across the 7+1 FH risk factors (risk factor commonality) we simply used the cross-sectional median computed over all the pairwise correlations, denoted by

$$\mathrm{P}_t = M_t\left(\rho_{l,m,t}\right) \tag{8}$$

where $\left(\rho_{l,m,t}\right)$ are all the pairwise dynamic conditional correlations between factors l and m with $l \neq m$.

IV. An EWS for the Hedge fund Industry

The monitoring risk system we propose for hedge funds pertains to the signal approach, largely used in the literature on sovereign crises (currency, banking, and debt crises). The objective of a signal approach is to realize a system in which a crisis is signaled when pre-selected leading economic indicators exceed some thresholds to be estimated according to a minimization procedure. The signal approach starts with Kaminsky et al. (1998) and recently a new generation of EWSs has been introduced using regression trees (Manasse and Roubini, 2009), which appear more robust since they consider simultaneously all possible risk signals issued by the various indicators allowing linear and nonlinear interactions.

Regression tree analysis is a statistical technique introduced in Breiman et al. (1984) through which the predictor space is recursively partitioned by a series of subsequent nodes that collapse into distinct partitions in which the distribution of the dependent variable, *Y*, minimizes the prediction error within each region. This method uncovers general forms of nonlinearity and provides a general non-parametric way of identifying multiple data regimes from a set of predictor variables (Durlauf and Johnson, 1995). Such a technique, we briefly explain in the next section, can be viewed as a collection of piecewise linear functions defined by disjoint regions wherein observations are grouped.

IV.1. Methodological issues

Let $\mathbf{X} = [(X_1, \ldots, X_r)]$ be a collection of *r* vectors of predictors, both quantitative or qualitative. Let T denotes a tree with $m = 1, \ldots, M$ terminal nodes, i.e. the disjoint regions $\tilde{T}_m$, and by $\Theta = \theta_1, \ldots, \theta_M$ the parameter that associates each *m*-th θ value with the corresponding node. A generic dependent variable *Y* conditional on Θ assumes the following distribution

(9) $$f(y_i | \Theta) = \sum_{m=1}^{M} \theta_m I\left(\mathbf{X} \in \tilde{T}_m\right)$$

where θ_m represents a specific $\tilde{T}_m$ region and *I* denotes the indicator function that takes the value of 1 if $\mathbf{X} \in \tilde{T}_m$. This signifies that predictions are computed by the average of the *Y* values within the terminal nodes, i.e.

(10) $$\hat{y}_i = \hat{\theta}_m \Rightarrow N_m^{-1} \sum_{\mathbf{x}_i \in \tilde{T}_m} y_i$$

with $i = 1, \ldots, N$ the total number of observations and N_m the number within the *m*-th region.

Computationally, the general problem for finding an optimal tree is solved by minimizing the following loss function[5]

(12) $$\underset{\Xi = \{T, \Theta\}}{\arg\min}\, L = \left[Y - f(Y | \Theta)\right]^2 .$$

This entails selecting the optimal number of regions and corresponding splitting values.

[5] In solving such minimization process a common procedure is to grow the tree then controlling for the overfitting problem by pruning the largest tree according to a cost-complexity function that modulates the tradeoff between the size of the tree and its goodness of fit to the data. See Hastie et al. (2009) for technical details.

Let s^* be the best split value and $R(m) = N_m^{-1} \sum_{\mathbf{x}_i \in \tilde{T}_m} \left(y_i - \hat{\theta}_m\right)^2$ be the measure of the variability within each node, the fitting criterion is given by

(11) $$\Delta R\left(s^*, m\right) = \max_{s^*} \Delta R(s, m)$$

with

(12) $$\Delta R(s, m) = R(m) - \left[R(m_1) + R(m_2)\right].$$

The procedure is run for each predictor then ranking all of the best splits on each variable according to the reduction in impurity achieved by each split. The selected variables and corresponding split points are those that most reduce the loss function in each partition.

Another interesting feature of regression trees is that they are conceived with the end to improve the out-of-sample predictability. The estimation process is indeed based on the cross-validation through which the data are partitioned into subsets such that the analysis is initially performed on a single subset (the training sets), while the other subset(s) are retained for subsequent use in confirming and validating the initial analysis (the validation or testing sets).

IV.2. Discussion

The previous points summarize the main technicalities of the regression trees approach, which appears as a useful way to inspect hedge fund tail events and contagion effect showing some interesting aspects. Indeed:

- They allow for non-linear relationships and predictors can be quantitative or qualitative detecting and revealing interactions in the dataset.
- The number of nodes as well as the corresponding splitting threshold values are the output of an optimization procedure then delivering the best aggregation of data within homogeneous clusters.

- The procedure is essentially a forecasting model conceived in a forward-looking basis making a trade off between fitting and forecasting ability.

Tree models can then be used to develop EWSs based on a collection of binary rule of thumbs such as "$x_{ji} \leq s_j$" or "$x_{ji} > s_j$" for each j predictor, realizing a risk stratification that can capture situations of extreme risk whenever the values of the selected variables lead to risky terminal nodes, i.e. those clusters denoted by the higher value of the predicted response variable *Y*.

In our study, the response variables, both defined according to Boyson et al. (2010), are:

- Worst Return (*WR*), which is a dummy variable assuming 0 for no *WR* and 1 whether we observe a *WR* defined as an extreme negative return falling within the 10% of the left side of the return distribution of a given index.
- Contagion (*C*), which is a counting variable and defined as the number of other hedge fund style indices experiencing a *WR* in the same month and ranging from 0, for no contagion, to $H-1$ with *H* the total number of hedge fund style indices, for maximum contagion.

Using the regression trees approach for the two dependent variables we determine a series of "red flags" for crowded-trade, leverage and risk factor commonality together with other potential predictors, delivering a sort of rating system through which we try to predict:

(i) an impeding worst return, giving the corresponding "physical" probability (i.e. the average number of worst returns over the total cases classified within each terminal node), i.e.

(11) $$\Pr(WR_i) \approx \hat{y}_i = \hat{\theta}_m \Rightarrow N_m^{-1} \sum_{\mathbf{x}_i \in \tilde{T}_m} WR_i \; ;$$

(ii) the number of hedge fund styles having a worst return in the same month (i.e. the average number of C measured within each terminal node)6. And since contagion is defined as the number of other hedge fund styles having an extreme negative return, the ratio "$\hat{C}/(H-1)$", with $\hat{C}$ be the prediction for C, gives a measure of the intensity of contagion with values ranging from 0 (no contagion) to 1 (maximum contagion). As a result, such a ratio can be viewed as a proxy for the (physical) probability of having a contagion within the hedge fund industry7, i.e.

$$\Pr(C_i) \approx \frac{\hat{y}_i}{(H-1)} = \frac{\hat{\theta}_m}{(H-1)} \Rightarrow \frac{N_m^{-1} \sum_{\mathbf{x}_i \in \tilde{T}_m} C_i}{(H-1)}. \tag{12}$$

V. Data

A. Hedge Fund Style Returns

The data used for hedge fund styles are the monthly returns of the CSFB/Tremont indices over the period January 1994–September 2008. These are ten asset-weighted indices of funds with a minimum of $10 million of AUM, a minimum one-year track record and current audited financial statements, including Convertible Arbitrage, Dedicated Short Bias, Emerging Markets, Equity Market Neutral, Event Driven, Fixed Income Arbitrage, Global Macro, Long/Short Equity, Managed Futures, Multi-Strategy. To avoid redundancies we do not consider the aggregate index computed from the CSFB/Tremont database, and the three sub-indices of Event Driven Index (Event Driven–Distressed; Event Driven–Multi-Strategy; Event Driven–Risk Arbitrage).

[6] In our empirical analysis we used a novel version of tree models. The algorithm, introduced in Vezzoli and Stone (2007), is a sort of generalized version of regression trees conceived when dealing with panel data. Briefly, the algorithm is in two steps: (1) in the first step, the subsets (the time series of each hedge fund style) in which the regression trees are estimated are repeatedly rotated for all the subsets of the sample, then generating multiple predictions; (2) in the second step, a final regression tree is grown using the average of predictions obtained in the first step in place of the original dependent variable. Vezzoli and Stone (2007) show that this two-step procedure represents a possible reconciling solution to our problem, since we obtain a parsimonious final model, with good predictions (accuracy), better interpretability and minimized instability.

[7] Consider, on this point, that regression trees are invariant to scale transformations of the data.

The time period used to inspect worst returns and contagion was split into two intervals, the first from January 1998 to December 2006 and the second from January 2007 to September 2008. The first sub-sample was used to estimate the dynamic conditional correlations and our EWS, using the second sub-sample as out-of-sample test set.

The asset pricing model used to estimate filtered returns and time-varying betas was estimated over the same estimation period January 1998-December 2006, using the time interval January 1994-December 1997 as a "pre-sample" for priors' estimation according to the Bayesian approach outlined in Savona (2009). Filtered returns and betas over the period January 2007-September 2008 are computed using the model estimated in-sample to better inspect the impact of the sub-prime crisis. In so doing we reduce the potential bias induced by model parameters if estimated up to September 2008, since they would incorporate the market stress events occurred over the out-of-sample period then spuriously measuring the crisis impact both in terms of filtered returns and betas. Descriptive statistics regarding the ten hedge fund styles indices are in Table 1 Panel A.

B. Systematic Risk Factors

The risk factors used to estimate the fund-specific style benchmark through a constant multi-beta model are the 7+1 risk factors used in Fung and Hsieh (2001, 2004, 2007a,b), who suggest to use: (i) three primitive trend-following strategies proxied as pairs of standard straddles and constructed from exchange-traded put and call options as described in Fung and Hsieh (2001); (ii) two equity-oriented risk factors; (iii) two bond-oriented risk factors, and (iv) one emerging market risk factor. The following are the indices used in the empirical analysis:

- Bond Trend-Following Factor;
- Currency Trend-Following Factor;
- Commodity Trend-Following Factor;
- Standard & Poors 500 index monthly total return;

- Size Spread, proxied by Wilshire Small Cap 1750 minus Wilshire Large Cap 750 monthly returns;
- 10-year Treasury constant maturity yield month end-to-month end change;
- Credit Spread, proxied by the month end-to-month end change in the Moody's Baa yield less the 10-year treasury constant maturity yield;
- MSCI Emerging Market Index.

Descriptive statistics regarding the 7+1 risk factors are in Table 1 Panel B.

C. Primitive Risk Signals

As briefly outlined in Section II, PRSs are contemporaneous variables that managers are assumed to use in changing their trading strategies and that enter into the beta and the benchmark equations. As discussed in Savona (2009), PRSs were chose by referring to empirical findings as well as theoretical explanations advanced in recent papers involved in the issue of risks in hedge funds. These are the following:

- CBOE Volatility Index (VIX);
- Month end-to-month end change in the 3-month T-bill;
- Term Spread, computed as the monthly difference between the yield on 10-year Treasuries and 3-month Treasuries;
- Innovations in the S&P's 500 monthly standard deviation (Inn) as the proxy for liquidity shocks and estimated by the equation $v_t - v_{t-1} = c_v(v_{t-1} - v_f) + s_t$; v_t and v_{t-1} are the market volatility at time t and $t-1$, respectively; c_v is the persistence volatility parameter that shrinks the volatility process towards the long-run fundamental volatility v_f, assumed to be constant; s_t is the error term used to proxy the liquidity shocks.

Descriptive statistics regarding the four PRSs are in Table 1 Panel C. In the estimation process, we standardized each PRS so as to obtain scale-independent coefficient estimates.

VI. Analysis and Results

Fist, estimating the 3-equation asset pricing model, then using filtered returns and time-varying beta estimates to, second, compute the dynamic conditional correlations, and, third, realize the EWS for the hedge fund industry through regression trees approach, are the three steps at the heart of this paper. The next sections describe and comment the main results obtained in our analysis, which are structured in order to give an answer to the following questions: (i) Are crowded-trade together with leverage and common risk factors commonalities, and other factors as liquidity shocks responsible to the increase in systemic risk of the hedge fund industry? (ii) Which values for excess correlations and other potential predictors for extreme negative returns and contagion effect should be considered as risk alarm thresholds? (iii) Are we able to put together all such predictors in order to get an EWS able to fit and predict past and future hedge fund extreme events which could propagate within the industry?

VI.1. Filtered Returns, Betas, and Correlations

Estimates of the 3-equation system used to compute filtered returns and time-varying betas are those in Savona (2009) and are summarized in Table 2, while results from the principal component analysis used to estimate correlations are reported in Table 3. The asset pricing model estimated to preliminarily explore hedge fund dynamics proves that PRSs significantly impact on the time variation of hedge fund betas, as indicated by the loadings (the λ parameters) which appear in some cases as all significant (Equity Market Neutral), also showing strong mean reversion in beta (the μ parameter). Moreover, the explained variance expressed by the adjusted R^2 denotes variability, with values ranging from 0.1086 (Multi-Strategy) to 0.7733 (Emerging Markets)[8].

Results from the principal component analysis indicate that for filtered returns we need 8 components to achieve an explained variance near 95% (Table 3 Panel A), while for betas the first 6

[8] Anyhow, as discussed in Savona (2009) the model proves to be better than the simple 7+1 FH risk factors model with constant betas, when considering both in-sample and out-of-sample predictability.

principal components explain over 97% of their variation (Table 3 Panel B), which is virtually the same value of the variance explained by the first 4 components for the 7+1 FH risk factors (Table 3 Panel C).

With these results and running the GARCH (1,1) models for filtered returns, betas and the 7+1 FH risk factors, we then estimated the dynamic conditional correlations as discussed in section III.2 and III.3. Descriptive statistics are in Table 4 which reports the *q*–quantiles of the dynamic conditional correlation (DCC) distributions with $q = 0.1, 0.5, 0.9$ as well as the min, max and the standard deviation. Value-weighted average of cross-sectional medians of pairwise correlations of filtered returns range from 0.265 to 0.874 while for time-varying betas the values of the same statistics range from 0.108 to 0.744, also denoting a slightly high time variation as indicated by the standard deviation (0.156 for betas vs. 0.129 for filtered returns). For the 7+1 FH risk factors, the overall median of pairwise correlations is more narrow both in terms of range, from 0.05 to 0.256, and volatility, since the standard deviation is 0.047. However, single factor correlations show substantial differences: S&P's exhibits on average higher correlations with values from 0.501 to 0.841, while the three primitive trend-following strategies show on average negative correlations.

The *q*–quantiles of the distributions are interesting since they give some preliminary insights about potential risk alarm thresholds. To put the point into perspective let first inspect the time evolution of the three commonality proxies (crowded-trade, levarage, common risk factors). Figure 1 shows the value-weighted median pairwise conditional correlations of hedge fund filtered returns (DCC Filter) and betas (DCC Beta), together with the overall median of the 7+1 FH risk factors cross-correlations (DCC FH) during the period January 1998–September 2008. The same figure plots the Gaussian Kernel smoothing we computed in order to detect trends and cycles occurred over time. The main findings are discussed in the next sub-sections.

A. DCC Filtered Returns

The correlations shown significant changes both in level and variations over the entire time period. The Kernel smoothing denotes two main phases. The first is from January 1998 to December 2004 in which the trend of correlations was descending, while the second starts in January 2005 and ends in September 2008 showing an increasing pattern. In more depth:

- From January 1998 to April 1998 the level was high reaching 0.66, then declining to about 0.4 in September 1998, i.e. one month after the LTCM collapse. These results are consistent with those of Adrian (2007), who presented evidence that the LTCM collapse was preceded by high correlations, due to an increase in return comovements, before declining in August 1998.[9]
- Significant structural breaks in correlations also occurred with the technology bubble of 2000, when values jumped from 0.45 in February 2000 to 0.7 in April 2000, i.e. surrounding the peak of the bubble, then sharply dropping to 0.36 in December 2000. Such a pattern seems to find a possible explanation with the findings of Brunnermeister and Nagel (2004) together with Adrian (2007). Brunnermeister and Nagel (2004) proved that hedge fund managers were riding the technology bubble, capturing the upturn and avoiding much of the downturn by reducing their holdings before prices collapsed. On the other hand, Adrian (2007) showed that volatility in the hedge fund sector declined from October 1998 to October 1999, becoming high in the time surrounding the peak of the bubble and then substantially declining from 2001. Combining the findings of the two papers, we could explain the behaviour of correlations over the tech bubble period with the patterns of "pure" comovements (covariances), because spikes in correlations were associated with analogous spikes in volatility.

[9] Adrian (2007) also notes that "By the time the LTCM crisis broke in August 1998, hedge fund return correlations had dropped from their peak levels in 1996 and 1997 to a level that was not particularly high. Some hedge fund strategies registered losses while others gained. By contrast, equity return correlations and volatilities increased sharply, a phenomenon known as financial market contagion. Thus, this episode provides evidence that while returns on equities and similar financial assets tend to move together during crises, returns on hedge funds tend to react independently, reflecting the differences in hedge fund exposures to various shocks."

- Besides the recent 2007 crisis, other two spikes in correlations appeared as significant. The first was during the 9/11 attacks at the World Trade Centre and the months later until December 2001, when the DCC reached a local maxima of 0.61 next plunging at low levels until December 2004 when the value was 0.26 (the minimum over the entire period 1998-2008). The second was surrounding the Ford and GM downgrade (in May 2005 they lost their investment grade ratings), when correlations rose from 0.39 in February 2005 to 0.56 in July 2005.
- From 2006 the dynamics of correlations shown an increasing trajectory moving towards higher and persisting levels. Such a strong linkage among hedge funds translated into high levels of systemic risk that exploded over the period 2007-2008. From July 2007 to November 2007 correlations jumped from 0.45 to 0.8, and, interestingly, during the months January-March 2008, the values slightly dropped to 0.7510. However, from April 2008, in conjunction with the Fed Funds rate cut[11], correlations returned above 0.8, signaling the higher level registered over the entire period inspected.

B. DCC Time-Varying Betas

The path of the Ω_{Beta} shown more cyclical variation than Ω_{Filter} exhibiting three major phases, as denoted by the Kernel smoothing:

- The first is from January 1998 to September 2002, wherein correlations were characterized by the peak of 0.72 in August 1998 next showing a cyclical downtrend plunging to its lowest level of 0.11 in September 2002, after a sharp rise occurred in March 2001, when correlations

[10] A possible explanation for such a drop in value could be ascribed to some signals, such as the assistance in the Bear Stearns bailout in March together with marked reversals across equities, bonds and the U.S. dollar, which may have been interpreted differently by hedge fund managers, which in turn implied less dependency among hedge fund returns. As pointed out in a report on the hedge fund industry in April 2008, “Some managers have inferred that most of the troubles related to the US subprime meltdown and the consequent credit crisis are now behind us, while many others strongly believe that it is only the first phase of turbulence that has subsided” (Eurekahedge, April 2008 Hedge Fund Performance Commentary, May 2008).

[11] On 30 April, the Federal Reserve brought the Fed funds’ rate to 2%, i.e. the lowest over the past 3 years.

reached 0.7. During this phase another point of interest was the behaviour of correlations until April 2000, when the corresponding value reached 0.3.

- The second phase is from October 2002 to October 2006; here correlations increased up to the higher level of 0.74.
- The third phase, that starts from November 2006 and ends in September 2008, exhibited a sharp decline reaching 0.31 at the end of the period. Relative to the path exhibited by the Ω_{Filter}, the main difference is the behaviour shown during the sub-prime crises when, on the one hand, leverage dynamics were different among hedge funds leading the correlations to low levels, on the other, crowded-trade became extremely high boosting the correlations over 0.8.

In Figure 1 we also report the value weighted average of time-varying betas using AUM of the indices as weights (see the next section), since we suspect that leverage commonality could move in level with leverage. As clearly depicted in the figure such hypothesis is confirmed since the overall leverage level of hedge funds shown the cyclical path commented for the leverage commonality, especially during the sub-prime crisis that was characterized by significant de-leveraging.

C. DCC 7+1 FH Risk Factors

The Kernel smoothing computed for the risk factor commonality denotes significant interdependence, namely a linkage among risk factors that over time more than doubled from January 1998, when the overall median was 0.08, to September 2008, when the value was over 0.2. Over time, several sharp up and down moves in correlations occurred, although the corresponding values stayed within modest levels compared to those of filtered returns and beta commonalities. However the overall median should be considered carefully, since single factors shown substantial differences as previously discussed. As a whole, the dynamics exhibited significant noise around the increasing trend. The strongest rise was associated with the LTCM collapse when values ranged significantly (1998-1999). The volatility was substantial also during the years 2000-2006, while starting from January 2007 the pattern of correlations was less noisy as indicated by ranges which became narrowed.

VI.2. An EWS for Extreme Negative Returns

Through the EWS our aim is to both explain and predict when and why hedge fund styles could experience an extreme negative return. After having estimated and commented the DCC as proxies for crowded-trade, leverage commonality, and risk factor commonality, and considering other potential predictors, the objective is to realize a collection of thresholds to best stratify the potential risk for single hedge fund styles. To do this we used the following 30 potential predictors:

- The three DCCs, using the cross-sectional median of all the pairwise correlations between the index *i* and all the remaining indices ($M_i\left(\rho_{i,j,t}\right)$), for filtered returns and time-varying betas, and the overall median for FH risk factors computed according to the equation (8). We both considered the levels of the three DCCs as well as their monthly differences, in order to capture sudden changes possibly induced by systemic risk impacts.
- The time-varying betas of each index estimated using our Bayesian asset pricing model. The reason we include betas is because they represent the leverage level of the funds, and as noted in Chan et al. (2006), "Leverage has the effect of a magnifying glass, expanding small profit opportunities into larger ones but also expanding small losses into larger losses. And when adverse changes in market prices reduce the market value of collateral, credit is withdrawn quickly, and the subsequent forced liquidation of large positions over short periods of time can lead to widespread financial panic, as in the aftermath of the default of Russian government debt in August 1998." Also in this case level and monthly changes have been considered.
- The "risk factors volatility" (*V*), computed as the cross-sectional weighted average conditional standard deviation of the 7+1 FH risk factors, using the time-varying standard deviations estimated before through the univariate GARCH (1,1) and the portions of the variance per component as weights. Mathematically,

(14) $$V_t = \sum_i w_{i,t} \sigma_{i,t} ,$$

where $w_{i,t}$ is the portion of variance for the *i*-th component at time *t*, i.e. the eigenvalue of the factor *i* over the total eigenvalues of the components extracted[12]; $\sigma_{i,t}$ is the conditional time-varying standard deviation for the factor *i* at time *t*. As is obvious, the volatility of hedge fund risk factors plays a critical role in the dynamics of hedge fund. With this proxy, we then explore whether and how the within-dispersion of hedge fund risk factors reflects on comovements across the strategies[13]. Level and monthly changes have been considered.

- The 7+1 FH risk factors together with the four PRSs, since we have reason to believe that they could help to explain not only the overall dynamics of hedge funds but also their extreme events.
- The measure of hedge fund illiquidity introduced in Getmansky et al. (2004) (Lo_ill) obtained by the cross-sectional weighted average first-order autocorrelations using a rolling window of 36 past monthly returns and the relative AUM as weights:

(15) $$\rho_t = \sum_i w_{i,t} \rho(1)_{i,t} ,$$

in which $\rho(1)_{i,t}$ is the average first-order autocorrelation for index *i* at time *t*. As discussed by Chan et al. (2006), the weighted autocorrelation could play a significant role in the dynamics of systemic risk. The authors prove, indeed, that rising autocorrelations in returns are

[12] As discussed in section VI.1 for the 7+1 FH risk factors we extracted 4 components. The total eigenvalues was then computed as the sum of the eigenvalues of these components, next used to express in relative terms the single eigenvalues.

[13] In studies on contagion, many authors used GARCH and ARCH models to estimate the volatility of some key variables then inspecting the volatility propagation across countries. For e.g., Edwards (1998) and Edwards and Susmel (2000) used interest rate data for a number of Latin American and East Asian countries to study the international volatility contagion.

connected to illiquid exposures taken by hedge funds, which imply indirect evidence of a rise in systemic risk in the industry. Level and monthly changes have been considered.

- The AUM by single hedge fund style to proxy the dimension of funds. It is indeed reasonable to assume that the dimension of funds expressed in terms of the assets they manage could play a signaling role of potential risk. On this point, the evidence indicates that larger funds perform worse than smaller funds (Getmansky et al., 2004).
- The Pastor and Stambaugh (2003) (PS) measures for US market liquidity, namely: (a) the levels of aggregate liquidity, which is a non-traded liquidity factor associated with temporary price fluctuations induced by order flow (PS1); (b) the innovations in the levels of aggregate liquidity factor (PS2); (c) the traded liquidity factor computed as the value-weighted return on the 10-1 portfolio from the ten sized portfolios sorted on historical liquidity betas (PS3).
- Contagion (*C*), measured as the number of other hedge fund styles experiencing a worst return in the same month; hence, since we have ten indices, the values range from 0 to 9. This is clearly expected to play a central role since it measures the intensity of the systemic risk.

All predictors were lagged one month in order to estimate the expected probability of *WR* at time *t* given the values of predictors observed in $t-1$. However, since contagion will be our variable of interest in the next section, we also used *C* measured at time *t*. Another reason of the use of *C* in *t* (together with *C* in $t-1$) is because regression trees could endogenously detect switching regimes based on contagion effect, and to do this it is essential considering the value of contagion at the same time of the dependent variable.

We pooled the data of the ten hedge fund indices and predictors based on the two time intervals January 1998-December 2006 and January 2007-September 2008. As indeed previously discussed, we used the period January 2007-September 2008 to perform the out-of-sample analysis based on models estimated in the period January 1998-December 2006. Moreover, to focus more closely on the two major systemic events occurred over the time period inspected, we estimated models also for the sub-periods 1998-1999 and 2007-September 2008.

A. In-Sample Hedge Fund Risk Stratification

The procedure outlined in section IV run over the period January 1998-December 2006 stratified the risk of having an extreme negative return in 10 clusters as depicted in Figure 2. The regression tree analysis selected 6 out 30 predictors, which are: 1) Contagion; 2) DCC Filter; 3) Credit Spread; 4) Change in Beta; 5) DCC Beta; 6) AUM. This result seems empirically confirm and extend the arguments developed in Stein (2009), since crowded-trade (DCC Filter), liquidity concerns (Credit Spread changes)[14] together with leverage dynamics (commonality, DCC Beta, and change in level, $d\beta$), and hedge fund style dimension (AUM), would contribute to explain worst returns especially in times of contagion.

An in-depth exploration of the partitions realized through our analysis leads to identify the following risk levels:

- **Extreme Risk**, signaled when contagion effect ($C_t \geq 3$) are associated with high leverage commonality ($\text{DCC Beta} > 0.6933$) and the style dimension is alternatively high ($\text{AUM} > 0.093$) or low ($\text{AUM} \leq 0.036$). The risk is slightly higher for smaller funds for which we estimate $\Pr(WR) = 0.8557$ against $\Pr(WR) = 0.7159$ for larger ones.
- **High Risk**, when substantial leverage commonality ($\text{DCC Beta} > 0.6933$) is connected, alternatively with (a) systematic risk reduction (de-leveraging) ($d\beta \leq -0.26231$), or (b) median dimension-based funds ($0.036 < \text{AUM} \leq 0.093$) during times of contagion effect ($C_t \geq 3$). The probability estimates for (a) and (b) are $\Pr(WR) = 0.4443$ and $\Pr(WR) = 0.3315$, respectively.
- **Medium Risk**, when crowded-trade is significantly negative, i.e. when proprietary trading strategies are, in some sense, opposite to other competitors ($\text{DCC Filter} \leq -0.263$), which is

[14] Credit Spread can be viewed also as a proxy for funding liquidity risk faced by hedge funds. Patton and Ramodarai (2010), for e.g., use the variable to capture variation in the availability of credit on account of changes in the probability of default.

the case for some Dedicated Short Bias funds[15]. For these funds, we define as Strong Short Bias, we estimate $\Pr(WR) = 0.2684$. Moreover, a similar risk level is signaled for all other funds, i.e. those having ($\text{DCC Filter} > -0.263$), whenever credit spread widens ($\text{CS} > 6.5\text{bp}$) together with substantial de-leveraging ($d\beta \leq -0.2086$), which seems delineate a situation in which market illiquidity (implied in widened credit spreads) forces hedge funds to reduce their leverage level. In this case we have $\Pr(WR) = 0.2271$.

- **Moderate Risk**, for funds exhibiting low commonality in leverage dynamics ($\text{DCC Beta} \leq 0.6933$) and for funds showing substantial leverage commonality ($\text{DCC Beta} > 0.6933$) with no extreme de-leveraging ($d\beta > -0.26231$). The probability estimates are, in order, $\Pr(WR) = 0.1561$ and $\Pr(WR) = 0.0831$.
- **Low Risk**, when Credit Spread does not widen significantly ($\text{CS} \leq 6.5\text{bp}$) and funds are not Strong Short Bias style ($\text{DCC Filter} > -0.263$). In this case we have the lowest probability to suffer from a WR with $\Pr(WR) = 0.0388$. Alternatively, the same risk level is when positive Credit Spread changes ($\text{CS} > 6.5\text{bp}$), and again the style is not Strong Short Bias ($\text{DCC Filter} > -0.263$), the funds tend to increase their systematic risk exposure ($d\beta > -0.2086$). Here the probability estimate is $\Pr(WR) = 0.06757$. The fact that Credit Spread is connected to changes in beta seems suggest that the predictor could indicate liquidity concerns when linked to fund de-leveraging. Indeed, the threshold for $d\beta$ discriminates between moderate risk, when $d\beta \leq -0.2086$, and low risk for $d\beta > -0.2086$.

The main conclusion coming from this analysis is that contagion and leverage commonality play the role of leading indicators in signaling extreme risk situations. Having 3 or more fund styles experiencing an extreme negative return and following strategies which imply significant communality in beta dynamics, i.e. greater than ≅ 0.7, leads to exhibit the higher probability of

[15] All funds clustered within this node were Dedicated Short Bias.

having a worst return. Interestingly, the time series which are located within the two higher risk clusters include the months August-October 1998, September 2001, April-May 2005, namely, the LTCM collapse, the terrorist attack of 09/11, and Ford and GM downgrade, respectively. Liquidity concerns seem to move in tandem with changes in leverage, since they lead to risky cluster when credit spread widens and funds tend to de-leverage.

B. In-Sample and Out-Of-Sample Model Accuracy

In order to assess the model accuracy of our EWS both in- and out-of-sample, we used common scoring- and signal-based diagnostic tests. The first is the Brier Score (*BS*), which is the average squared deviation between predicted probabilities and actual outcomes, assigning lower score for higher accuracy,

(16) $$BS = N^{-1} \cdot \sum_i 2(\hat{y}_i - y_i)^2 \qquad BS \in [0, 2].$$

Secondly, we rely to signal-based diagnostic tests using the ROC curve. These includes: (1) the Youden Index, which is a summary measure of the model accuracy both considering type-I and type-II errors which is commonly used to find the optimal cut-off point in classification (predicting *WR*, 1, and no-*WR*, 0). The measure is computed as $[(1-\alpha)+(1-\beta)-1]$ where α and β are type-I and type-II errors; (2) the optimal cut-off point, corresponding to that value of the probability estimate which maximizes the Youden Index; (3) Sensitivity, which is the ratio of *WR* correctly classified over the actual *WR,* namely $(1-\alpha)$; (4) Specificity, which is the ratio of no-*WR* correctly classified over the actual no-*WR*, namely $(1-\beta)$; (5) the Area Under the ROC Curve (AUC), which is a measure of the model classification ability ranging from 0 (random model with no classification ability) to 1 (perfect model) and it is the area under the ROC curve which is a function mapping sensitivity onto type-II errors for each possible thresholds, then visualizing the trade-off between type-I and type-II errors.

The results reported in Table 5 show that the overall performance of the EWS as measured by the AUC is quite similar in- and out-of-sample, while sensitivity and specificity computed using the optimal cut-off points through the Youden Index denote significant changes in- and out-of-sample. Indeed, looking at type-I errors, we note that the model predicts 59 out 90 *WR*s in-sample hence having a sensitivity of 0.6556, and 33 out 36 *WR*s out-of-sample with a corresponding sensitivity of 0.9167. On the other hand, specificity is 0.7340 in-sample and 0.6149 out-of-sample. In other terms, the EWS modulates the classification errors showing higher ability in predicting *WR*s (true positive) out-of-sample to the detriment of specificity, since false alarms increase from the first to the second time period. This is the reason why we obtain an AUC which is 0.7294 and 0.7115 in- and out-of-sample, respectively. When instead focusing on Brier Score, the difference between in- and out-of-sample is relatively significant since we have 0.1412 and 0.3004, then indicating a deterioration in the model accuracy assessed in the holdout period.

The main conclusion from this analysis is that while the performance of the EWS in-sample is enough, although the number of missed *WR*s is substantial, out-of-sample the model is extremely good in predicting whether hedge funds will experience an extreme negative return, but false alarms are in this case considerable. However, this could be a reasonable compromise being more sensitive to type-I errors, which is the case for risk adverse investors.

C. LTCM Vs. Sub-Prime Crises

To better inspect the two major systemic events we carried out the regression trees analysis over the two sub-period January 1998-December 1999 and January 2007-September 2008. In so doing, we expect to detect what really happened in both crises, making clear which were the reasons why many funds experienced extreme negative returns.

Figure 3 and 4 report the risk stratification for the two sub-periods and diagnostics of model accuracy are reported in Table 6.

The LTCM collapse appears as a pure contagion event since the higher risk is for cases in which the proxy was greater than 3 ($C_t > 3$). Interestingly, the extreme risk cluster is for substantial leverage commonality ($\text{DCC Beta} > 0.3008$) and all cases clustered within such a node are observations over the months August 1998-October 1998. This suggests that the main reason underlying the LTCM collapse was mainly due to extreme commonality in leverage dynamics. In that period, the level in beta was substantial, thus high correlations were associated with high leverage level. This is one of the difference between the LTCM and the sub-prime crises.

In fact, the sub-prime crisis seems instead strongly linked to commonality in (filtered) returns. The risk partition obtained over the period January 2007 – September 2008 and reported in Figure 4, shows that crowded-trade and contagion proxies lead to extreme risk cluster. In this cluster, where $\Pr(WR) = 0.8569$, $\text{DCC Filter} > 0.8293$ and funds tend to crowd more and more as signaled by $d\text{DCC Filter}$ required to be stable or positive ($d\text{DCC Filter} > -0.0012$). Such a partition mainly selected the observations of July 2008 and September 2008, when indeed the number of *WR* was 6 and 8, respectively. Similarly, for August 2007, when the number of *WR* was 5, the model clustered the corresponding observations within a node with $\Pr(WR) = 0.5296$ and characterized by a slightly high crowded-trade, while less than 0.8293, together with substantial drop in leverage commonality ($d\text{DCC Beta} > -0.0476$) due to substantial de-leveraging occurred in the summer 2007 as we commented in previous section VI.1.

As a whole, by observing Figure 4 contagion clearly play the role of leading indicator, since having more than 1 other fund styles experiencing a *WR* the probability estimates are for all clusters greater than 0.35, except for funds having a moderate commonality in returns ($\text{DCC Filter} \leq 0.7797$) and no extreme contagion ($C_t \leq 4$) for which the probability estimate is $\Pr(WR) = 0.0708$. These funds denote medium and high values of probability to get extreme negative returns. Moreover, in times of no contagion ($C_t \leq 1$), the risk arises for funds denoting negative return commonality, i.e. for

Strong Short Bias funds. For these funds we have indeed a moderate risk profile with $\Pr(WR) = 0.2361$.

From a pure statistical viewpoint, for both the sub-periods the accuracy of the model is high as proven by the diagnostics reported in Table 6, which documents the ability in correctly classifying *WR* for 77.14% (1998-1999) and 80.56% (2007-09/2008) of total cases, as well as for no-*WR* with 96.22%% (1998-1999) and 85.63% (2007-09/2008) of total tranquil time observations.

VI.3. An EWS for Contagion

The proxy for contagion has been previously used as a contemporaneous covariate relative to extreme negative returns. At first sight, this could sound as problematic when the objective is to realize an EWS, since all the predictors should be observed in t to make predictions for $t+1$. As discussed above, the reason why we did not lagged contagion is because the objective was to endogenously detect switching regimes based on specific splitting values. And this is what we did by inspecting *WR* as our first dependent variable.

Now our interest is on contagion itself, which is our second variable of interest that we try to predict using the same set of covariates used for *WR* with the following minor changes, due to the fact that the perspective is global and not style-specific, as for *WR*:

- The DCC for filtered returns and time-varying betas were computed according to the equation (7), i.e. using the aggregate measure of commonality based on value-weighted average of cross-sectional median correlations of hedge fund indices.
- Instead of using the time-varying betas of each index we included a measure for the “industry beta”, computed as the value-weighted average of the single betas, using the relative monthly AUM as weights:

$$\mathrm{B}_t = \sum_i w_{i,t} \beta_{i,t} \,, \tag{17}$$

in which $w_{i,t}$ are the proportion of assets under management for index *i* at time *t* and $\beta_{i,t}$ are the betas for each index *i* at time *t* with $i = 1, \ldots, 10$.

According to what done for *WR*, level and monthly changes were used for both DCC and industry beta.

A. Predicting Contagion Through EWS

The tree structure realized over the period 1998-2006 and reported in Figure 5 shows that to predict Contagion we need 8 predictors: (1) hedge fund illiquidity (Lo_ill) (equation 15); (2) the aggregate DCC Filter (Ω_{Filter}) (equation 7) and (3) its monthly change ($d\Omega_{Filter}$); (4) the Pastor and Stambaugh (2003) measure of aggregate liquidity (PS1); (5) Credit Spread; (6) the 10-year Treasury constant maturity yield month end-to-month end change (10yr); (7) the MSCI Emerging Market Index (MSCI EM); (8) the risk factors volatility (*V*) (equation 14). As discussed in the methodological section, since contagion is a counting variable ranging from 1 to 9 the predictions realized through the regression tree analysis can be used to assess the probability of having a contagion within the hedge fund industry using equation (12). The analysis of Figure 5 leads to identify two major risk clusters corresponding to two distinctive regimes. These clusters are classified as extremely risky on the basis of the previous findings, which identified a value for contagion greater than (or equal to) 3 as for the risk alarm threshold.

The first regime is characterized by low hedge fund illiquidity ($\text{Lo\_ill} \leq 0.0906$) that was typical until October 1998, together with moderate crowded-trade ($\Omega_{Filter} \leq 0.5372$), which is coherent with the behaviour of the DCC of filtered returns shown until the end of 1998 we commented in section VI.1. These two splitting rules lead to the higher level of systemic risk ($\hat{C} = 5.102$ and $\Pr(C) = 0.5669$).

The second regime is instead characterized by high hedge fund illiquidity ($\text{Lo\_ill} > 0.0906$), low Credit Spread ($\text{CS} \leq 6.5\text{bp}$), together with high changes in crowded-trade ($d\Omega_{Filter} > 0.068$) and positive changes in 10-yr government bond yield ($10\text{yr} > 0.315\%$). Essentially, such a second regime seems to be characterized by increasing commonality in returns together with “inside” and “outside” liquidity problems. Hedge fund illiquidity (inside illiquidity) is in fact connected with changes in Treasury bond yield (outside illiquidity) which incorporate flight-to-liquidity element due to variation in the perceived safety of U.S. Treasury bonds thus reflecting variations in the liquidity component of sovereign credit spreads (Longstaff, et al., 2010). And indeed, associated with this path, emerged with Ford and GM downgrade of April 2005, we have high systemic risk level ($\hat{C} = 3.466$ and $\Pr(C) = 0.3851$).

From a pure statistical perspective the risk stratification obtained through the tree seems to be quite robust in-sample, as indicated by the Accuracy Ratio reported in Table 7 which is 0.6443[16]. However, the economic interpretation is difficult and possibly masked by some predictors that over the entire period 1998-2006 may obscured the contribution of other potential interesting variables in explaining the inner mechanism of contagion, in particular for the LTCM collapse. This is with all likelihood the case for hedge fund illiquidity which behaviour denotes strong autocorrelation with negative values until September 1998, next ranging from 0.1 to 0.4. Furthermore, the out-of-sample analysis carried out over the period 2007-September 2008 proved that the EWS realized in sample is a poor predictor in particular for high contagion: while the Accuracy Ratio is moderately low 0.2095 the EWS fails to predict contagion greater than 3.

B. The Changing Nature of Contagion Effects

Previous results relative to in- and out-of-sample model accuracy is interesting not only from a pure statistical perspective but also because they seem suggest a changing nature of contagion over time.

[16] This is simply obtained as the ratio of the number of correct over the total count, in our case computed for each value assumed by contagion.

Indeed, the fact that the splitting rules obtained by mining the data from 1998 to 2006 do not allow to predict severe contagion occurred with the sub-prime crisis can be due to the dynamics of systemic risk which could changed over time with the changing behaviour of hedge funds. To explore this possibility and to make more clear the economic interpretation of the inner causes of contagion, we then focused on the two sub-periods 1998-1999 and 2007-09/2008. The major findings are as follows.

- **LTCM Collapse**. The analysis of the period 1998-1999 gave robust estimates of contagion as denoted by the Accuracy Ratio which is 0.7818 (Table 8). The tree partitions lead to conclude that leverage commonality and shock in liquidity were the main drivers of contagion (Figure 6). In more depth, the contagion triggered by the LTCM collapse is associated with,
  1. High correlations in betas ($\Omega_{Beta} > 0.6892$) with risk factors volatility (*V*) playing the discriminating role between extreme contagion ($\hat{C} = 6.309$ and $\Pr(C) = 0.701$), when the volatility is low ($V \leq 0.0279$), and high contagion ($\hat{C} = 4.5060$ and $\Pr(C) = 0.5007$), with high volatility ($V > 0.0279$);
  2. Significant illiquidity ($\mathrm{Inn} > 1.2381$) no matter about the leverage commonality ($\Omega_{Beta} \leq 0.6892$)[17]. Also in this case the systemic risk level is high ($\hat{C} = 4.494$ and $\Pr(C) = 0.4993$).
- **Sub-Prime Crisis**. Also in this case the model is statistically robust as denoted by the Accuracy Ratio which is 0.8361 (Table 8). The transmission channels underlying the systemic risk over the period 2007-09/2008 seem to be different from those of the LTCM collapse. Indeed, looking at the risk partitions reported in Figure 7, we note what follows.
  1. Volatility of risk factors ($V > 0.03219$) is the main triggering factor of the higher contagion, which occurred in September 2008 when the volatility of all international

[17] As outlined in the methodological section, the PRSs were all standardized in order to obtain scale-independent coefficient estimates. Hence, the value 1.2381 can be viewed as 0.8922 cdf. In other terms, whenever we observe values of the variable pertaining to the higher percentile (exceeding about 0.9), together with moderate leverage commonality, we expect significant contagion effects.

financial markets sparked by the Lehman default. The systemic risk level was the higher ever ($\hat{C} = 7.21$ and $\Pr(C) = 0.8011$).

2. Contagion effect is also severe when changes in leverage commonality ($d\Omega_{Beta} > -0.0661$) move with strong monthly negative returns in S&P's ($\mathrm{S\&P} \le -0.0735$). This was the case of July 2008, when severe market pressures forced a rescue of Fannie Mae and Freddie Mac, and the large mortgage specialist IndyMac bank was closed by federal regulators. And indeed, the systemic risk estimate is extremely high ($\hat{C} = 5.377$ and $\Pr(C) = 0.5974$).

3. The third risk level is instead associated with strong corrections to the leverage dynamics with sharp reduction in leverage commonality ($d\Omega_{Beta} \le -0.0661$). As previously discussed, this reflects the severe de-leveraging occurred over the sub-prime period when crowded-trade became extremely high. This cluster, which exhibits high level of systemic risk ($\hat{C} = 3.666$ and $\Pr(C) = 0.4073$), gathers the quant crisis of August 2007 and March 2008, when market illiquidity forced Bear Stearns to be bought by the JP Morgan Chase with a 98% discount to its book value.

These findings seem to prove that contagion changed over time as for its inner transmission mechanisms. The contagion effect occurred in August-October 1998 (LTCM collapse) was mainly due to extreme interconnectedness in leverage dynamics together with illiquidity shocks but no crowded-trade. Instead, in the sub-prime crisis the transmission channels were, first, the dramatic de-leveraging and de-correlations in leverage dynamics due to liquidity concerns together with strong crowded-trade (August 2007), second, the huge systematic volatility of hedge fund risk factors which exploded with the Lehman crash (September 2008).

VII. Conclusion

This paper developed an early warning system for hedge funds based on specific red flags that help to stratify the risk of future extreme negative returns and contagion effect. To do this we relied on regression tree analysis through which the predictor space is partitioned by a series of splitting rules based on specific thresholds which act as risk signals. What we find as interesting and promising for future works is that such a technique is not vulnerable to common criticisms of parametric approaches and allows to uncover forms of nonlinearity and complexities as well as 'regime shifts'. While contagion and clustered negative returns in hedge fund industry are now well understood thanks to Boyson et al. (2009), what is yet not clear is how to signal warnings to be used in preventing potential abnormalities that could propagate on a systemic level. If hedge fund interconnectedness and liquidity shocks are assumed to be responsible to the increase and the explosion of systemic risk, which values for such predictors should be considered as risk alarm thresholds? The methodology proposed in this paper tries to give an effective and pragmatic answer to this question, realizing an EWS based on a collection of binary rule of thumbs such as "$x_{ji} \le s_j$" or $x_{ji} > s_j$ for each predictor *x* thus realizing a risk stratification that can capture situations of extreme risk whenever the value of the selected variables *x* exceeds pre-specified thresholds *s*.

Our empirical findings prove that contagion, leverage commonality, crowded-trade and liquidity concerns are the leading indicators to be used in monitoring the risk dynamics of hedge funds. We document that our EWS estimated using data from 1998 to 2006 would have been able to predict more than 90 per cent of the total worst returns occurred over the period 2007-2008, while false alarms have been significantly high. Again, a closer look at the mechanism underlying contagion effect revealed a changing nature of systemic risk. The LTCM collapse was mainly due to extreme interconnectedness in leverage dynamics together with illiquidity shocks but no crowded-trade. On the other hand, the sub-prime crisis was more complex to understand exhibiting changing transmission channels. Indeed, during the quant crisis (August 2007) dramatic de-leveraging and de-correlations in leverage dynamics due to liquidity concerns together with strong crowded-trade were at the core of contagion. In September 2008 the triggering event was instead the huge volatility of hedge fund risk factors exploded with the Lehman crash. The changing nature of contagion reflected on poor predicting ability of our model. What is indeed clear from the empirical analysis is that using our EWS, the recent sub-prime crisis was not predictable even when having a clear understanding of the reasons underlying the LTCM collapse.

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Table 1: Descriptive Statistics of CSFB/Tremont Indexes, 7+1 FH Risk Factors and PRSs – from January 1998 to September 2008

	Mean (%)	Min (%)	Max (%)	StdDev (%)
Panel A: Hedge Fund Index Returns				
Convertible Arbitrage	0.477	-12.256	3.568	1.889
Dedicated Short Bias	-0.053	-8.692	22.712	5.130
Emerging Markets	0.609	-23.026	15.338	4.120
Equity Market Neutral	0.757	-1.407	2.477	0.677
Event Driven	0.723	-11.775	3.274	1.814
Fixed Income Arbitrage	0.298	-6.965	2.069	1.401
Global Macro	0.839	-12.455	3.907	1.873
Long/Short Equity	0.820	-11.524	4.657	1.980
Managed Futures	0.649	-6.155	3.810	1.325
Multi-Strategy	0.605	-6.965	2.069	1.401
Panel B: 7+1 FH Risk Factors				
S&P	0.246	-14.580	9.670	4.317
Size Spread	0.275	-16.370	18.410	3.751
10yr Treasury Yield	-0.016	-0.530	0.650	0.219
Credit Spread	-0.016	-0.480	0.250	0.149
PTFSBD	-1.778	-25.356	68.856	14.263
PTFSFX	0.905	-29.995	66.013	17.705
PTFSCOM	0.167	-24.202	64.750	14.407
MSCI EM Index	0.765	-29.285	13.550	7.120
Panel C: PRSs				
VIX	20.861	10.420	44.280	6.676
Change in 3m Tbill	-0.031	-0.860	0.450	0.235
Term Spread	1.422	-0.530	3.696	1.222
Innovation in S&P Vol	0.863	-9.814	35.932	6.550

The table reports summary statistics for CSFB/Tremont indexes, 7+1 FH Risk Factors and PRSs over the period 01/1998-08/2008. Mean is the annualized mean return. Min and Max are the minimum and maximum monthly return respectively. StdDev is the annualized standard deviation.

Table 2: Asset Pricing Model Estimates – from January 1998 to December 2006

	HF Returns		Time-Varying Betas					
	α	Adj. R^2	ϕ	μ	$\gamma 1$	$\gamma 2$	$\gamma 3$	$\gamma 4$
Convertible Arbitrage	-0.0469***	0.1377	-0.0687	1.7696***	0.041	-0.2378**	-0.8161***	-0.0588
Dedicated Short Bias	-0.0048	0.5836	-0.2444	0.987***	-0.0985**	-0.1036**	0.1982***	-0.0255
Emerging Markets	-0.0063	0.7733	0.1904	1.1321***	-0.0496	0.1009***	-0.0105	0.0687
Equity Market Neutral	-0.0294***	0.3231	0.0928	1.2896***	0.1191***	-0.0987**	-0.3736***	-0.1868***
Event Driven	0.0257***	0.6934	0.1344	0.7415***	-0.0399	-0.0569***	-0.2323***	-0.079**
Fixed Income Arb	0.0022	0.568	0.8007***	0.2822***	0.0737	0.0325	-0.0595	-0.1468***
Global Macro	-0.1277***	0.1179	-0.0712	2.4736***	0.0478	-0.1548	-0.8424***	-0.1801
Long/Short Equity	0.0351	0.7245	0.6983	0.3029	0.0774***	0.0052	-0.0382	-0.2365***
Managed Futures	0.003	0.3462	-0.4601	1.3121***	0.5064***	-0.0139	0.2803***	-0.0029
Multi-Strategy	-0.0446***	0.1086	-0.0677	1.5918***	0.2223***	0.017	-0.4426***	0.0305

The table reports estimates of the system (1)-(4) using the four PRSs VIX, TBILL, TERM and INN. The same Panel reports also the volatility of the time-varying betas generated by the system and corresponding explanatory power expressed as R-squared of betas regressed against the mean reverting term together with the PRSs. η is the unexplained beta variation (stochastic component). Panel B presents correlations among the PRSs computed over the period from 01/1994 to 12/2006 and from 01/1998 to 12/2006. ***, **, * denote significance at 0.01, 0.05, and 0.1 level, respectively.

Table 3: Eigenvalue Analysis and Factor Weights

	1	2	3	4	5	6	7	8
Panel A: Filtered Returns								
Eigenvalue	3.7348	1.6886	1.0375	0.8866	0.7620	0.5479	0.5100	0.3508
% Variance per Component	37.3478	16.8861	10.3752	8.8659	7.6205	5.4787	5.1000	3.5080
Cumulative explained variance	37.3478	54.2339	64.6091	73.4750	81.0955	86.5742	91.6742	95.1822
Factor weights								
Convertible Arbitrage	0.8595	0.0524	-0.2363	0.2003	-0.1243	-0.1270	-0.1460	0.1046
Dedicated Short Bias	-0.2342	0.7661	0.0162	0.4122	-0.0650	0.2528	-0.1889	-0.2171
Emerging Markets	0.4849	0.5205	-0.1397	-0.5724	0.0433	-0.0891	-0.1941	-0.2497
Equity Market Neutral	0.5493	0.1802	-0.2210	0.2384	0.6962	-0.0188	0.2669	-0.0503
Event Driven	0.7806	-0.2672	-0.0584	0.0326	0.1571	-0.0312	-0.4513	0.1432
Fixed Income Arbitrage	0.7477	0.0618	-0.0360	0.1252	-0.3726	-0.3639	0.2828	-0.1663
Global Macro	0.5247	0.5923	0.1815	-0.3365	-0.0611	0.2236	0.2148	0.3261
Long/Short Equity	0.5604	-0.5879	0.2056	-0.2365	0.0542	0.3378	0.0784	-0.2699
Managed Futures	0.2317	0.1293	0.9107	0.1219	0.1564	-0.2157	-0.0805	-0.0215
Multi-Strategy	0.7700	-0.0855	0.0612	0.3023	-0.2473	0.3398	0.0410	0.0074
Panel B: Time-Varying Betas								
Eigenvalue	1.6805	0.5498	0.2916	0.1257	0.1096	0.0486		
% Variance per Component	58.2704	19.0624	10.1112	4.3582	3.7993	1.6857		
Cumulative explained variance	58.2704	77.3329	87.4441	91.8023	95.6016	97.2873		
Factor weights								
Convertible Arbitrage	-0.5963	0.2942	-0.2360	0.2387	-0.2893	0.5843		
Dedicated Short Bias	0.0912	0.1478	-0.0009	-0.2143	-0.1620	0.1501		
Emerging Markets	-0.0065	-0.1324	0.1785	0.2274	0.0670	0.0092		
Equity Market Neutral	-0.3046	-0.0522	0.0970	-0.3557	0.1558	-0.1380		
Event Driven	-0.2016	-0.0139	0.1539	-0.1930	-0.1342	0.0089		
Fixed Income Arbitrage	-0.2067	-0.8344	-0.3484	0.0085	-0.3399	-0.0873		
Global Macro	-0.5856	0.1181	0.1720	-0.3950	0.0585	-0.3790		
Long/Short Equity	-0.1404	-0.3933	0.4184	-0.0062	0.5506	0.5360		
Managed Futures	0.1194	0.0357	-0.6762	-0.4768	0.4112	0.2247		
Multi-Strategy	-0.2881	0.0707	-0.3099	0.5460	0.5021	-0.3576		
Panel C: 7+1 FH Risk Factors								
Eigenvalue	0.0389	0.0185	0.0157	0.0057				
% Variance per Component	48.2045	22.8929	19.4135	7.0121				
Cumulative explained variance	48.2045	71.0974	90.5108	97.5229				
Factor weights								
S&P	0.0661	-0.0377	0.0115	-0.4346				
Size Spread	-0.0104	-0.0378	-0.0047	-0.1347				
C10yr	0.0019	0.0008	-0.0019	-0.0053				
Credit Spread	0.0017	-0.0004	-0.0004	-0.0055				
PTFSBD	-0.3383	0.8893	0.2688	-0.1488				
PTFSFX	-0.8074	-0.4330	0.3977	-0.0376				
PTFSCOM	-0.4687	0.0758	-0.8772	-0.0684				
MSCI EM Index	0.0977	-0.1141	0.0008	-0.8745				

The table reports results from Principal Component Analysis computed for hedge fund returns (Panel A), hedge fund betas (Panel B), and 7+1 FH Risk Factor returns (Panel C).

Table 4: DCC – from January 1998 to September 2008

	Min	10%	50% (Median)	90%	Max	StdDev
Panel A: Median DCC - Filtered Returns						
Convertible Arbitrage	0.376	0.491	0.618	0.790	0.910	0.114
Dedicated Short Bias	-0.618	-0.391	-0.215	-0.101	-0.022	0.120
Emerging Markets	0.217	0.326	0.483	0.659	0.865	0.136
Equity Market Neutral	0.284	0.431	0.537	0.721	0.887	0.123
Event Driven	0.413	0.548	0.657	0.842	0.931	0.107
Fixed Income Arbitrage	0.340	0.492	0.604	0.790	0.909	0.115
Global Macro	0.305	0.406	0.511	0.737	0.887	0.127
Long/Short Equity	0.033	0.193	0.360	0.651	0.845	0.171
Managed Futures	0.098	0.132	0.233	0.490	0.721	0.143
Multi-Strategy	0.336	0.492	0.617	0.823	0.925	0.124
VW Average	***0.265***	***0.384***	***0.495***	***0.708***	***0.874***	***0.129***
Panel B: Median DCC - Time-Varying Betas						
Convertible Arbitrage	0.167	0.396	0.693	0.890	0.937	0.196
Dedicated Short Bias	-0.897	-0.859	-0.714	-0.454	-0.360	0.155
Emerging Markets	-0.187	-0.082	0.025	0.105	0.153	0.072
Equity Market Neutral	0.172	0.425	0.660	0.844	0.917	0.165
Event Driven	0.207	0.322	0.609	0.848	0.906	0.198
Fixed Income Arbitrage	0.146	0.247	0.490	0.786	0.878	0.206
Global Macro	0.245	0.416	0.620	0.856	0.924	0.173
Long/Short Equity	-0.121	0.263	0.507	0.740	0.837	0.182
Managed Futures	-0.730	-0.620	-0.411	-0.191	-0.122	0.162
Multi-Strategy	0.172	0.267	0.561	0.809	0.878	0.204
VW Average	***0.108***	***0.295***	***0.510***	***0.697***	***0.744***	***0.156***
Panel C: Median DCC - 7+1 FH Risk Factors						
S&P	0.501	0.763	0.793	0.821	0.841	0.037
Size Spread	0.324	0.370	0.438	0.495	0.567	0.051
10yr	0.103	0.363	0.438	0.495	0.567	0.063
Credit Spread	0.198	0.567	0.642	0.677	0.712	0.064
PTFSBD	-0.416	-0.239	-0.201	-0.171	-0.131	0.036
PTFSFX	-0.460	-0.219	-0.156	-0.108	-0.074	0.052
PTFSCOM	-0.399	-0.193	-0.054	0.056	0.073	0.097
MSCI EM Index	0.627	0.731	0.758	0.791	0.810	0.025
Overall Median	***0.050***	***0.092***	***0.146***	***0.215***	***0.256***	***0.047***

Panel A and B of the table report summary statistics for cross-sectional median dynamic conditional correlations (DCC) for filtered returns and time-varying beta, as well as the corresponding value-weighted average using the monthly proportion of single AUM as weights. In Panel C we report the same statistics for the cross-sectional median computed for the 7+1 FH risk factors. Min, 50% (Median) and Max are the minimum, the median and the maximum monthly DCC, respectively. 10% and 90% are the corresponding quantile distributions and StdDev is the standard deviation.

Table 5: In-Sample and Out-Of-Sample Model Accuracy – Worst Returns

	In-Sample 1998-2006	**Out-Of-Sample 2007-09/2008**
Brier Score	0.1412	0.3004
Optimal Cut-off	6.70%	8.30%
Youden Index	38.96%	53.16%
AUC	0.7294	0.7115
Numbers of *WR*	90	36
WR correctly classified	59	33
Sensitivity	65.56%	91.67%
Specificity	73.40%	61.49%

The table shows the diagnostics used to assess the models' accuracy in-sample (1998-2006) and out-of-sample (2007-09/2008), namely the Brier score computed using (16), the Optimal Cut-off which is the probability value used to maximize the Youden index, obtained as $[(1-\alpha)+(1-\beta)-1]$ with α and β the type-I and type-II error, respectively. AUC is the area under the ROC curve. The table reports also the overall number of worst returns (*WR*) and the number of worst returns correctly classified. Sensitivity and Specificity are computed as 1 minus type I-error and 1 minus type II-error, respectively.

Table 6: LTCM vs. Sub-Prime Crises Model Diagnostics – Worst Returns

	LTCM 1998-1999	**Sub-Prime 2007-09/2008**
Brier Score	0.1266	0.1796
Optimal Cut-off	50.00%	35.00%
Youden Index	73.36%	66.19%
AUC	0.8792	0.8836
Numbers of *WR*	35	36
WR correctly classified	27	29
Sensitivity	77.14%	80.56%
Specificity	96.22%	85.63%

The table reports the same diagnostics used in Table 5 computed for the two sub-periods, 1998-1999 and 2007-09/2008.

Table 7: In-Sample and Out-Of-Sample Model Accuracy – Contagion

Contagion	**In-Sample 1998-2006**		**Out-Of-Sample 2007-09/2008**	
	Expected	*Actual*	*Expected*	*Actual*
0	525	572	41	112
1	71	312	0	20
2	73	105	3	17
3	4	29	0	25
4	0	22	0	11
5	10	10	0	11
6	0	7	0	4
7	0	3	0	8
8	-	-	0	2
Total	*683*	*1060*	*44*	*210*
Accuracy Ratio		**0.6443**		**0.2095**

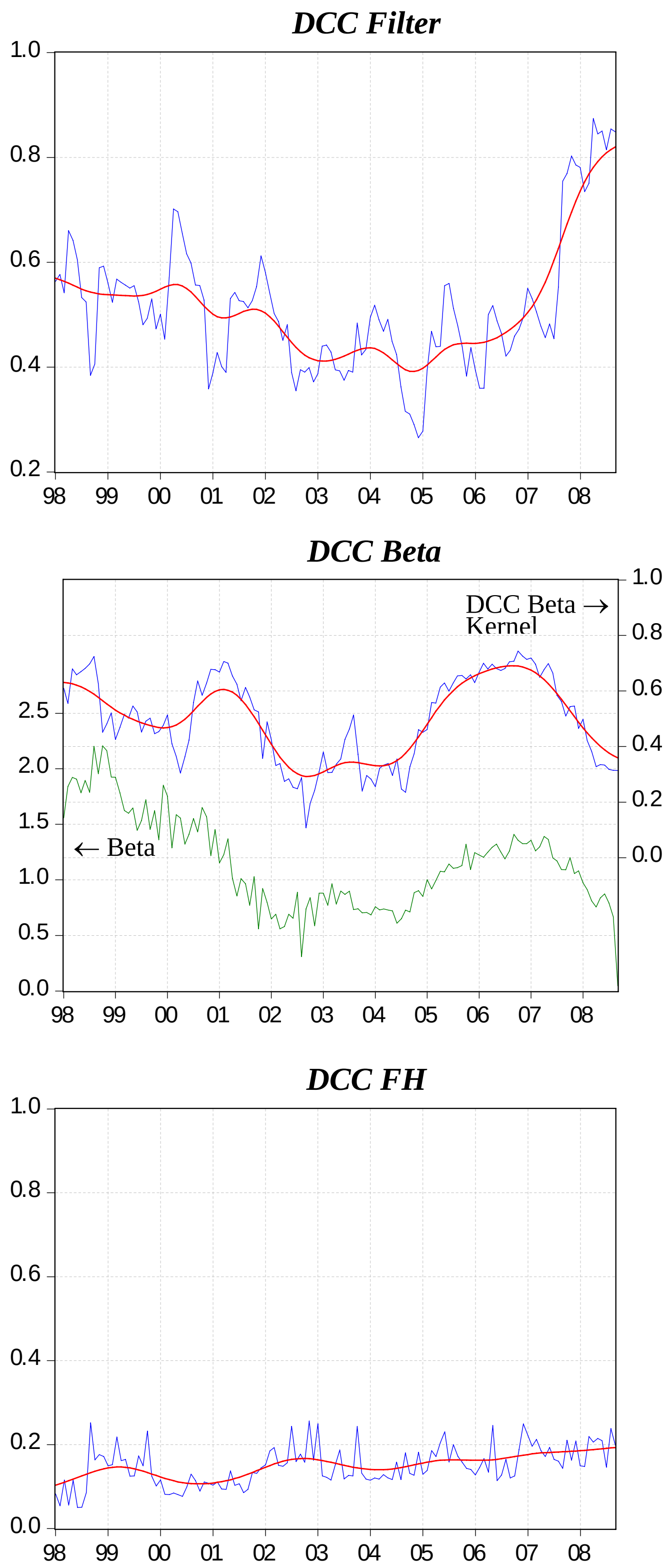
The table reports the expected and actual number of contagion splitted for each value from 0 (no contagion) to 8 (the maximum number of contagion empirically observed) for the two periods 1998-2006 and 2007-09/2008. The Accuracy Ratio gives a measure of the overall classification ability of the model and it is computed as the ratio of the total number of correct (Expected) over the total count (Actual).

Table 8: LTCM vs. Sub-Prime Crises Model Accuracy – Contagion

Contagion	**LTCM**		**Sub-Prime**	
	1998-1999		**2007-09/2008**	
	Expected	*Actual*	*Expected*	*Actual*
0	41	52	111	112
1	90	114	9	20
2	24	24	8	17
3	-	-	14	25
4	5	10	11	11
5	5	10	6	11
6	7	7	0	4
7	0	3	8	8
8	-	-	0	2
Total	*172*	*220*	*153*	*183*
Accuracy Ratio		**0.7818**		**0.8361**

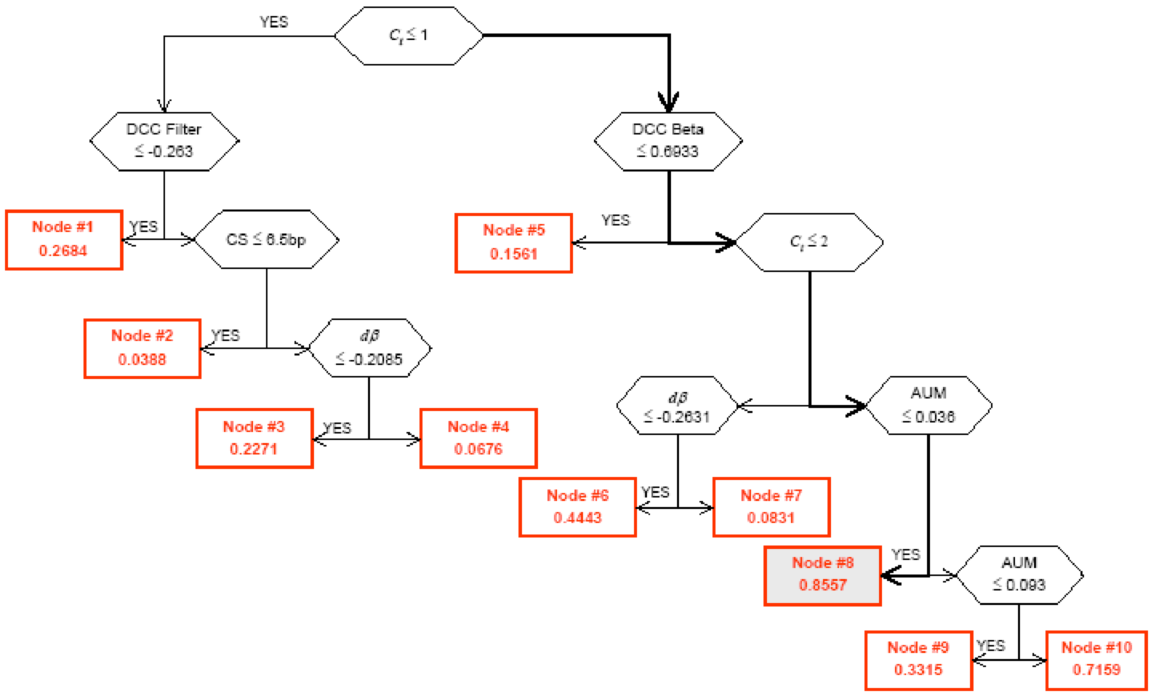
The table reports the same diagnostics used in Table 7 computed for the two sub-periods, 1998-1999 and 2007-09/2008.

Figure 1: DCC and Cycles – from January 1998 to September 2008



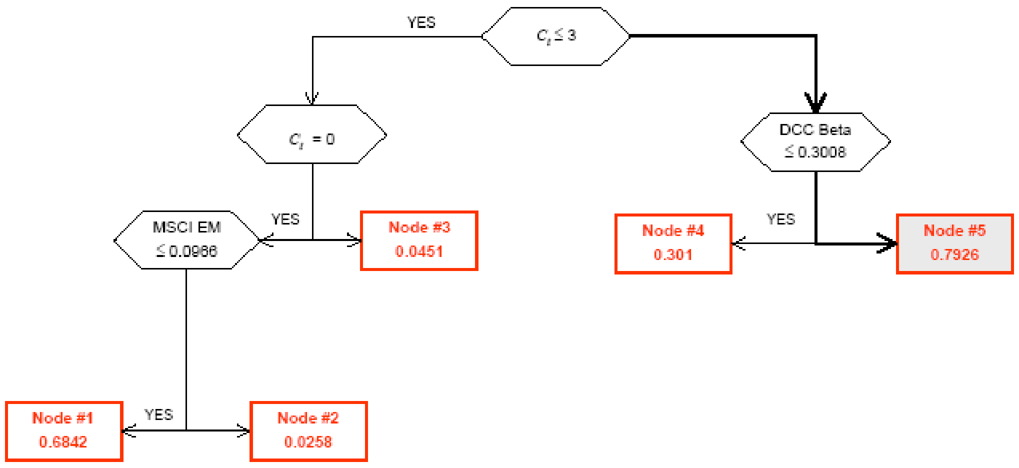
The Figure reports the DCCs computed for filtered returns, betas and the 7+1 FH Risk factors. Blue lines are the original time series while red lines are the corresponding kernel smoothing. For betas the graph reports also the value-weighted average of time-varying betas depicted in green line.

Figure 2: EWS for Worst Returns – from January 1998 to December 2006



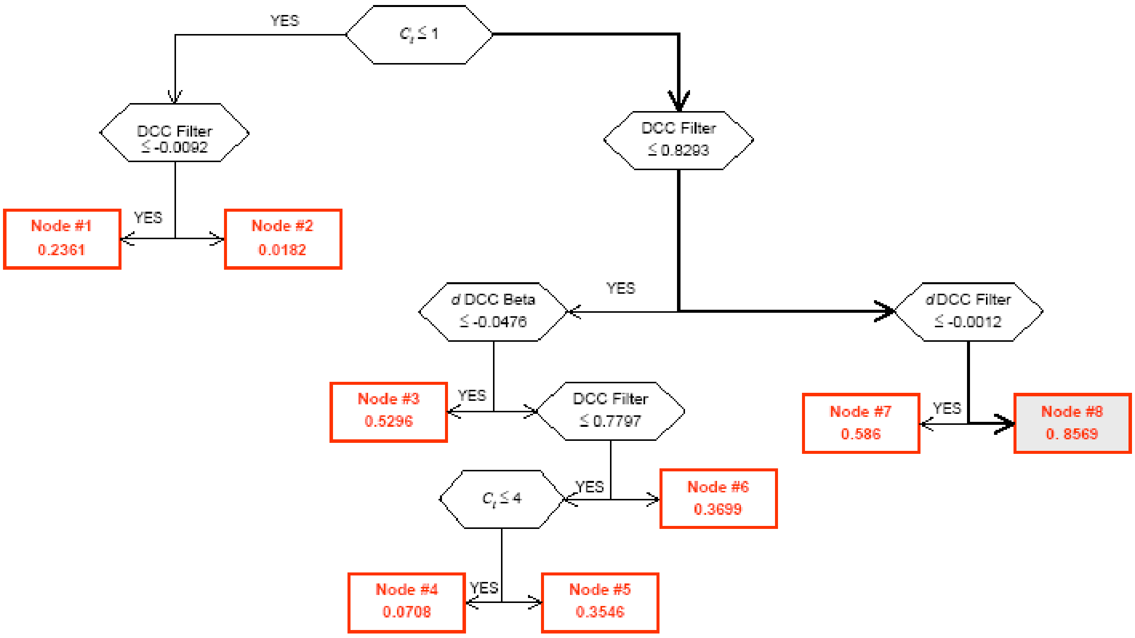
The figure depicts the structure of the EWS for worst returns (*WR*) estimated over the period 1998-2006. For each split, we specify the variable and the corresponding threshold, also indicating the paths towards the terminal nodes. The values reported within each terminal node are the estimated probabilities of *WR*. The most risky node is indicated by the grey area also highlighting the paths towards the higher probability with the bold line.

Figure 3: EWS for Worst Returns – LTCM crisis (1998-1999)



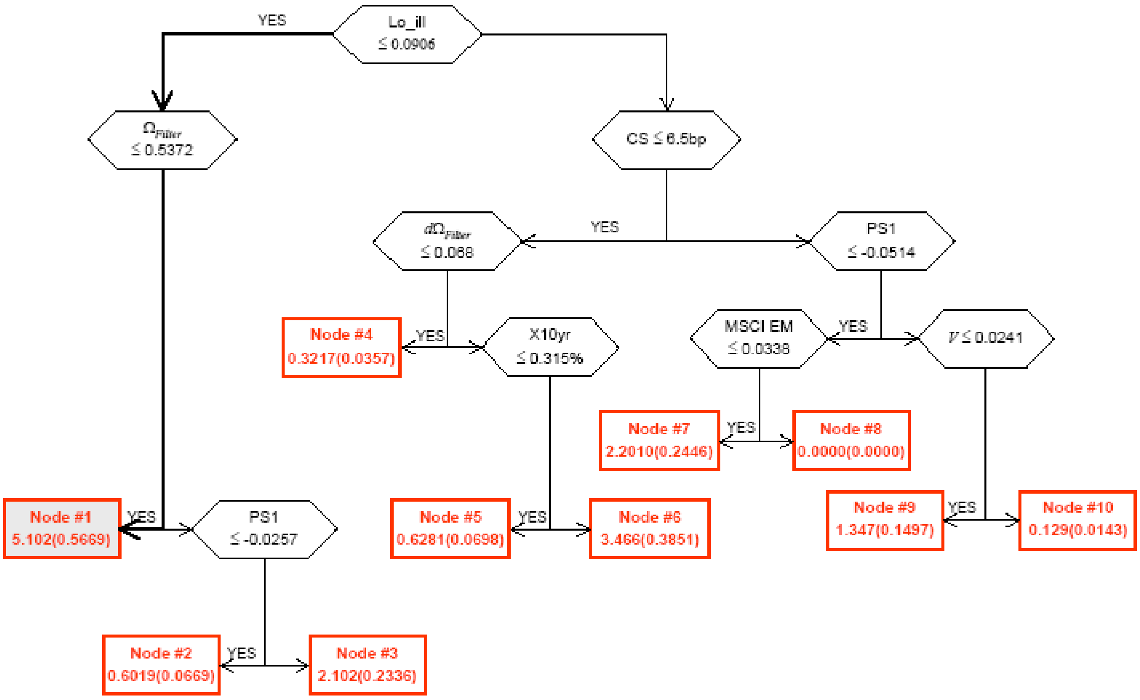
The figure depicts the structure of the EWS for *WR* estimated over the period 1998-1999 as in Figure 3.

Figure 4: EWS for Worst Returns – Sub-Prime crisis (2007-09/2008)



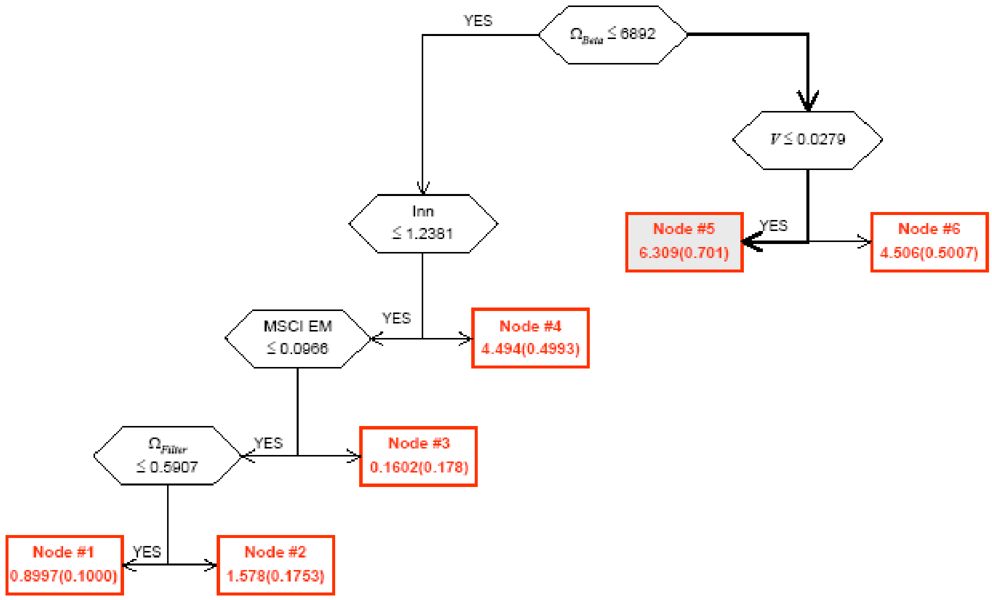
The figure depicts the structure of the EWS for *WR* estimated over the period 2007-09/2008 as in Figure 3.

Figure 5: EWS for Contagion – from January 1998 to December 2006



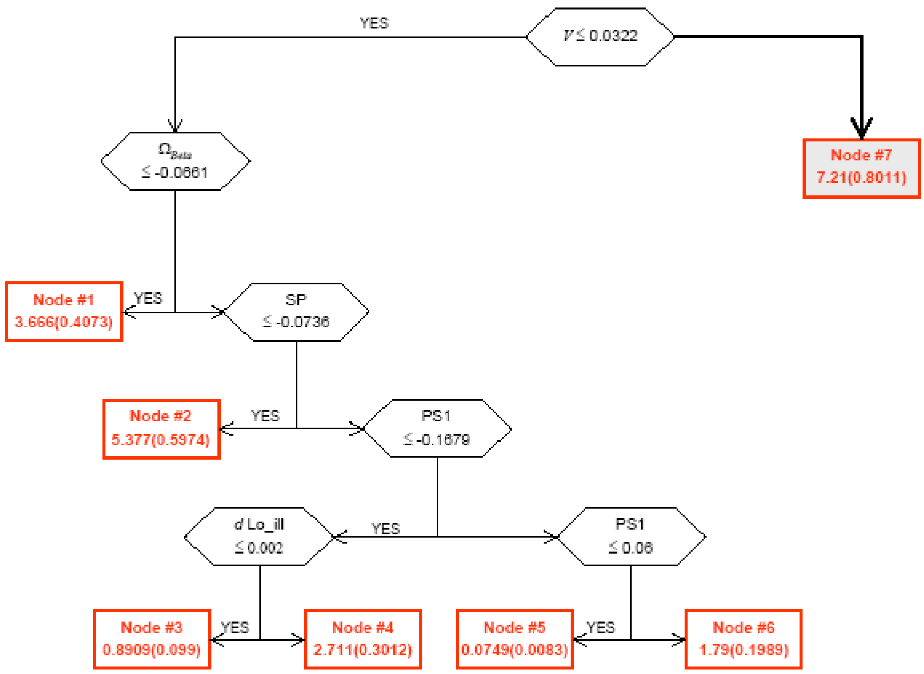
The figure depicts the structure of the EWS for contagion estimated over the period 1998-2006. As for *WR*, For each split, we specify the variable and the corresponding threshold, also indicating the paths towards the terminal nodes. The values reported within each terminal node are the estimated number of contagion and the corresponding probability estimate in parenthesis, obtained as the ratio of the predicted value over the theoretical maximum which is 9. The most risky node is indicated by the grey area also highlighting the paths towards the higher value/probability with the bold line.

Figure 6: EWS for Contagion – LTCM crisis (1998-1999)



The figure depicts the structure of the EWS for contagion estimated over the period 1998-1999 as in Figure 5.

Figure 7: EWS for Contagion – Sub-Prime crisis (2007-09/2008)



The figure depicts the structure of the EWS for contagion estimated over the period 2007-09/2008 as in Figure 5.