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Measuring the contagion across hedge fund industry

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Abstract— **The aim of this research is to study the impact of financial crisis on hedge funds and to detect the presence of the effect of contagion in this industry. We choose a Markov Switching-Regime Regression model (MSR) to measure the dynamic risk exposures of hedge funds to different risk factors during different market volatility conditions. We perceive that hedge fund exposure depends on the equity market (S&P 500) is the up-state, which is characterized by both low volatility market and high returns or down-state, which is also characterized by both high volatility market and low returns. Furthermore, by exploring the possibility of all hedge fund strategies in high volatility regime simultaneously, we deem it as strong evidence of the presence of contagion among different hedge fund strategies. Based in our sample, the Long-Term Management (LTCM) crisis of August 1998 precipitated contagion across the hedge fund industry. These results were only generated by this crisis. Other crises including the recent subprime mortgage crisis of August 2007 and the recent global financial crisis of September 2008 have affected hedge funds and did not cause contagion among hedge funds.**

Keywords— **hedge funds, contagion, a Markov Switching Regime Regression model (MSR)**

1. Introduction

Since the mid-1990s, international financial markets have experienced various episodes of economic and financial distress. The major financial crises observed in recent years were located in different regions: from Mexico in December 1994, to Asia beginning in July 1997, Russia in August 1998, the USA (with the collapse of the U.S. hedge fund Long-Term Capital Management in September 1998 and the recent August 2007 subprime mortgage crisis), the Japanese in March 2001. The hedge fund industry has affected adjacent to these events. The regulators and risk managers were asked about the potential impact of opportunistic strategies of hedge funds on the international capital markets. Moreover, the number of hedge fund has seen a considerable increase. And the availability data of hedge funds data has attracted a lot of attention in academic literature. In our research, we study the effect of financial crises on hedge fund risk and we test the presence of contagion among hedge funds strategies during extreme events.

Several empirical studies in the literature have focused on the hedge funds returns to examine the relationship between their returns and risk factors. Sharpe (1992) and Fung and Hsieh (1997) studied respectively mutual funds' performance and hedge funds dynamics. Their results indicate to significant nonlinear dependencies of hedge funds returns against to risk factors. The authors justify this nonlinearity by complexity of financial instruments and the dynamic strategies implemented by hedge funds to realize absolute returns: for example short selling, leverage, derivatives, illiquid assets…These instruments may to generate a complex and asymmetrical relationship between hedge fund returns and traditional assets. Furthermore, the reaction of hedge funds may also be time varying, claimed that the market in upturns or downturns.

In this respect, we propose a factor model based on regime-switching in volatility, taking into account nonlinearity and dynamic hedge funds exposures to risks factors. Our approach is coherent with the time-varying market integration perspective proposed by Bekaert and Harvey (1995) and the work of Bollen and Whaley (2007) who show that allowing for switching in risk exposure is essential when analyzing hedge fund performance. The regime switching model enables us to measure hedge fund risk exposures in different market states: up-state, normal, and down state. This model allows us to capture the switch in volatility of the idiosyncratic risk factor. Also, this enables us to investigate the presence of contagion among hedge funds strategies. In our framework, we define contagion among hedge funds strategies when we observe that all hedge funds are in state of high volatility (down market). Our work is therefore to test the presence of contagion across the hedge fund industry using the Markov switching regime regression model. In our knowledge, we firstly introduce the Markov regime switching regression approach to can distinguish whether the distressed in the hedge fund industry is generated from the dynamic exposure to risk factors that are affected by financial crisis, from the contagion in the hedge fund industry, or both. The remainder of this paper is organized as follows. Section 2presents our methodology and the econometric model. The data are described in section 3 and the estimation results are presented and discussed in section 4. Section 5 concludes.

2. Methodology

As mentioned in introduction, returns of hedge funds' strategies are widely known by their complexity and mostly by their dynamics on market over time. To estimate the dynamics of hedge funds returns and theirs exposures to risk factors, we shall begin firstly with determining the number of states taken into consideration. So, we shall characterize the S&P 500 behavior by a switching regime model. Then, we shall estimate our multi factor models.

2.1 Presentation of model

The capital asset pricing model (CAPM) and the arbitrage pricing theory (APT) remain to be popular asset pricing literature on both theoretical and empirical level. For this, we consider the following multi factor model applied to hedge fund returns:

$$R_t = \alpha + \beta I_t + \sum_{k=1}^{k} \theta_k F_{kt} + \omega \mu_t \qquad (1)$$

Where Rt is the return of a hedge fund index in period t, It is the market factor (in our example S&P500) , Fkt is the return of k-th risk factor at time t, and μt is IID.

This model allows us to identify the exposure of hedge fund returns to risk factors It and Fkt . Hence, implying that relation between risk factors and returns must be linear. However, Fama and French argue that the failure of the CAPM in empirical tests implies that most applications of the model are invalid. Thus, we state an important assumption about the non linearity of several financial series, i.e., hedge funds returns are characterized by implementation of dynamic strategies. Our paper aims to analyze the relationship between hedge funds returns and risk factors in a non linear framework. For this reason, we propose a more flexible model for capturing this behavior: regime switching model.

Formally, this model could be represented as:

$$\mathrm{R_t} = \alpha(Z_t) + \beta(S_t) I_t + \sum_{k=1}^{k} \theta_k(S_t) F_{kt} + \omega(Z_t)\mu_t \qquad (2)$$

$$I_t = \mu(S_t) + \gamma(S_t)\varepsilon_t \qquad (3)$$

Where St and Z_t are the Markov chains with n_S and n_z states respectively and transition probability matrices P_s and P_z respectively.

The state of the market index It is described by the Markov chain S_t . Each state of the market index has its own mean and variance. This means that if there are k states, there will be k values for μ and δ2. If there is only one state of the world (S_t =1), formula (3) takes the Sharpe of $I_t = \mu + \varepsilon_t$ and it can be treated as a simple linear regression model under general conditions.

The Markov chain Z_t characterizes the change in volatility of residuals. Hedge fund mean returns are related to the states of market index It and to the states of the volatility of residuals. In both cases β and θ_k could be different conditional on a state of the risk factor I. Assuming now that the model in (2) has two states (k=2). In addition to aiding intuition, using the two-regime case is a popular specification in applied work. If $n_s = 2$ (states labels are denoted as 1 and 2), β and θ_k depend on the state variable S_t.

$$\beta(S_t) = \begin{cases} \beta_1 si S_t = 1 \\ \beta_2 si S_t = 2 \end{cases} \qquad (4)$$

And the matrix P_s will control the probabilities of making in switch from one state to the other. It can be represented as:

$$P_s = \begin{pmatrix} P_{11} & P_{12} \\ P_{21} & P_{22} \end{pmatrix} \qquad (5)$$

With P_{12} =1 - P11 and P_{22} = 1 - P21, where P_{ij} controls the probability of a switch from state j to state i. In our example, P_{12} means that the probability of moving from state 2 to state 1.Likewise, the parameters P_{11} and P_{22} determine probabilities of staying in same regime. This model allows us to make dynamic forecasts. Despite the fact that the states S_t and Z_t are unobservable, but they can be statistically estimated (see for example Hamilton (1990, 1989)). Moreover, once parameters are estimated, the likelihood of regime changes can be easily obtained, as well as forecasts of β itself. Furthermore, the k-step transition matrix of a Markov chain St is given by P_{ks} , the conditional probability of the regime S_{t+k} given date t data $R_t = (R_t, R_{t-1},\ldots,R_1)$. In our case when number of regime is 2(regime 1 and 2), the conditional probability is given as:

$$\mathrm{P}(S_{t+k} = 0 \setminus R_t) = \pi_1 + (P_{00} - (1 - P_{11}))^k \left[P(S_t = 0 \setminus R_t) - \pi_1 \right] \qquad (6)$$

$$\pi_1 = \frac{(1 - P_{11})}{(2 - P_{00} - P_{11})} \qquad (7)$$

Where P(St=1\ Rt) is the probability that the date-t regime is 0 given the historical data up to and including date t. more generally, the conditional probability of the regime S_{t+k} given date t data is:

$$P(S_{t+k} = 0 \setminus R_t) = P_s^{k'} a_t \qquad (8)$$

$$a_t = \left[P(S_t = 0 \setminus R_t) P(S_t = 1 \setminus R_t) \ldots P(S_t = n \setminus R_t) \right]' \qquad (9)$$

In a similar way, the conditional probability of the Markov chain Zt+k , that characterizes the switch in volatility of the innovations (residuals) , given date t data for strategy i.

$$P(Z_{i,t+k} = 0 \setminus R_{i,t}) = P_{n_z}^{k'} b_{i,t} \qquad (10)$$

$$b_t = \left[P(Z_{i,t} = 0 \setminus R_{i,t}) P(Z_{i,t} = 1 \setminus R_{i,t}) \ldots P(Z_{i,t} = n_s \setminus R_{i,t}) \right]' \qquad (11)$$

Therefore, our test of contagion is based on determination of the joint probability that all n hedge fund strategies are in high volatility of residuals. Thus, we define contagion among hedge fund strategies when we observe a significant change in the joint probability that all hedge funds are in the high volatility regime (down market).

2.2 Sample and Data

For the empirical analysis in this paper, our data consist hedge fund returns and risk factors. We consider 7 different hedge fund strategies that may be classified into three styles: directional, arbitrage and event driven styles. Arbitrage style managers are interested in exploiting price spreads between closely related assets. Directional or trading style managers seek to take benefit from a gamble on the overall direction market and involve taking positions on forwards and options markets, and on global market. While, event driven style tends to profit from events affecting companies such as mergers and restructuring.

For Hedge Funds data, we use monthly hedge fund index return data from Hedge Funds Research (HFR) beginning with January 1994 up to November 2011. This database includes more than 18800 funds. The HFR indexes are equally weighted and net of fees. There are seven single strategies indices of different styles: Arbitrage style such as Fixed Income and Equity Market Neutral strategies and Directional style naming Emerging Market strategy, as well as Event Driven style such as Merger Arbitrage, Distressed Securities, Multi-Strategy and Event Driven.

Regarding risk factors, we consider three important variables (factors) that we wish to measure their impact on different hedge fund strategies. Therefore, we consider the stock, currency and volatility markets where hedge funds strategies are mainly exposed to these risk factors selected. Principally, these risk factors may portray all different strategies, and are represented by the following indexes: S&P500, TWEXB (Bank of England Trade Weighted Index) and VIX (CBOE Volatility Index). We introduce the VIX to depict strategies, where some funds take long positions in volatility. Overall, these variables are considered the main risk factors for hedge funds and are usually referred to in the literature. We use these factors to estimate risk models for the seven hedge funds indices.

Summary descriptive statistics for the returns on monthly hedge funds strategies indices are statistic provide that hypothesis of normality of several hedge fund strategies is rejected. Therefore, the asymmetry, leptokurtic excess and non-normality are indicators of non-linearity that can be justified by the complexity of financial instruments and dynamic strategies used by hedge.

The correlation coefficients between the returns of hedge fund indices and those risk factors stock market, foreign exchange and volatility show that the returns of hedge funds seem to be highly correlated. Moreover, the correlation of S&P 500 with several hedge fund strategies at frequencies is lowest. The exception is the correlation with the Event Driven strategy, which a value is 0.5. Likewise, hedge fund strategies returns are weakly and negatively correlated with other risk factors (TWEXB and VIX). These results suggest a complex and specific relationships between different hedge fund strategies returns and risk factors returns.

2.3 Analyses and Results

2.3.1 Switching regime model of S&P500

To determine the number of regimes used in the estimation, we estimate and test different models with different number of regimes. We decide that using two regimes is optimal for our analysis. Using two regimes is consistent with the literature that well recognizes the presence of upturns and downturns of the equity market. The results of estimation are presented in (table 1). The empirical estimates provide strong evidence that the equity market move in two states, where state 1 has relatively low monthly volatility of 0.0454%. We denote this regime as an up-market regime, which is persistent (The probability to remaining in this regime in the following month is 0.97). Regime 2, which is often associated with financial crisis, captures market downturns and has volatility of 0.4469%. This is also a persistent regime and the probability of remaining in it is 0.99. Using the Hamilton and filter and smoothing algorithms (Hamilton 1994) allows us to identify when the S&P 500 was in one of the two regimes for each date of the sample.

Based on the first part of the sample, we notice from January 1994 to December 1996(see figure 1), the S&P 500 returns are frequently characterized by the up-market. The period from 1997 to 2002, is characterized by down market regime. This can be mainly explained by high instability of the financial markets starting from Asian down-market in 1997, then the collapse of LTCM in 1998. Moreover, the Japanese down-market of March 2001, September 11, 2001 are captured mostly by regime 2. And the part of the sample from January 2003 through the first quarter of 2007 is characterized by an up market. Finally, starting August 2007, the S&P 500 returns are again in regime of down market, where market returns are affected by the subprime crisis (2007) and the current financial crisis 2008. Accordingly, the regime switching approach allows us to identify periods when the market return distribution belongs to large volatility periods characterized by return downturns. Thus, we may face positive or negative return.

Our findings confirm that the null hypothesis of single regime is strongly rejected and that there is strong evidence of switching-regime on the U.S. stock market. Moreover, we distinguish that there are two regimes with a persistent low-volatility state (regime1) and a high volatility state (regime2), which is characterized by a major crisis in the stock market. In this respect, we estimate our switching regime regression model for each hedge fund strategy with endogenous risk factors, with a number of states is equal to 2.

Table 1. Results of estimation

	Regime 1	Regime 2
α	0.0127 (0.00)	**0.0072** **(0.21)**
Standard deviation (σ^2)	0.000454 (0.00)	0.004469 (0.00)
Probabilities of being in same regime	0.97 (0.00)	0.99 (0.00)
log Likelihood	**321.689**	
Duration	29.43	107.83

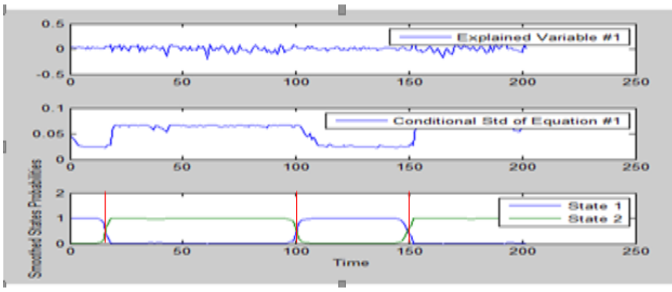

Fig . 1 Transition of probabilities

2.3.2 Markov Switching-Regime Regression Model (MSR):

As discussed above, the graphical analysis of returns of different hedge fund strategies shows us that hedge funds have registered significant and important losses during periods of crisis and especially during the collapse of LTCM (in 1998) , during the subprime and the recent financial crisis (in 2008). In this respect, our estimate of the multi factor model is done in two sub-periods: the first is ranging from 01/01/1994 to 31/12/2005 and the second is going from 01/01/2006 to 01/11/2011.

In this section, we estimate the multi-factor model for each hedge fund strategy using MSR approach and reported the main results in table 4. Using MSR allows us to analyze dynamics exposures of different hedge funds strategies to risk factors selected in different regimes (up and down market). We are considering nonlinear exposures to systemic risk factors: S&P500, VIX and TWEXB. For each factor, we estimate two exposures: $\beta_{i,1}$ is a hedge fund exposure for a factor i when the S&P500 is in the up state and $\beta_{i,2}$ is a hedge fund exposure for a factor i when the S&P500 is in down state. We estimate different factor loadings $\beta_{i,j}$ relative to the S&P500 regimes for all hedge funds indexes. Firstly, we consider the coefficients relating to risk factor equity market. We find the exposures all strategies to the S&P 500 during crisis periods are lesser or negative compared with to tranquil periods. This suggests that hedge fund managers are capable to hedge market exposures, especially during financial crisis. For example, the exposure of hedge fund returns of Equity Market Neutral strategy to S&P500 during tranquil periods is 0.0095 and is reduced to 0.0025during market down returns, as shown in (Appendix 2). While, the exposures of the strategy are positive during down and up market conditions. These results confirm the hypothesis that the market neutral strategy can neutralize the effects of normal fluctuations of the market, but when the market is abruptly moving to another regime, so to hedge against these changes, the exposure becomes positive. Almost strategies have a positive market exposure both when the market is characterized by the down market state and up market state. The exposures of these strategies are significant and different from zero in at least one regime for both sub periods. The Event Driven strategy presents a negative exposure in the down market for both sub periods. These results are in line with the fact that the Event Driven strategy can be affected negatively by flight to quality episodes (episodes of significant declines as the example of the U.S. sovereign debt). Thus, we find that the risk factor of the stock market is a risk factor common for all different hedge fund strategies. However, other risk factors play a role as important as the S&P 500 to describe the dynamic hedge fund exposures. Secondly, we consider the exposures of hedge fund strategies to risk factor of the volatility VIX for two sub periods. Moreover, we find that another risk common factor for all hedge fund strategies is VIX. We note that all different strategies show a negative exposure to this variable in up market (state 1) for both sub periods. Whereas three out of seven strategies present a positive exposure to VIX in the down market during first period of this study. In fact, the coefficients β_2 VIX of these strategies (Event Driven, Emerging Market and Equity Market Neutral) are a significant and positive where theirs β_2 VIX are respectively as following (0.0504, 0.0349 and 0.0084). As expected, an increase of volatility during crisis periods is more probably to lead to hedge fund losses compared with up market time. When, higher volatility is associated with lower liquidity, higher correlations, higher credit spreads and flight to quality. Therefore, in the down-market the change in volatility negatively affects the returns for most strategies, and in up-market, all strategies register additional returns. For most of the strategies considered, exposures to the VIX have opposite signs in down and up markets for both sub periods. This implies that the different strategies of hedge funds take advantage of negative changes in market volatility. Finally, we consider a risk factor of change which is indexed by the index TWEXB. We find that the estimation results indicate that the most strategies of hedge fund have a negative exposure to this variable TWEXB for both regimes up and down markets. In fact, the coefficients βTWEXB associated to this risk factor are a significant and negative in up-market period. While, there are strategies act positively with price fluctuations in the currency exchange market. This implies that strategies are not affected same by simple variations on the market. Indeed, we find that this risk factor is not inherent factor for Merger Arbitrage, Fixed Income and Emerging Market strategies for first period. Contrariwise, for these strategies, the exposure to TWEXB is significant during the second sub period. In addition, Emerging Market, Multi strategy and Event Driven strategies take advantage of when the market knows drop episodes, which theirs coefficients of β_2 are positive and significant (

respectively 0.8842, 0.8889 et 0.334). As also, hedge funds may to cover against this currency risk by tacking on forward contracts. In conclusion, we find convincing evidence that for different hedge funds strategies are affected by the various risk factors identified and theirs factor exposures are different for various factors conditional with state of the market.

Moreover, this model shows that factor exposures are dynamic which are changing conditional on the volatility of the market risk factor. Therefore, our initial hypothesis that the exposures to various risk factors are time-varying and are changing with conditional volatility of the market risk factor. It is important to confirm that most different hedge fund strategies are affected by extreme returns, especially financial crises. This leads us to our main objective of this study, the identification of the presence of contagion across hedge fund strategies in times of crisis. Indeed, we estimate the joint probability with the regime switching model for each hedge fund strategy. We note that the regime 1 (up-market) is more persistent than regime 2(down market) for all identified strategies where the probability p_{11} (is probability of state in the same regime 1) is greater than p_{22} (is the probability of state in the same regime 2) for the two sub-periods. In addition, we estimate the volatility of model for each strategy. We perceive that volatility is characterized by two different regimes with high and low volatility for seven hedge fund strategies during the first study period. In fact, Emerging Market strategy presents widest volatility (σ^2_2 = 0. 201%). In contrast, for the second sub-period, the volatility of the model for four out seven strategies evolves in a one regime (up market). This means that these strategies have registered significant earnings during this period.

Monthly probabilities (p_{11} and p_{22}) and volatilities (σ^2_1 and σ^2_2) of the different strategies during the period of this study from 01/01/1994 to 01/11/2011 are shown in the graphics (see Appendix1). We see that evolution of the volatility of different strategies of hedge funds is slightly different. We observe that all most different strategies are be in regime 1 which is characterized by low volatility than in regime 2 which is characterized by high volatility, especially during first sub period where is characterized by many times of crises. These graphs allow us to see the change in volatility, also as the switching from one regime to another. In particular, we observe that different strategies present a high probability of being in high volatility regime during periods of crisis from 1997 till 2001. This indicates that the exposure to the S&P 500 is changing, where the hedge funds indices can switch to the high volatility at the same time when the market is characterize by turbulence. This may be explained by contagion among hedge fund strategies. Thus, our aim is to prove that the evidence of existence of contagion across hedge fund industry.

– The collapse of LTCM 1998:

By concentrating on the first sub-period from 01/01/1994 to 31/12/2005, we are able to explore whether the volatility of hedge fund indices was high during the collapse of LTCM. We find that the probability of being in high volatility regime for all hedge fund strategies increased in August 1998, the month of the LTCM collapse. We also observe that the all hedge fund strategies without exception are in high volatility state (down market) as shown graphics (see Appendix 1). The results suggests that even after accounting for market and other factor exposures, the liquidity crisis precipitated by the collapse of LTCM was affected all hedge fund strategies. This proves strong evidence that the presence of contagion across hedge fund industry during one extreme event which is the LTCM failure.

– 2007 Subprime Mortgage Crisis and 2008 Financial Crisis:

The last part of the sample includes the most recent subprime mortgage crisis of August 2007 and the recent September 2008 global financial crisis. We then test the hypothesis that all different hedge fund strategies might be affected by these crises. We perform a similar analysis for this second sub period; calculating joint probabilities of different two states for all seven strategies. We find that the probability of being in high volatility regime for Distressed, Emerging Markets, Event driven and Equity Market Neutral is significant and different from zero. Therefore, these strategies were affected by crises, even after taking into account systemic risk exposure. However, Merger Arbitrage and Multi strategy had a zero probability of being in high volatility regime (down market) during the whole time period. Furthermore, the joint probability of a high volatility state for all hedge fund strategies is zero during the subprime mortgage crisis of August 2007 and the global financial crisis of September 2008. These crises affected separate hedge fund strategies but not hedge fund industry. This did not lead to contagion among all hedge fund strategies. We can explain that one by the increase in the systematic linkages during periods of crisis.

3. Conclusion:

This paper investigates the impact of financial crises on hedge fund industry. We analyze risk exposures for different hedge fund strategies, especially in the down state of the market characterized by a high volatility. We use the Switching regime regression model to characterize the dynamic exposure of hedge fund index to risk factors identified. This approach allows us to study time varying risk exposure for hedge funds in different state of the market. First, we find that the dynamics of hedge fund returns and their relationship with risk factors exhibit nonlinearity and asymmetry. This switching regime regression model (MSR) may to analyze the relationship between hedge fund returns and risk factors selected. Second, we find that the relationship between hedge funds and risk factors varies regularly and depends on the regime: downturns, upturns and crisis, etc. This MSR model allows us to capture the evolution of hedge fund exposure to risk and to analyze hedge funds reaction in periods of financial crisis. Furthermore, our MSR model should be able to capture contagion across hedge fund industry. Our findings suggest that all the identified hedge funds strategies exhibit a high volatility regime only during extreme event which is the collapse of LTCM. We find that the joint probability of high volatility regime for all hedge funds is approximately 1, at the LTCM crash. This provides strong evidence that even after accounting for market and other factor exposures, the LTCM crisis generated contagion across the hedge fund industry, even though the market was characterized by other crisis in the sample considered. Finally, our study shows that crisis including the recent subprime mortgage crisis and the global financial crisis 2008 affected hedge funds but not lead to contagion among hedge funds.

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Appendix 1:

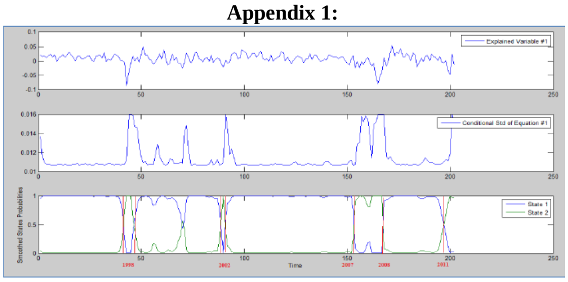

Fig . 2 Distressed strategy

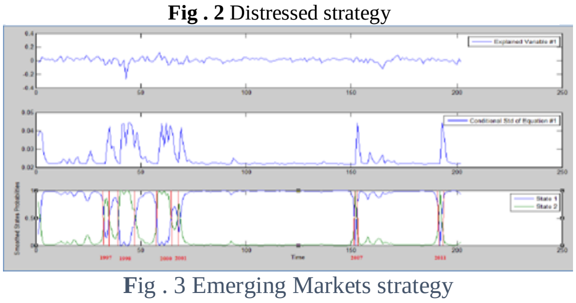

Fig . 3 Emerging Markets strategy

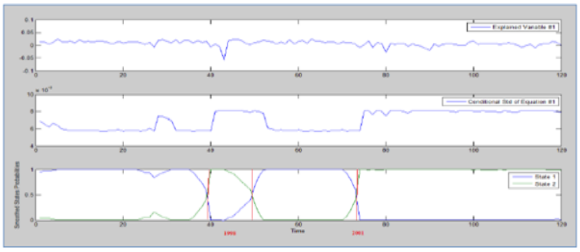

Fig . 4 Merger Arbitrage strategy

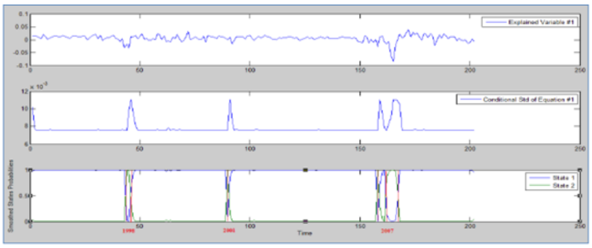

Fig . 5 Multi-strategy

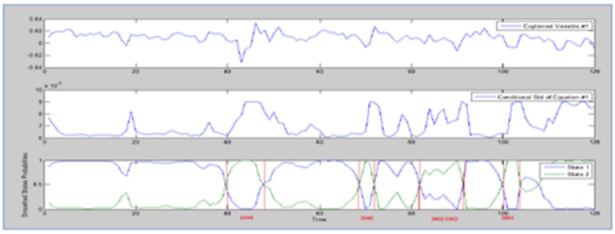

Fig . 6 Event Driven strategy

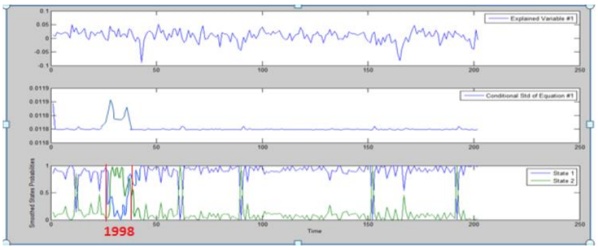

Fig . 7 Fixed Income strategy

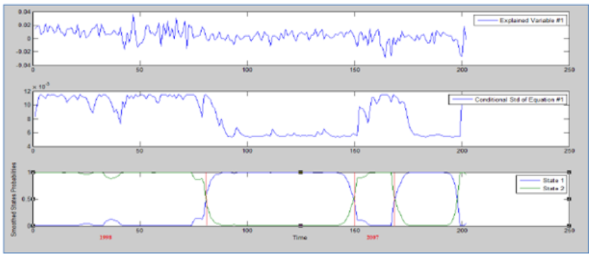

Fig . 8 Equity Market Neutral strategy

Appendix 2: Table 2 Multi-factor model

	Index	Distressed	Merger Arbitrage	Multi Strategy	Event Driven	Emerging Markets	Fixed Income	Equity Market Neutral
First period from 01/01/1994 to 31/12/2004	α_1	0.0.121 (0.00)	0.0133 (0.00)	0.008 (0.00)	0.0088 (0.00)	0.0086 (0.01)	0.013 (0.00)	0.00103 (0.00)
	α_2	-0.0034 (0.74)	0.002 (0.00)	0.001 (0.73)	0.0007 (0.00)	-0.0064 (1)	0.0016 (0.48)	0.0025 (0.00)
	$\beta_{1(SP500)}$	0.3455 (0.01)	-0.0087 (0.59)	0.0733 (0.00)	0.1914 (0.00)	0.3384 (0.00)	0.51 (0.51)	0.0095 (0.00)
	$\beta_{2(SP500)}$	0.0865 (0.045)	0.1599 (0.00)	-0.0057 (0.89)	-0.186 (0.00)	-0.3065 (1)	0.1044 (0.00)	0.0025 (0.00)
	$\beta_{1(TWEXB)}$	-0.3157 (0.00)	0.0078 (0.91)	-0.0969 (0.02)	-0.2632 (0.01)	-0.2821 (0.21)	-0.0098 (0.88)	-0.0179 (0.00)
	$\beta_{2(TWEXB)}$	0.5523 (0.46)	-0.125 (0.15)	0.4067 (0.12)	0.2738 (0.00)	0.4751 (1)	0.0107 (0.93)	-0.1397 (0.00)
	β_1(VIX)	-0.0232 (0.01)	-0.0048 (0.00)	-0.004 (0.00)	-0.0548 (0.00)	-0.108 (0.00)	-0.0089 (0.00)	-0.0041 (0.00)
	β_2(VIX)	-0.0373 (0.17)	-0.0061 (0.00)	-0.0562 (0.00)	0.0504 (0.00)	0.0349 (0.00)	-0.0074 (0.00)	0.0084 (0.00)
	Log- likelihood	355.753	415.754	425	368.09	296.31	407.12	405.52
	σ^2_1	0.000094 (0.00)	0.000032 (0.00)	0.000024 (0.00)	0.000172 (0.00)	0.001 (0.00)	0.000033 (0.00)	0.00001 (0.00)
	σ^2_2	0.000831 (0.09)	0.000067 (0.00)	0.000152 (0.00)	0.00183 (0.00)	0.002 (0.00)	0.000093 (0.00)	0.00025 (0.00)
	P_{11}	0.94	0.96	0.96	0.94	0.97	0.91	0.99
	P_{22}	0.54	0.98	0.86	0.26	0.5	0.85	0.99
Second period from 01/01/2006 to 31/11/2011	α_1	0.0107 (0.00)	0.0049 (0.00)	0.0043 (0.00)	0.0042 (0.00)	0.0052 (0.00)	0.0064 (0.02)	0.0032 (0.00)
	α_2	-0.0099 (0.02)	0.0032 (0.00)	-0.00192 (0.00)	0.0108 (0.00)	0.0056 (0.00)	-0.0055 (0.32)	-0.0035 (0.34)
	$\beta_{1(SP500)}$	0.0523 (0.1)	0.0443 (0.00)	0.042 (0.00)	0.0984 (0.00)	0.1269 (0.00)	0.024 (0.00)	0.00258 (0.1)
	$\beta_{2(SP500)}$	-0.005 (0.98)	0.0631 (0.00)	0.0258 (0.00)	-0.4112 (0.00)	0.1141 (0.00)	-0.1744 (0.31)	0.0377 (0.52)
	$\beta_{1(TWEXB)}$	-0. 4054 (0.00)	-0.0556 (0.00)	-0. 4259 (0.00)	-0. 4126 (0.00)	-0.6336 (0.00)	-0.7275 (0.00)	-0.0324 (0.61)
	$\beta_{2(TWEXB)}$	-0.4027 (0.08)	-0.3112 (0.00)	0.8889 (0.00)	0.334 (0.00)	0.8842 (0.00)	0.4222 (0.5)	0.0037 (0.98)
	β_1(VIX)	-0.0489 (0.00)	-0.023 (0.00)	-0.0366 (0.00)	-0.0445 (0.00)	-0.0634 (0.00)	-0.0753 (0.00)	-0.01 (0.01)
	β_2(VIX)	-0.0408 (0.00)	-0.2179 (0.00)	-0.134 (0.00)	-0.0391 (0.00)	-0.2133 (0.00)	-0.0522 (0.00)	-0.009 (0.5)
	Log- likelihood	242.775	278.528	323.009	240.407	262.868	201.453	289.224
	σ^2_1	0.000089 (0.00)	0.00006 (0.00)	0.0001 (0.00)	0.000155 (0.00)	0.000344 (0.00)	0.000428 (0.00)	0.000024 (0.00)
	σ^2_2	0.0002 (0.01)	0.0004 (0.00)	0 (0.00)	0.004 (0.00)	0 (0.00)	0.000012 (0.48)	0.000157 (0.00)
	P_{11}	0.97	1	0.96	1	1	0.99	0.96
	P_{22}	0.97	0	0	0.06	0.71	0.79	0.97