

Hedge funds: Drivers of co-movements among financial assets

Preliminary Draft

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Abstract

This empirical paper seeks to figure out the role of Global macro hedge funds in the co-movement process among financial markets, and the contagion during the financial crisis in 2008. Indeed, the alternative management strategies of hedge funds can be a channel for transmitting shocks between markets. The dynamic of hedge fund portfolios leads to a diversified exposure to risks explaining the co-movements among asset returns.

To verify this hypothesis, we propose the following methodology: after evaluating the co-movements of financial assets by using a DCC-GARCH model, the series of conditional correlations are exploited in a non-linear model to understand the impact of Global macro funds' performance regimes and their risk factor exposure, computed with a space-state model estimated by Kalman filter, on these co-movements.

The results reveal a significant contribution of hedge funds in the co-movement among assets, especially considering the statistical dependencies with the US stock market.

Key words: Contagion, co-movements, Hedge funds, DCC-GARCH, Space-State Model, Kalman filter, Non-linear model.

1 Introduction

In a context of financial integration and market decompartmentalization, the economic and financial shocks are transmitted to all corners of global financial system. In a few weeks, the burst of the US mortgage bubble, leading to the sharp fall in stock prices, has affected all financial markets.

The financial crisis has revealed the role of many factors and an alternative measure of the linkage between markets that reflects by the contagion effects. The concept of contagion proposed by Forbes and Rigobon (2002) [24], as "a significant increase in cross-market linkages after a shock to one country (or group of countries)", presents a number of operational advantages, highlighted by Horta et al. (2008) [26]. Firstly, because it concentrates on the changes of relationships between markets, rather than on the magnitude of those relationships, it allows the assessment of the effectiveness of international diversification in periods of financial turmoil. A strategy of international diversification, as a means to decrease the risk of a portfolio without compromising its expected return, may be successful only if correlations between markets do not increase in times of crisis. It is therefore the change suffered by correlations, and not the correlations themselves that are of critical importance in such a context.

Some interesting applications of multivariate GARCH model using conditional correlations analysis to test for shifts in linkages across financial markets during crisis periods can be seen in the works of Engle (2002) [20], Tse and Tsui (2002) [44] and Cappiello, Engle and Sheppard (2006) [12]. Some researchers choose a BEKK specification such as Shamiri (2010) [37] to model time-varying correlations. Others use Engle's (2002) [20] dynamic conditional correlations model (DCC) which is a generous model allowing for time-varying correlations as well as a convenient estimation. Using dynamic conditional correlation (DCC), Cho and Parhizgari (2008) [15] reconsider the definition and measurement of contagion by analyzing the 1997 East Asian financial crisis in the equity markets of eight countries. Their findings indicate the presence of contagion in the equity markets across all the fourteen pairs of source-target countries that are considered. Hwang and al. (2010) [27] find evidence of financial contagion not only in emerging markets but also in developed markets during the U.S. subprime crisis by using a dynamic conditional correlation generalized autoregressive conditionally heteroskedastic (DCC-GARCH) model on 38 country data.

Along with seeking to define and measure contagion, researchers have looked at possible channels through which contagion or spillover effects might operate, including trade linkages, financial linkages, and the presence of common economic and financial fragilities. The first category accentuates spillovers resulting from the fundamental interdependences among market economies. The interdependence means that shocks,

whether of a global or local nature, will be transmitted across countries because of their real and financial linkages. Calvo and Reinhart (1996) [11] call this type of crisis propagation "fundamentals-based contagion"¹. The other category involves a financial crisis which cannot be linked to observed changes in macroeconomic or other fundamentals and is solely the result of the behavior of investors or other financial agents. Calvo [10] suggests that margin calls could lead many sophisticated investors to liquidate many positions if they practice the leverage. Moreover Schinasi and Todd-Smith (2000) [36], for example, demonstrate that portfolio diversification and leverage are sufficient to explain why an investor will find it optimal to significantly reduce all risky asset positions when an adverse shock impacts just one asset. On the other hand contagion is often said to be caused by "irrational" phenomena, such as financial panic, herd behavior, loss of confidence, and increases in risk aversion. We may also mention the point of view of Cipriani and Guarino (2003) [16] or Bikhchandani and Sharma (2000) [5] for a more complete review of the literature. Furthermore, in Broner et al. (2004) [9], investors holding bonds with long maturities are exposed to price risk, arising from the absence of liquid secondary markets. Therefore countries willing to issue long maturities must compensate investors for this risk, making long debt so expensive that sovereigns prefer shorter maturities, even at the cost of possibly facing sudden capital outflows. Finally, the contagion can be explained by the "cross-market hedging", seen in the work of Kodres and Pritsker (2002) [29] which proves that differentially informed investors transmit idiosyncratic shocks from one market to others by rebalancing their portfolios' exposures to common macroeconomic risks.

If we look for concrete examples of a sophisticated investor, we might consider the case of hedge funds. Indeed, the hedge funds are already suffering from the past crises, such as the near-failure of Long-Term Capital Management (LTCM) in September 1998 or the speculative attacks on pound sterling in 1992, but also from a kind of mythology, feeding on the opacity of the universe in which they operate: offshore funds, absence of regulation, massive use of leverage and complex assets... Beyond the simple suspicion, some serious elements fuel the debate about their role in the crisis and especially in the crisis spread. Very involved in the credit derivatives markets, with nearly 50% of CDOs and 70% of the riskiest tranches, (Aglietta and Rigot (2009) [2], Teiletche (2009) [39]), the hedge funds must face liquidity problems, leading to unbuckling positions to fulfill margin calls from their brokers (Cartapanis and Teiletche (2010) [14]). It's probably a spiral toward the market leak, driving the crisis spread (Cartapanis (2008) [13]). This scenario is more probable since failures of liquidity in markets appear to be a critical factor in the transmission of shocks across assets (Backus et al. (2002) [3]), and since the hedge funds industry seems to be particularly sensitive (Boyson et al. (2010) [8]).

¹ Common shocks (Schinasi et Todd-Smith (2000) [36]), trade links (Edwards (2000) [18]), competitive devaluations and financial links (Corsetti et al. (1998) [17]) are in the group of fundamentals-based contagion

Therefore, based on these elements, we propose to investigate a channel of contagion - the portfolios of Global Macro hedge funds, considering they are an archetype of the investors described above. Indeed, this strategy involves a diversified portfolio of liquid and complex assets, hence allowing a very dynamic management. If a such phenomenon has already been considered (Monarcha and Pochon (2008) [31]), with a lower level than the banking industry (Van Rijckeghem and Weder (1999) [45]), we did not find any empirical work in this perspective. There is may be an important gap and our paper aims to help fill this one.

Thereby, our study adopts a heuristic approach and attempts to build a new methodology, basing on well-known models: after evaluating the co-movements of financial assets by using a DCC-GARCH model, the series of conditional correlations are exploited in a non-linear model to understand the impact of Global macro funds' performance regimes and their risk factor exposure, computed with a space-state model estimated by Kalman filter, on these co-movements.

Our analysis is based on the daily returns in local currency of seven indices (HFRX-MAC, SPCOMP, MSEMKFL, JGUSAU\$, MSEMKF\$, CRBSPOT, CRUDOIL) representing respectively hedge funds Global Macro, U.S. stock, emerging stock, U.S. bond, emerging bond, crude oil, commodities markets and the exchange rate Euro-Dollar (MSEREUR). The full sample begins in September 2003 and ends in September 2010. This paper is structured as follows: In section 2, data description and analysis are discussed. Section 3 presents the preliminary steps: estimation of DCC-GARCH model and replication of hedge funds Global Macro' portfolio by Kalman filter. The following section presents the study of nonlinear dependence of dynamic conditional correlations to the performance of hedge funds and their strategies. The last section provides conclusions and some lines of deepening future studies.

2 Data descriptions

2.1 Data

The indices of financial assets investigated in this study are the US stock, emerging stock, US government bond, emerging government bond, crude oil, commodities markets and the exchange rate Euro-Dollar. The hedge funds index used is the Global macro funds, provided by Hedge Funds Research, corresponding to the net asset value of portfolio securities. Daily index observations of the markets were obtained from

Datastream database. The indices span a period of seven years from September 2003 to September 2010.

The daily returns of indices (excepting the exchange rate Euro-Dollar) consisted of daily closing price P_t , which is measured in US dollar and computed as $R_t = \ln(P_t/P_{t-1})$.

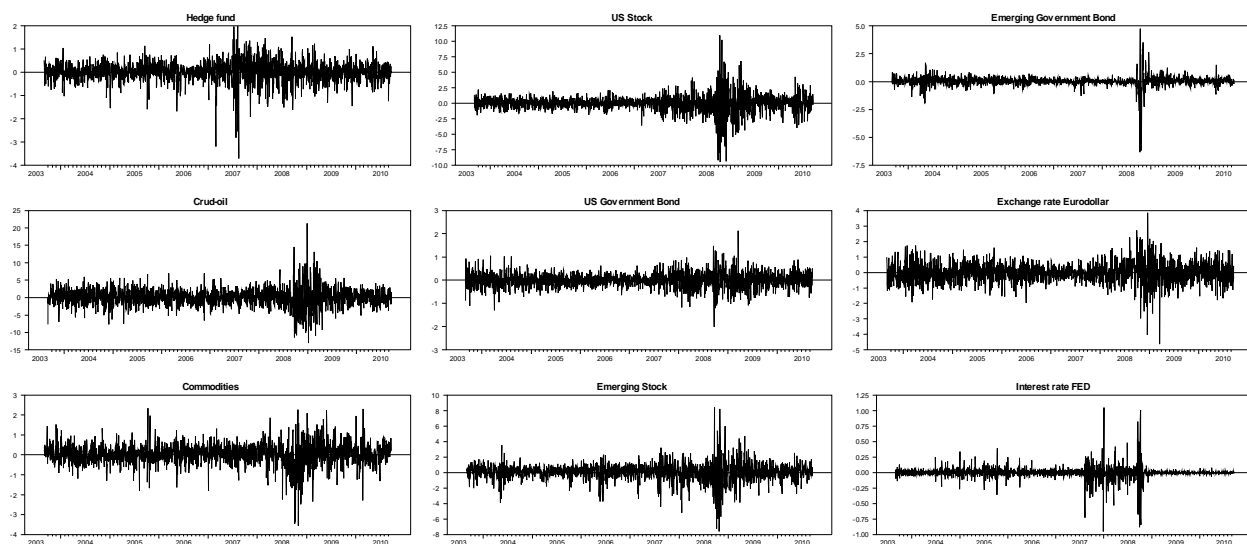


Figure 1. Evolution of financial assets' daily returns

Table 1
Descriptive statistics of data

Indices	Moyenne	Écart-type	Erreur Standard	Skewness	Kurtosis (Excès)	Jarque-Bera	ARCH		
							Q(12)	ARCH-Q(12)	ARCH-LM
US Stock	0.006	1.821	1.349	-0.266	11.688	10500.8	61.903***	2173.061***	606.118***
Emerging Stock	0.048	1.373	1.171	-0.393	7.725	4625.2	95.191***	2163.444***	544.937***
Hedge fund Global Macro	0.005	0.210	0.458	-1.070	6.820	3919.6	48.758***	740.765***	740.765***
Crudoil	0.045	6.687	2.586	0.285	5.608	2437.6	33.965***	978.149***	373.729***
Commodities	0.034	0.2953	0.543	-0.692	5.164	2596.1	124.084***	620.785***	243.024***
US Government Bond	0.004	0.105	0.324	0.048	2.909	649.9	38.827***	264.913***	147.791***
Emerging Government Bond	0.037	0.208	0.456	-2.214	51.519	205111.4	292.64***	1378.979***	599.787***
Exchange rate Euro-dollar	-0.009	0.412	0.642	-0.157	3.851	1145.6	33.532***	291.328***	161.952***

Note : Nombre d'observations = 1841 ; Q(12) est le test d'autocorrélation des résidus de Ljung-Box d'ordre de 12 ; ARCH-Q(12) est le test de McLeod-Li et ARCH-LM est le test d'Engle (1982) pour tester l'hétéroscédasticité conditionnelle des résidus; ***, **, * indiquent que l'hypothèse H_0 est rejetée aux seuils de 1%, 5% et 15% respectivement.

Table [1] reports the descriptive statistics of asset daily returns for the full period. The mean returns in all markets are positive and crude oil and US stock are respectively the highest and the less volatile markets for the sample period. The skewness coefficients are positive for crude oil and US government bond and negative for other indices. They are statistically significant which indicate that the tail on the left side of the probability density function is rather longer than the right side and the bulk of the values (possibly including the median) lie to the right of the mean. In addition, all returns are characterized by an excess kurtosis statistically significant and positive, indicating that the tails of return distribution are thicker than that of normal distribution and therefore the distribution is leptokurtic. The Jarque-Bera test statistic provides clear evidence to reject the null hypothesis of normality for all the index returns series.

Ljung-Box statistics ($Q(12)$) for serial correlation in the standardized squared returns are also reported. They confirm that the null hypothesis of white noise residuals can be rejected. With evidence of ARCH effects through the results of McLeod-Li and Engle's Lagrange Multiplier tests, it is possible to proceed to the second step of the analysis focused on the multivariate GARCH, modelling of the dynamics of market's volatility.

3 Preliminary stages: Estimations of DCC-GARCH and State-Space models

3.1 DCC-GARCH

This section focuses on the estimation of dynamic conditional correlations between asset returns: crude oil, commodities, US stock, emerging stock, US bond and emerging bond. We aim to compute the time-varying conditional correlations for pairs of asset markets as a measure of co-movements. The underlying assumption is to regard the phenomenon as a continuing process whose magnitude varies over time.

Here, we employ a multivariate DCC-GARCH model for the study of financial contagion. The DCC-GARCH model proposed by Engle (2002) [20] is a generalization of Bollerslev et al. (1992) [7] constant conditional correlation (CCC) model. This model allows for not only heteroscedasticity in market returns but also time-varying correlation processes. In particular, this model has computational advantages over other multivariate GARCH models, including the BEKK-GARCH, in the study of financial contagion because the number of parameters to be estimated in the correlation process is independent of the number of series to be correlated. This is mainly due to the fact that DCC-GARCH model, which is a multivariate model that builds on the already estimated univariate processes of volatility, can be estimated simultaneously

for a significant number of time series.

The index returns follow an AR(1):

$$R_t = \alpha + \beta R_{t-1} + \varepsilon_t \quad (1)$$

ε_t is white noise that follows a normal distribution $N(0, \sigma^2)$.

The conditional covariance matrix H_t of the DCC-GARCH model is:

$$H_t = D_t C_t D_t \quad (2)$$

where $D_t = \text{diag}\sqrt{H_{it}}$ is the (2×2) diagonal matrix of time-varying standard deviations from univariate GARCH models, and C_t is the (2×2) time-varying correlation matrix. The DCC-GARCH model is designed to allow for a two-stage estimation of the conditional covariance matrix H_t . In the first stage, univariate volatility models are fitted to each of the stock return residuals and estimates of $\sqrt{h_{it}}$ are obtained. In this paper, we use a GARCH (1,1) model:

$$h_{i,t} = \omega_i + \alpha_i \varepsilon_{i,t-1}^2 + \beta_i h_{i,t-1} \quad (3)$$

where α_i measure the ARCH effect. Volatility persistence is measured by γ_i .

The evolution of the correlation in the standard DCC model is given by:

$$Q_t = (1 - q_a - q_b)\bar{Q} + q_a \varepsilon_{t-1} \varepsilon'_{t-1} + q_b Q_{t-1} \quad (4)$$

where $Q_t = \{q_{ij,t}\}$ is a (2×2) residuals variance-covariance matrix; $\bar{Q} = E(\varepsilon_t \varepsilon'_t)$; α and β are positifs and $\alpha + \beta < 1$ to satisfaire the stationary condition.

Since Q_t in equation (4) has no unit element, we have:

$$C_t = \text{diag}(Q_t)^{\frac{1}{2}} Q_t \text{diag}(Q_t)^{-\frac{1}{2}} \quad (5)$$

An element of C_t has the form as follows:

$$\rho_{i,j} = \frac{q_{ij,t}}{\sqrt{q_{ii,t}}\sqrt{q_{jj,t}}} \quad (6)$$

where $i, j = 1, 2, \dots$ and $i \neq j$

$\rho_{i,j}$ is the key to this methodology because it represents the conditional correlation between returns on stock market indexes.

As proposed by Engle (2002) (see [20]), the DCC-GARCH model can be estimated by using the log-likelihood function:

$$L(\theta) = -\frac{1}{2} \sum_{t=1}^T [(n \log(2\pi) + 2 \log |D_t| + \varepsilon_t' D_t D_t^{-1} \varepsilon_t) + (\log |V_t| + \eta_t' V_t^{-1} \eta_t - \eta_t \eta_t^{-1})] \quad (7)$$

where n is the number of equations T is the number of observations, θ is the vector of parameters to estimate, D_t is the diagonal matrix and V_t is the correlation matrix.

The DCCs series are shown in Figure [2] below.

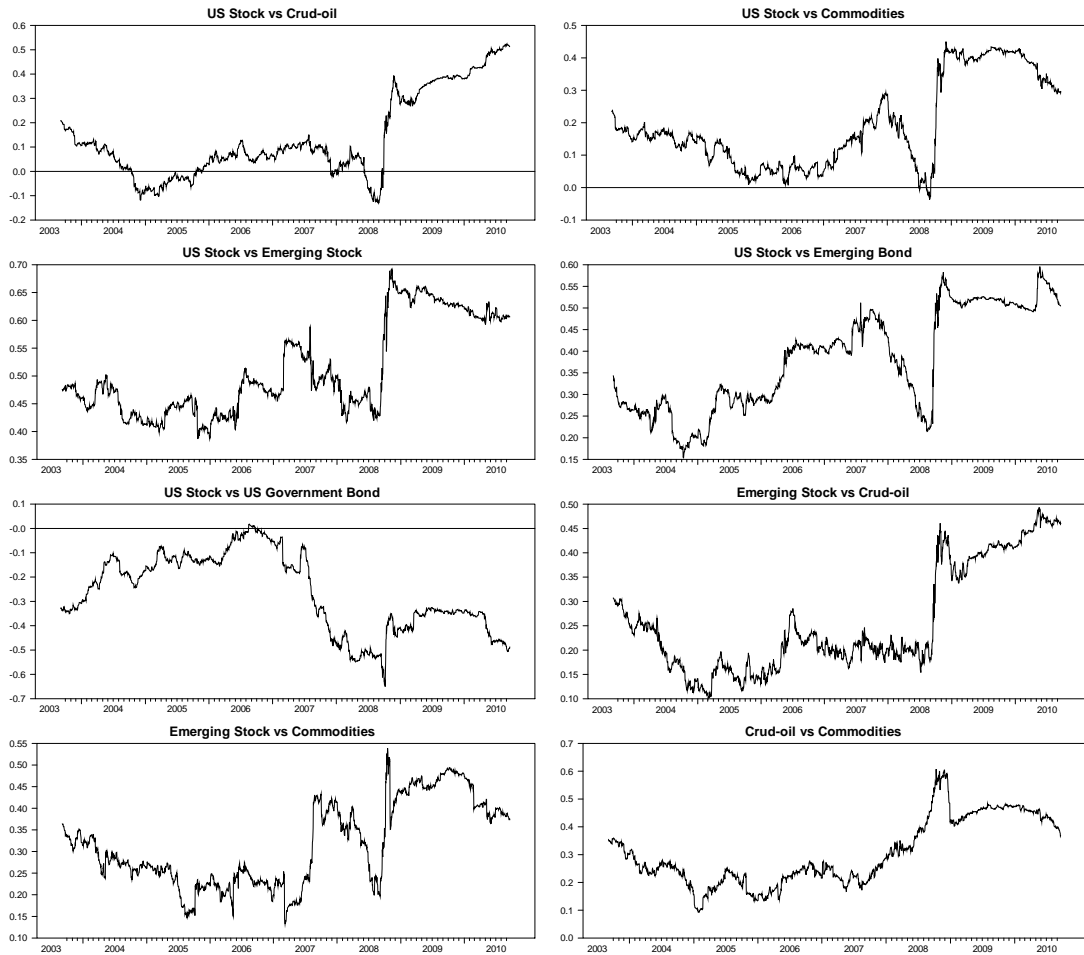


Figure 2. Dynamic conditional correlations

The estimation of DCC-GARCH model highlights short-term interdependencies be-

tween selected indices, and financial crisis' effects on this relationship. Regarding the figure [2], firstly, we verify that dynamic conditional correlations vary over time, sometimes positive and sometimes negative.

During pre-crisis period (2003-2006), the conditional correlation between U.S. stock and emerging stock market returns was moving around 0.45. At the beginning of the subprime crisis on February 2007, this coefficient increased by 0.1 and fluctuated with a bearish trend. However, after the bankruptcy of Lehman Brothers on September 2008, this coefficient increased dramatically (0.35) to remain at this level until the end of 2010. This increase suggests an intensification of interdependence between these markets, following the bankruptcy of Lehman Brothers. This result consistent with the finding in Forbes and Rigobon (2002) [24] shows that an increase in correlation during crisis periods due to the increased volatility of global equity markets.

However, the correlation between U.S. stock and bond experienced an adverse scenario. During the period 2003-2007, the coefficient was small and negative but with a bullish trend. However, once the crisis began, the coefficient plunged rapidly to (-0.6) in September 2008. This drop in correlation suggests a "flight to quality" phenomenon occurring when investors sell what they perceive to be higher-risk investments and purchase safer investments, such as government bonds, gold or land. This is considered a sign of fear in the marketplace, as investors seek less risk in exchange for lower profits.

The correlation between U.S. stock and crude oil market returns was moving around 0. However, after Lehman Brothers collapse, this coefficient increased dramatically to 0.4 in December 2008 and stabilized around 0.5. The crisis therefore constituted a rupture in the dependence of these two assets.

The correlation curves of U.S. stock vs commodities and emerging bonds; emerging bonds vs crude oil and commodities have generally the same style. The coefficients are generally positive, then fall at the beginning of the crisis. They quickly recover their values after the collapse of Lehman Brothers, and continue to rise until the present time.

3.2 State-space model estimated by Kalman filter

Identification of risk factors for hedge funds has become an important area of investigation for both academic and professional, especially when classical models seem to be unable to reproduce accurately performance and risk portfolios. The risks are ex-

posed to non-linear factors (Billio et al. (2006) [6]), and present "option like pay-offs", potentially exposing to "extreme losses" related to the nature of leptokurtic distributions (Agarwal and Naik (2004) [1]). Thus, strategies such as "trend following" can be replicated using "straddles" on stocks, currencies or interest rate products (Fung and Hsieh (2001) [25]).

Different from a traditional mutual fund, hedge funds are not always "long only" and can take short-positions (short bias), practice strategies in "spread" (Fung and Hsieh (2001) [25]), or be over-invested through leverage. A strategy such as "Tactical Asset Allocation" (TAA), generates dynamic risk exposures and important alpha related to the manager skill in "stock picking" (Monarcha (2009) [31]).

Moreover, a simple rolling regression on a factor model, by OLS, is unable to capture the dynamics of portfolio (Teiletche and Roncalli (2008) [34]). Therefore the replication of hedge funds requires more sophisticated methods such as Markov switching models (Billio et al. (2006) [6]), particle filters (Weisang and Roncalli (2009) [33]) or state-space models estimated by Kalman filter (Monarcha (2009) [31]).

Therefore, basing on these works, we provide an estimation of the portfolio structure of global macro hedge funds. We use a state-space model estimated by Kalman filter, according to the specification proposed by Monarcha (2009) [31] and Roncalli and Teiletche (2008) [34] to adequately manage the dynamics of portfolio. The model is of the form:

$$\begin{cases} R_t^{HF} = \sum_{j=1}^7 \beta_{j,t} R_{j,t} + \epsilon_t \\ \beta_t = \beta_{t-1} + \eta_t \\ Q_t = \text{diag}(\sigma_1^2, \dots, \sigma_7^2) \end{cases} \quad (8)$$

with the covariance matrix of η_t .

The results of state-space model estimated by Kalman filter are shown in the figure below.

The "straddles" provided by Fung and Hsieh (2001) [25] prove insignificant as well as indicators of spread strategies as a position in S&P500 versus EURSTOXX50, or S&P500 versus Russel2000 (Weisang and Roncalli (2009) [33]). The same conclusion for changes in federal funds is found. The alpha (not shown here) is not significant. Though a view with caution, all of these observations, pleading for funds adopting mainly "buy-and-hold" strategies, and not practice the "long/short" or the "trend following".

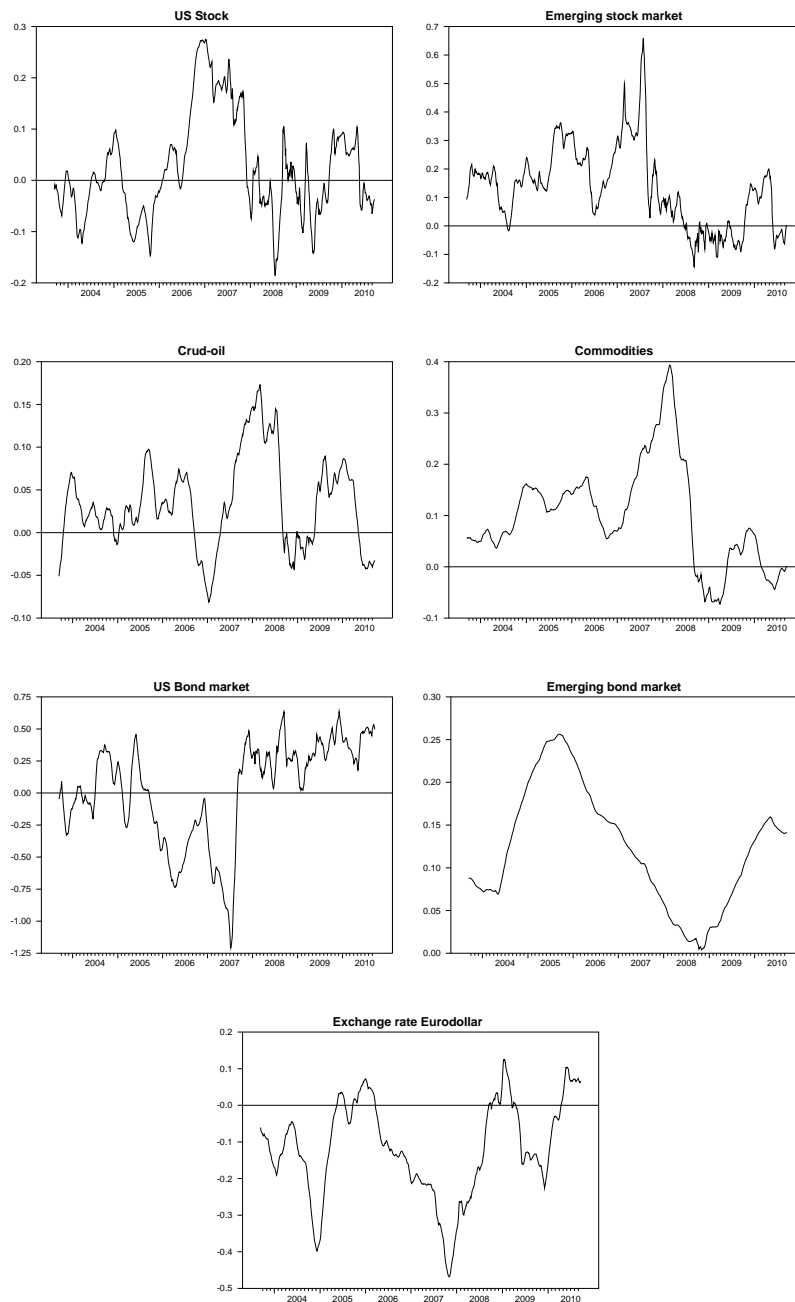


Figure 3. Hedge Funds risk exposures

The graphs clearly show both patterns and sequences. Firstly, there is a particular enthusiasm for emerging-market equities and bonds during the period preceding the crisis. Although the U.S. stock position is lower than the emerging stock, we can see important similarities, i.e. a maximum level at the beginning of the crisis and a rapid "unwinding". Positions in oil and commodities markets also show similarities. They reflect mainly a mirror image of the U.S. stock market exposure and appear to be some kind of "safe havens" from mid-2007 to mid-2008. It should be noted the high volatility of oil exposure which is one of the lowest. Finally, U.S. government bonds appear to be an active choice. If it is the only one with a permanent negative position, for example with a very pronounced bet on the rise in interest rates before mid-2007, they are re-balanced to levels previously reserved for emerging stock market.

4 Non-linear modelisation of adjustments in conditional correlations among assets

This section presents the final stage which assesses the impact of hedge funds strategies in the co-movements among financial assets. Thus we use a non-linear model to capture possible asymmetric adjustments. Indeed, whereas the structure of portfolio funds is not independent of their past performance, different regimes of past performance are introduced as an explanatory variable to capture possible different impacts depending on the sign of the latter. On the one hand, the regime of performance being a distant proxy for the underlying strategies, the coefficients of risk exposures, estimated by Kalman filter is used in order to better capture the impact of re-balancing of portfolios. On the other hand, in order to account for the inertia of strategies, we also considered two regimes, bull and bear, for these parameters. All these variables are introduced at time $t - 1$ to avoid any suspicion of endogeneity. Finally, the lags of endogenous variable is added, according to the evaluation of BIC, in order to purge the residues of any form of serial autocorrelation.

The non-linear model used is:

$$\Delta\rho_t^{ij} = \alpha + S^- R_{t-1}^{HF} + S^+ R_{t-1}^{HF} + \sum_{k=1} \gamma_k \Delta\rho_{t-k}^{ij} + \theta_i^- \Delta\beta_t^i + \theta_i^+ \Delta\beta_t^i + \theta_j^- \Delta\beta_t^j + \theta_j^+ \Delta\beta_t^j + \epsilon_t \quad (9)$$

where

- ρ_t^{ij} represents the dynamic conditional correlation between two financial assets i and j in period t

- R_{t-1}^{HF} : the percent variation of logarithmic returns of hedge funds in period $t - 1$
- β_t^i : risk exposure of Global macro hedge funds to asset i in period t
- β_t^j : risk exposure of Global macro hedge funds to asset j in period t

ϵ_t is white noise.

and

- S^- : the coefficient associated with the contraction regime of hedge funds' returns
- S^+ : the coefficient associated with the expansion regime of hedge funds' returns
- θ_i^- : the coefficient associated with the contraction regime of hedge funds' risk exposure factor i
- θ_i^+ : the coefficient associated with the expansion regime of hedge funds' risk exposure factor i
- θ_j^- : the coefficient associated with the contraction regime of hedge funds' risk exposure factor j
- θ_j^+ : the coefficient associated with the expansion regime of hedge funds' risk exposure factor j

A first approach of probabilities of two regimes of performance is modeling as a Markov chain². However it is not used directly in the model, the latter being estimated by non-linear least squares.

² Available in Appendix

Table 2

Analyse of Dynamic conditional correlations - Non-linear estimation

$\Delta\rho_t^{US-OIL}$	Const	$R_{t-1}^{HF(-)}$	$R_{t-1}^{HF(+)}$	$\Delta\rho_{t-1}^{US-OIL}$	$\Delta\rho_{t-2}^{US-OIL}$	$\Delta\rho_{t-3}^{US-OIL}$	$\Delta\rho_{t-4}^{US-OIL}$	$\Delta\rho_{t-5}^{US-OIL}$	$\Delta\beta_t^{US(-)}$	$\Delta\beta_t^{US(+)}$	$\Delta\beta_t^{OIL(-)}$	$\Delta\beta_t^{OIL(+)}$
	φ	S^-	S^+	γ_1	γ_2	γ_3	γ_4	γ_5	θ_{US}^-	θ_{US}^+	θ_{OIL}^-	θ_{OIL}^+
Estimation	0.338	-1.142	-4.948***	-0.125***	-0.130***	-0.139***	-0.049*	-0.107***	0.003	0.020*	0.022	0.003
Écart-type	0.658	1.512	1.903	0.024	0.028	0.025	0.028	0.022	0.013	0.013	0.017	0.017

Note : ***, ** et * indiquent que l'hypothèse H_0 est rejetée aux seuils de 1%, 5% et 15% respectivement, $R^2 = 0.049$.

$\Delta\rho_t^{US-COM}$	Const	$R_{t-1}^{HF(-)}$	$R_{t-1}^{HF(+)}$	$\Delta\rho_{t-1}^{US-COM}$	$\Delta\rho_{t-2}^{US-COM}$	$\Delta\rho_{t-3}^{US-COM}$	$\Delta\beta_t^{US(-)}$	$\Delta\beta_t^{US(+)}$	$\Delta\beta_t^{COM(-)}$	$\Delta\beta_t^{COM(+)}$
	φ	S^-	S^+	γ_1	γ_2	γ_3	θ_{US}^-	θ_{US}^+	θ_{COM}^-	θ_{COM}^+
Estimation	-0.020	-1.707*	-0.286	-0.199***	-0.020	-0.091***	0.026***	0.002	-0.005	-0.004
Écart-type	0.413	0.955	1.201	0.026	0.025	0.025	0.008	0.008	0.008	0.010

Note : ***, ** et * indiquent que l'hypothèse H_0 est rejetée aux seuils de 1%, 5% et 15% respectivement, $R^2 = 0.045$.

$\Delta\rho_t^{US-EM}$	Const	$R_{t-1}^{HF(-)}$	$R_{t-1}^{HF(+)}$	$\Delta\beta_t^{US(-)}$	$\Delta\beta_t^{US(+)}$	$\Delta\beta_t^{EM(-)}$	$\Delta\beta_t^{EM(+)}$
	φ	S^-	S^+	θ_{US}^-	θ_{US}^+	θ_{EM}^-	θ_{EM}^+
Estimation	-0.068*	-0.280***	0.337***	-0.001*	0.000	0.001	-0.001**
Écart-type	0.043	0.099	0.124	0.000	0.000	0.001	0.001

Note : ***, ** et * indiquent que l'hypothèse H_0 est rejetée aux seuils de 1%, 5% et 15% respectivement, $R^2 = 0.006$.

$\Delta\rho_t^{US-EMB}$	Const	$R_{t-1}^{HF(-)}$	$R_{t-1}^{HF(+)}$	$\Delta\rho_{t-1}^{US-EMB}$	$\Delta\beta_t^{US(-)}$	$\Delta\beta_t^{US(+)}$	$\Delta\beta_t^{EMB(-)}$	$\Delta\beta_t^{EMB(+)}$
	φ	S^-	S^+	γ	θ_{US}^-	θ_{US}^+	θ_{EMB}^-	θ_{EMB}^+
Estimation	-0.134*	-0.532***	0.578***	-0.075***	0.000	0.000	0.002	-0.000
Écart-type	0.073	0.170	0.214	0.024	0.001	0.001	0.003	0.002

Note : ***, ** et * indiquent que l'hypothèse H_0 est rejetée aux seuils de 1%, 5% et 15% respectivement, $R^2 = 0.009$.

$\Delta\rho_t^{US-USB}$	Const	$R_{t-1}^{HF(-)}$	$R_{t-1}^{HF(+)}$	$\Delta\rho_{t-1}^{US-USB}$	$\Delta\beta_t^{US(-)}$	$\Delta\beta_t^{US(+)}$	$\Delta\beta_t^{USB(-)}$	$\Delta\beta_t^{USB(+)}$
	φ	S^-	S^+	γ	θ_{US}^-	θ_{US}^+	θ_{USB}^-	θ_{USB}^+
Estimation	-0.883***	-4.493***	2.648***	-0.207***	0.004	-0.011*	0.004	-0.006
Écart-type	0.331	0.757	0.975	0.022	0.008	0.007	0.006	0.006

Note : ***, ** et * indiquent que l'hypothèse H_0 est rejetée aux seuils de 1%, 5% et 15% respectivement, $R^2 = 0.061$.

$\Delta\rho_t^{EM-OIL}$	Const	$R_{t-1}^{HF(-)}$	$R_{t-1}^{HF(+)}$	$\Delta\beta_t^{EM(-)}$	$\Delta\beta_t^{EM(+)}$	$\Delta\beta_t^{OIL(-)}$	$\Delta\beta_t^{OIL(+)}$
	φ	S^-	S^+	θ_{EM}^-	θ_{EM}^+	θ_{OIL}^-	θ_{OIL}^+
Estimation	-0.268***	-1.307***	0.911***	0.000	-0.001	-0.002	-0.005**
Écart-type	0.110	0.255	0.311	0.002	0.002	0.002	0.002

Note : ***, ** et * indiquent que l'hypothèse H_0 est rejetée aux seuils de 1%, 5% et 15% respectivement, $R^2 = 0.013$.

$\Delta\rho_t^{EM-COM}$	Const	$R_{t-1}^{HF(-)}$	$R_{t-1}^{HF(+)}$	$\Delta\beta_t^{EM(-)}$	$\Delta\beta_t^{EM(+)}$	$\Delta\beta_t^{COM(-)}$	$\Delta\beta_t^{COM(+)}$
	φ	S^-	S^+	θ_{EM}^-	θ_{EM}^+	θ_{COM}^-	θ_{COM}^+
Estimation	-0.342***	-2.051***	0.982***	0.003*	-0.001	-0.001	-0.011***
Écart-type	0.109	0.255	0.312	0.002	0.002	0.002	0.002

Note : ***, ** et * indiquent que l'hypothèse H_0 est rejetée aux seuils de 1%, 5% et 15% respectivement, $R^2 = 0.042$.

This section provides a synthetic and hierarchical reading of estimation results.

Firstly the model can explain about 4 - 5% of the variance of correlations, especially in the cases between U.S. stock market and crude oil, commodities and U.S. bonds. The model provides a goodness of fit of similar order with respect to the correlation between commodities and emerging stock markets. Otherwise, the model's explanatory power is particularly limited and can explain less than 1% of the variance of correlations. If the quality of adjustment seems small, keep in mind that this work has no claim to explain the entire phenomenon, whose causes are likely multiple and the global macro hedge funds index covering a very small part of the spectrum of financial flows.

As expected, in general the past performance of funds helps to explain the evolution of correlations between assets. In most cases, the two regimes are significant but with different signs and coefficients. Thus, contraction regime of performance usually associates with negative signs, indicating the existence of an inverse relationship between bearish performance and co-movement evolution. Considering a negative shock on the past performance of funds in a crisis scenario with successive losses, hedge funds will cause an increase in correlations among markets. From this point of view, we experience the special power of this adjustment in U.S. stock and bond markets.

The regimes of positive returns have generally positive signs, indicating a positive relationship between past performance and market correlations. Regarding correlations between emerging stock and commodities or crude oil markets, these adjustments will probably draw a directional bet based on strong growth in emerging countries whose corollary would be a rise in energy prices and commodities.

The co-movement between crude oil and U.S. stock market is exceptionally, but understandable in the respect of the exposure of funds to these markets (they always seem to play against each other). It should be noted that the coefficient, very significant, is the highest in absolute value, recorded in this work. As a result, the contribution of hedge funds, analyzed through the prism of performance, does not constitute a restoring force on the correlations among markets.

The introduction of the parameters of risk exposure, while offering more contrasted results, is rather encouraging. Indeed, the regressions allow usually identify, at least, one of these parameters as significant through their different regimes and argue for a particular role of stock positions, exceptionally U.S. stock market. So far, we do not find the recurrence in the signs of coefficients or the significance of particular regimes. It would therefore be imprudent to try to interpret in terms of investment strategies.

However the position of U.S. stock market seems to be the major determinant in the evolution of correlations among assets. In contrast, the strategies of emerging markets are fairly neutral and their dependence to commodities and crude oil appears to be related to exposures to these latter.

5 Conclusion

The present study tried to evaluate the contribution of hedge funds to the phenomenon of co-movements among assets and attempted to provide empirical evidence of the impact of portfolio management strategies on the statistical dependence of index. The measurement of such mechanics required the construction of an original methodology, based on known methods to obtain a battery of results which might question the scientific community. Indeed, these latter reveal a significant impact of hedge funds strategies on co-movement and corroborate the intuition that contagion also depends on the structure of portfolios of diversified investors. This transmission channel is particularly probative if we consider the relationship of dependence with the U.S. stock market, which is confirmed by the significance of the exposure of hedge funds to this market.

However, the results' analyse should be considered with measure. A potential imprecision can be related to the fact that both endogenous and exogenous variables are themselves derived from previous estimates. In addition, all models in this study assume Gaussian distributions which are frequently violated in reality. On the other hand, it is currently impossible to reconstruct, in an obvious way, the fund strategies which generated the process studied. Indeed, failure to take into account the correlations among assets in the Kalman filter specification might lead to the inability of non-linear model to capture these effects. Finally, a more rigorous consideration of the Markov chain, presented in this work, appears to be a perspective for future researches.

References

- [1] AGARWAL, V. and NAIK, N. (2004), 'Risk and portfolio decisions involving hedge funds', *Review of Financial Studies*, Vol 17 (1), 63-98.
- [2] AGLIETTA, M. and RIGOT, S. (2009), 'Hedge funds : la fin du laissez-faire', *Revue Economique*, Vol. 60 (3).
- [3] BACKUS, D., FORESI, S. and WU, L. (2002), *Contagion in Financial Markets*, Finance 0207009, EconWPA.
- [4] BAIG, T. and GOLDFAJN, I. (1999), *Financial Market Contagion in the Asian Crisis*, IMF Working Paper, 46(2), 167-95.
- [5] BIKHCHANDANI, S. and SHARMA, S. (2000), Herd Behavior in Financial Markets: A Review, IMF Working Paper 00/48.
- [6] BILLIO, M., GETMANSKY, M. and PELIZZON, L. (2006), *Dynamic Risk Exposure of Hedge Funds: A Regime-Switching Approach*.
- [7] BOLLERSLEV, T. (1986), 'Generalized Autoregressive Conditional Heteroskedasticity', *Journal of Econometrics*, 31, 307-327.
- [8] BOYSON, N. M., STAHEL, C. W. and STULZ, R. M. (2010), *Hedge Fund Contagion and Liquidity Shocks*, Working Paper.
- [9] BRONER, F., GELOS, G. R. and REINHART, C. (2004), *When in Peril, Retrench: Testing the Portfolio Channel of Contagion*, IMF Working Papers 04/131, International Monetary Fund.
- [10] CALVO, G. A. (1999), *Contagion In Emerging Markets: When Wall Street Is a Carrier*, College Park, University of Maryland.
- [11] CALVO, S. and REINHART, C. (1996), 'Capital Flows to Latin America: Is there Evidence of Contagion Effect?' in G. A. Calvo, M. Goldstein, and Eduard Hochreiter, eds, *Private Capital Flows to Emerging Markets After the Mexican Crisis*, Institute for International Economics, Washington, D. C.
- [12] CAPPIELLO, L., ENGLE, R. F. and SHEPPARD, K. (2006), 'Asymmetric Dynamics in the Correlations of Global Equity and Bond Returns', *Journal of Financial Econometrics*, 4, 537-572.
- [13] CARTAPANIS, A. (2008), 'Hedge funds, risque systémique et procyclicité de la finance : le cas de la crise des subprime', *Revue d'Economie Financière*, juillet.

- [14] CARTAPANIS, A. and TEÏLETCHÉ, J. (2010), *Les Hedge Funds et la crise financière internationale*, Fiche de lecture.
- [15] CHO, J. H. and PARHIZAGARI, A. M. (2008), 'East Asian Financial Contagion under DCC-GARCH', *The International Journal of Banking and Finance*, Vol. 6. No. 1, 17-30.
- [16] CIPRIANI, M. and GUARINO, A. (2003), *Herd Behavior and Contagion in Financial Markets*, Working Paper, New York University.
- [17] CORSETTI G., PERICOLI M., and SBRACIA M., (2005), *Some Contagion, Some Interdependence: More Pitfalls in Tests of Financial Contagion*, *Journal of International Money and Finance*, Vol. 24, 1177-1199.
- [18] EDWARDS, S. (2000), *Interest Rates, Contagion and Capital Controls*, NBER Working Paper 7801.
- [19] ENGLE, R. F. (1982), 'Autoregressive Conditional Heteroscedasticity with Estimates of Variance of United Kingdom Inflation', *Econometrica*, 50, 987-1008.
- [20] ENGLE, R. F. (2002), 'Dynamic Conditional Correlation: A Simple Class of Multivariate Generalized Autoregressive Conditional Heteroskedasticity Models', *Journal of Business and Economic Statistics*, American Statistical Association, vol. 20(3), 339-50.
- [21] ENGLE, R. F. and KRONER, K. F. (1995), 'Multivariate Simultaneous Generalized ARCH', *Econometric Theory*, Cambridge University Press, vol. 11(01), 122-150.
- [22] ENGLE, R. F. and SHEPPARD, K. (2001), *Theoretical and Empirical properties of Dynamic Conditional Correlation Multivariate GARCH*, NBER Working Papers 8554, National Bureau of Economic Research, Inc.
- [23] FRANK, N., GONZALEZ-HERMOSILLO, B. and HESSE, H. (2008), *Transmission of Liquidity Shocks: Evidence from the 2007 Subprime Crisis*, IMF Working Paper, WP/08/200.
- [24] FORBES, K. and RIBOGON, R. (2002), 'No Contagion, Only Interdependence: Measuring Stock Market Co-Movements', *The Journal of Finance*, 57, 5, 2223-2261.
- [25] FUNG, W. and HSIEH, D. (2001), 'The Risk in Hedge Fund Strategies: Theory and Evidence from Trend Followers', *The Review of Financial Studies*, Vol. 14, No. 2, 313-341.

- [26] HORTA, P., MENDES, C. and VIEIRA, I. (2008), *Contagion effects of the US Subprime Crisis on Developed Countries*, CEFAGE-UE Working Paper.
- [27] HWANG, I., IN, F. and KIM, T. (2009), *Contagion Effects of the U.S. Subprime Crisis on International Stock Markets*, Document de travail, KAIST Business School.
- [28] KING, M. and WADHWANI, S. (1990), 'Transmission of volatility between stock markets', *Review of Financial Studies*, 3 (1), 5-33.
- [29] KODRES, L. E. and PRITSKER, M. (1998), *A rational expectations model of financial contagion*, Board of Governors of the Federal Reserve System, Finance and Economics D.P. 48.
- [30] LONGIN, F. and SOLNIK, B. (2001), 'Extreme Correlation of International Equity Markets', Forthcoming Journal of Finance.
- [31] MONARCHA, G. (2009), *A Dynamic Style Analysis Model for Hedge Funds*, SSRN Working Paper Series, December.
- [32] MONARCHA, G. and POCHON, F. (2008), *Supervision of the hedge fund industry*, Natixis Special Report, Juillet.
- [33] RONCALLI, T. and G. WEISANG (2009), *Hedge Fund Replication and Alternative Beta*, Laboratoire J. A. Dieudonné, Université de Nice Sophia-Antipolis.
- [34] RONCALLI, T. and TEÏLETSCHE, J. (2008), 'An Alternative Approach to Alternative Beta', *Journal of Financial Transformation*.
- [35] ROSS, S. (1976), 'The arbitrage theory of capital asset pricing', *Journal of Economic Theory*, Vol. 13 (3), 341-360.
- [36] SCHINASI, G. and TODD-SMITH, R. (2000), *Portfolio diversification, leverage and financial contagion*, IMF Staff Papers, Vol. 47(2), 159-176.
- [37] SHAMIRI, A. and ISA, Z. (2010), 'The US Crisis and the Volatility Spillover Across South East Asia Stock Markets', *International Research Journal of Finance and Economics*.
- [38] SHARPE, W. F. (1964), 'Capital asset prices: A theory of market equilibrium under conditions of risk', *Journal of Finance*, 19 (3), 425-442.
- [39] TEÏLETSCHE, J. (2009), *Les Hedge Funds*, Collection Repères, La Découverte Edt.

- [40] TONG, H. (1978), *On a Threshold Model in Pattern Recognition and Signal Processing*, ed. C. H . Chen, Amsterdam - Sijhoff and Noordhoff.
- [41] TONG, H. (1990), *Non-linear time series: a dynamical system approach*, Oxford University Press, Oxford.
- [42] TONG, H. and LIM, K. S. (1980), 'Threshold Autoregression, Limit Cycles and Cyclical Data', *Journal of the Royal Statistical Society*, Ser. B, 42, 245-292.
- [43] TSE, Y. K. (2000), 'A test for constant correlations in a multivariate GARCH model', *Journal of Econometrics*, 98, 107-127.
- [44] TSE, Y. K. and TSUI, K. C. (2002), 'A multivariate generalized autoregressive conditional heteroscedasticity model with time-varying correlations', *Journal of Business and Economic Statistics*, 20, 351-362.
- [45] VAN RIJCKEGHEM, C. and WEDER, B. (1999), *Sources of Contagion: Finance or Trade ?*, IMF Working Papers 99/146, International Monetary Fund.
- [46] XIAO, L. and DHESI, G. (2010), 'Volatility spillover and time-varying conditional correlation between the European and US stock markets', *Global Economy and Finance Journal*, Vol. 3, No. 2, 148-164.

6 Annexe

6.1 Markov-Switching Models of Regime Change

In this section, we use the Markov-Switching models of regime change, developed by Hamilton (1996) to verify the existence of regimes of hedge funds global macro returns. In this model, the average of the variable studied (hedge funds returns) depends on the initial state (expansion or recession), indicated by a variable called state S_t which is being 1 in expansion and 0 in recession:

$$y_t - \mu_{S_t} = \varepsilon_t \quad (10)$$

where $\mu_{S_t} = \mu_0(1 - S_t) + \mu_1 S_t$ with $\mu_0 < \mu_1$ and S_t follows a Markov process defined by a transition matrix to estimate average durations between two different states.

The probabilities of transitions is written:

$$Pr(S_t = 0/S_{t-1} = 0) = P_{11} \quad (11)$$

$$Pr(S_t = 1/S_{t-1} = 1) = P_{22} \quad (12)$$

The matrix of probabilities is: $\begin{pmatrix} P_{11} & 1 - P_{22} \\ 1 - P_{11} & P_{22} \end{pmatrix}$

Evolution of hedge funds weekly returns and the probability of two regimes of hedge funds are presented in the following graph:

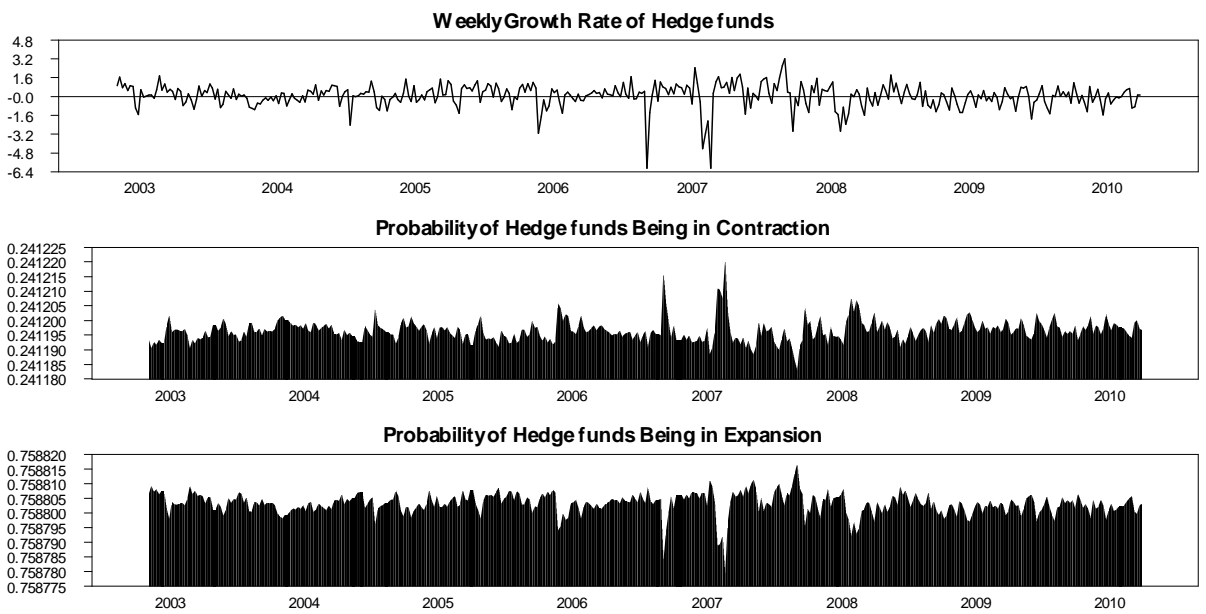


Figure 4. Evolution of hedge funds weekly returns and the probability of two regimes of hedge funds

Table 3

Transition probabilities and average probabilities of two regimes of hedge funds

Probability	P_{11}	$1 - P_{11}$	P_{22}	$1 - P_{22}$	\bar{P}_1	\bar{P}_2
	0.669	0.331	0.894	0.106	0.238	0.761

Note : P_{11} désigne la probabilité de transition d'un régime de baisse à un régime de baisse; P_{22} désigne la probabilité de transition d'un régime de hausse à un régime de hausse; \bar{P}_1 désigne la probabilité moyenne du régime de baisse; \bar{P}_2 désigne la probabilité moyenne du régime de hausse.

6.2 Sigmas estimated by linear State-Space model and Kalman filter

Table 4

Sigmas estimated by linear State-Space model and Kalman filter

	Const	R_t^{US}	R_t^{EM}	R_t^{PE}	R_t^{MP}	R_t^{EMB}	R_t^{ER}	R_t^{USB}
	$\sigma(1)$	$\sigma(2)$	$\sigma(3)$	$\sigma(4)$	$\sigma(5)$	$\sigma(6)$	$\sigma(7)$	$\sigma(8)$
Estimation	-0.000	0.021 ***	0.027 ***	0.008 ***	0.013 ***	0.007 ***	0.019 ***	0.061 ***
Écart-type	0.000	0.001	0.003	0.000	0.003	0.003	0.003	0.004

Note : ***, ** et * indiquent que l'hypothèse H_0 est rejetée aux seuils de 1%, 5% et 10% respectivement.

6.3 Autocorrelation of DCC series

Table 5

Degree of autocorrelation of DCC series

Series	$\Delta\rho^{US-OIL}$	$\Delta\rho^{US-COM}$	$\Delta\rho^{US-EM}$	$\Delta\rho^{US-EMB}$	$\Delta\rho^{US-USB}$	$\Delta\rho^{EM-OIL}$	$\Delta\rho^{EM-COM}$
BIC	5	3	0	1	1	0	0
Lags							

6.4 Unit root tests

In time series models in econometrics, a unit root is a feature of processes that evolve through time that can cause problems in statistical inference if it is not adequately dealt with. A linear stochastic process has a unit root if 1 is a root of the process's characteristic equation. Such a process is non-stationary. If the other roots of the characteristic equation lie inside the unit circle - that is, have a modulus (absolute value) less than one - then the first difference of the process will be stationary. Therefore, we conduct the Augmented Dickey-Fuller test to verify that the return series are all stationary, which are confirmed by the significance of the test statistics under the 1% level (see Table [6]).

Table 6
Unit root tests

Indices		SPCOMP	MSEMKFL	HFRXMAC	CRUDOIL	CRBSPOT	JGUSAU\$	MSEMKF\$	MSEREUR
		US	EM	HF	OIL	COM	USB	EMB	ER
ADF	No-intercept, No-trend	-35.418*** (1)	-34.472*** (1)	-38.054*** (1)	-45.105*** (1)	-17.192*** (3)	-33.679*** (1)	-11.317*** (10)	-41.803*** (1)
	Intercept	-35.409*** (1)	-34.511*** (1)	-38.049*** (1)	-45.110*** (1)	-17.319*** (3)	-33.685*** (1)	-11.540*** (10)	-41.802*** (1)
	Intercept, Trend	-35.411*** (1)	-34.513*** (1)	-38.058*** (1)	-45.118*** (1)	-17.314*** (3)	-33.692*** (1)	-11.538*** (10)	-41.824*** (1)

Note: ADF représente les tests de Dickey-Fuller Augmenté; les chiffres entre parenthèses sont les nombres de retards retenus sur la base du critère AIC et BIC; ***, **, * indiquent que l'hypothèse H_0 de non-stationnarité est rejetée aux seuils de 1%, 5% et 15% respectivement.