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1. Introduction

Hedge funds are alternative investment vehicles that engage in dynamic and complex strategies, with great flexibility with respect to the types of securities they hold and the types of positions they take. Hedge funds use leverage, take concentrated bets and have non-linear payoff (Billio et al., 2012). These characteristics allow for investment strategies that offer low correlations to traditional portfolios of cash, bonds and equities, and differ significantly from traditional regulated investments, such as mutual funds (Fung and Hsieh, 2001). In the last decade the hedge fund industry has been the fastest growing asset class in the financial sector.

When financial markets are in a bad condition, hedge funds can be a source of systemic risk to the financial system. Hedge funds create systemic risk to the extent that they can disrupt the ability of financial intermediaries or financial markets to efficiently provide credit (Kambhu et al., 2007). Some reports suggest that hedge funds are moving increasingly into less liquid markets, with structured credit and distressed debt at the top of the list (Chan et al., 2006). In the presence of leverage, the combination of relatively illiquid assets and short-term financing exposes the hedge fund to possibly significant liquidity risk.

Moreover, rising financial globalization has allowed financial institutions and investors to trade assets across time zones and geographical locations. By reducing frictions to trade across markets, this process should enable better risk sharing and increase market liquidity, particularly in previously segmented markets. A consequence of financial globalization, however, is that shocks originating in one market are more quickly transmitted to other markets increasing the risk of contagion (Rogoff et al., 2003). Indeed, banking and financial crises have occurred on many occasions in many countries over the past decade. After all, investors realized that their hedge fund portfolios were more correlated and less diversified than they had previously thought. By this work, we aim to answer queries about hedge funds. We study the eight style-categories of hedge funds (Event Driven, Global Macro, Relative Value Arbitrage, Equity Hedge, Absolute Return, Distressed Restructuring, Equity Market Neutral and Merger Arbitrage) from January 2005 to June 2012 in order to examine if the hedge fund returns and correlations are affected by the financial crisis.

The contribution of our study is threefold. First, we pattern the hedge fund returns by using the asymmetric generalized dynamic conditional correlation model, which permits for series-specific news and conditional asymmetries in correlation dynamics. "The AG-DCC specification is well suited to examine correlation dynamics among different asset classes and investigate the presence of asymmetric responses in conditional variances and correlations to negative returns" (Cappiello et al., 2006). In effect, the AG-DCC-GARCH estimations in our study highlight evidence of the asymmetric effects of positive and negative shocks on volatilities and correlations of hedge fund returns. We have found in all cases a bigger impact in volatilities and correlations after the bad news (negative shocks) than the good news (positive shocks). Second, the ajustement of the variable Dummy in correlation construction helps to investigate the structural effect from breaks during crisis periods. This ajustement has been verified significant and adequate in our work. Thirst, researches have used the AG-DCC-GARCH model to investigate the correlation dynamics in the equity markets (Hyde et al., 2007; Kenourgios et al., 2011) or between equities and bonds (Cappiello et al., 2006). Nevertheless, despite a large literature concerning about hedge fund, to our knowledge, there are not much works which appropriate hedge fund correlations. Moreover, we are first to use AG-DCC models to study hedge fund correlation dynamics.

The remainder of this paper is organized as follows: In Section 2, we discuss the methodology. Next, we present the data and the empirical results in Section 3. Finally, Section 4 offers some concluding remarks.

2. Econometric methodologies

2.1. Asymmetric Generalized Dynamic Conditional Correlation GARCH models

It's well-know that the complexity of hedge fund strategies exposes their portfolios to a plethora of economic risk factors and raises the possibility of model mis-specification, since there exists no generally accepted model (Meligkotsidou and Vrontos, 2008; Vrontos et al., 2008). In our study, in order to investigate the hedge fund strategies' exposures and the correlation dynamics between different strategies of hedge funds, we employ the asymmetric generalized dynamic conditional correlation GARCH model (AG-DCC-GARCH) of Cappiello et al. (2006). This model is the generalization of the DCC-MVGARCH model of Engle (2002) to capture the conditional asymmetries in correlation. Firstly, the returns of hedge fund indices in mean equations are modeled as follows:

$$Y_{kt} = c_k + \sum \xi_{m,k} X_{m,t} + \varepsilon_{kt} \tag{1}$$

where Y_{kt} represents the weekly returns of hedge fund k (in our study, k = Event Driven, Global Macro, Relative Value Arbitrage, Equity Hedge, Absolute Return, Distressed Restructuring, Equity Market Neutral and Merger Arbitrage); c_k is a constant; $X_{m,t}$ is a vector of hedge fund risk factors (m = U.S. stock, 10 Year U.S. Treasury bond, EMU stock, EMU government bond, crude oil, GSCI commodity, S&P500 futures, global income and currency fund) and ε_{kt} is an error term (the residual). $\xi_{m,k}$ are coefficients to estimate.

The residuals are assumed to be normally distributed:

$$\varepsilon_t | I_{t-1} \sim N(0, H_t) \tag{2}$$

where I_{t-1} represents the information set at time $t-1$. The conditional covariance matrix H_t of the model is:

$$H_t = D_t R_t D_t \tag{3}$$

where $D_t = diag\sqrt{H_{it}}$ is the $(n \times n)$ diagonal matrix of time-varying standard deviations from univariate GARCH models, R_t is the $(n \times n)$ time-varying correlation matrix, and the standardized residuals are defined as: $\eta_t = D_t^{-1}\varepsilon_t$, $t = 1, ..., T$.

Thus, we have:

$$R_t = diag(Q_t)^{-\frac{1}{2}} Q_t diag(Q_t)^{-\frac{1}{2}} \tag{4}$$

The AG-DCC-GARCH model is designed to allow for a three-stage estimation of the conditional covariance matrix H_t. Univariate volatility models are fitted to each of asset return residuals and estimates of $\sqrt{h_{it}}$ are obtained. Thus, the elements in D_t are obtained from an univariate GARCH(1,1) model. As Engle and Sheppard (2001) indicate, any univariate GARCH process that is covariance stationary and assumes normally distributed errors can be used to model the variances. However, since the conditional variance is an asymmetric function of past innovations, which increases proportionately more after a negative than after a positive shock of the same magnitude, the so-called asymmetric effects thus becomes another important issue in the applications of the univariate GARCH models. A popular asymmetric model is the GJR-GARCH model known as such after the authors who introduced it, Glosten et al. (1993). Therefore, in this study, we use the GJR-GARCH model specification which is selected according to the Bayesian information criterion (BIC). The conditional variance $h_{i,t}$ on the i^{th} diagonal of the matrix D_t has following form:

$$h_{i,t} = \omega_i + \alpha_i \varepsilon_{i,t-1}^2 + \beta_i h_{i,t-1} + \gamma_i \Omega[\varepsilon_{i,t-1} < 0]\varepsilon_{i,t-1}^2 \tag{5}$$

where α_i measure the ARCH effect. Volatility persistence (GARCH effect) is measured by β_i. γ_i is the coefficient that measures the asymmetric effect, $\Omega[\varepsilon_{i,t-1} < 0] = 1$ if innovation in last period is negative ($\varepsilon_{i,t-1} < 0$) and $\Omega[\varepsilon_{i,t-1} < 0] = 0$ otherwise. The sufficient conditions for variance stationarity are: $\alpha_i + \beta_i + \frac{1}{2}\gamma_i < 1$, $\omega_i > 0$, $\alpha_i \geq 0$, $\beta_i \geq 0$, $\alpha_i + \gamma_i \geq 0$.

In the second stage, after the GJR-GARCH model are estimated, the standardized residuals, $\eta_t = D_t^{-1}\varepsilon_t$ are calculated to estimate the parameters of the dynamic conditional correlations. In the standard DCC model, the evolution of the correlation is given by:

$$Q_t = (1 - a - b)\overline{Q} + a\eta_{t-1}\eta_{t-1}^{'} + bQ_{t-1} \tag{6}$$

where $Q_t = \{q_{ij,t}\}$ is a $(n \times n)$ residual variance-covariance matrix; $\overline{Q} = E(\eta_t \eta_t^{'})$; a and b are positive and $a + b < 1$ to satisfy the stationary condition.

Cappiello et al. (2006) generalized the DCC-GARCH model by including asymmetric effects. In their AG-DCC-GARCH model the dynamics of Q_t is the following:

$$Q_t = (\overline{Q} - A^{'}\overline{Q}A - B^{'}\overline{Q}B - G^{'}\overline{F}G) + A^{'}\eta_{t-1}\eta_{t-1}^{'}A + B^{'}Q_{t-1}B + G^{'}\vartheta_{t-1}\vartheta_{t-1}^{'}G \tag{7}$$

where A, B, and G are $(n \times n)$ parameter matrices, $\overline{Q} = E(\eta_t\eta_t^{'})$, $\overline{F} = E[\vartheta_t\vartheta_t^{'}]$ with $\vartheta_t = \Omega[\eta_t < 0]o\eta_t$, where o denotes the Hadamard product, $\Omega[\eta_t < 0]$ is the indicator function which takes on value 1 if $\eta_t < 0$ and 0 otherwise. This term will capture the conditional asymmetries in correlations. It is clear from equation (7) that Q_t will be positive definite if $(\overline{Q} - A'\overline{Q}A - B'\overline{Q}B - G'\overline{F}G)$ is positive definite. The generalized DCC (G-DCC) is a special case of AG-DCC when $G = 0$.

The asymmetric DCC (A-DCC) is obtained as a special case of AG-DCC if the matrices A, B, and G are replaced be scalars:

$$Q_t = (1 - a^2 - b^2)\overline{Q} + g^2(\vartheta_{t-1}\vartheta_{t-1}' - \overline{N}) + a^2\eta_{t-1}\eta_{t-1}' + b^2 Q_{t-1} \tag{8}$$

a sufficient condition for Q_t to be positive definite is that the matrix in parentheses is positive semi-definite. A necessary and sufficient condition for this to hold is: $a^2 + b^2 + \delta g^2 < 1$ where $\delta =$ maximum eigenvalue $[\overline{Q}^{-\frac{1}{2}}\overline{FQ}^{-\frac{1}{2}}]$.

In Equation 7, if the matrices A, B, and G are assumed to be diagonal, the AG-DCC specification reduces to:

$$Q_t = (ll' - aa' - bb')o\overline{Q} + gg'o(\vartheta_{t-1}\vartheta_{t-1}' - \overline{N}) + aa'o\eta_{t-1}\eta_{t-1}' + bb'oQ_{t-1} \tag{9}$$

where l is a vector of ones and a, b, and g are vectors containing the diagonal elements of the matrices A, B, and G, respectively. In this case, a sufficient condition for Q_t to be positive definite for all t is that the intercept, $((ll' - aa' - bb')o\overline{Q} - gg'o\overline{N})$ is positive semi-definite and the matrix Q_0 is positive definite.

It should be noted that the AG-DCC generalization comes at the cost of added parameters and complexity, which actually require $2n$ parameters in each correlation term. Therefore, in our study, we chose to use the three simplified modifications of AG-DCC models: (i) the scalar version known as the Asymmetric Generalized DCC model (AG-DCC), where has only 3 parameters, (ii) the diagonal matrix version known as Generalized Diagonal DCC model (GD-DCC), where has $2n$ parameters (iii) the diagonal matrix version known as the Asymmetric Diagonal DCC model (AD-DCC), where has $3n$ parameters[1].

Cappiello et al. (2006) also proposed to extend the model allowing for structural breaks in mean, in dynamics, or in both. Then assume that, for example, researchers are interested in examining whether a structural break has occurred in the intercept. Let Dum_t be a dummy variable which takes on value 1 when $t = crisis - times^2$, and 0 otherwise. In this case, the following model can be tested:

[1]Likelihood value and Bayesian information criterion have been used to compare the efficient performance of the DCC-GARCH, A-DCC-GARCH, GD-DCC-GARCH and AGD-DCC-GARCH models.

[2]In the absence of an agreed definition of turbulence in global financial markets, we use the Chicago Board Options Exchange Market Volatility Index (VIX), a widely quoted indicator of market sentiment, to identify episodes of turbulence in global stock markets. We use the Zivot-Andrew test to find the structural break points in the VIX and the intervals of crisis are identified by this points (Zivot and Andrews, 1992; Bai and Perron, 2003). The result of these tests is reported in Table 1.

$$Q_t = (\overline{Q_1} - A^{'}\overline{Q_1}A - B^{'}\overline{Q_1}B - G^{'}\overline{F_1}G)(1 - Dum_t) + \\ (\overline{Q_2} - A^{'}\overline{Q_2}A - B^{'}\overline{Q_2}B - G^{'}\overline{F_2}G)Dum_t + A^{'}\eta_{t-1}\eta_{t-1}^{'}A + B^{'}Q_{t-1}B + G^{'}\vartheta_{t-1}\vartheta_{t-1}^{'}G \quad (10)$$

where Q_t is the modified covariance matrix that governs the dynamics of the time-varying correlation matrix R_t in the above standard DCC model, and both $\overline{Q}_1$ and $\overline{Q}_2$ are the new correlation matrices of the residuals. $\overline{Q}_1 = E(\eta_t\eta_t^{'})$, $t = crisis - time$, $\overline{Q}_2 = E(\eta_t\eta_t^{'})$, $t \neq crisis - time$. We might wish to test whether a structural break has occurred in the intercept following the global financial crisis which started in 2007 (U.S. Subprime industry collapse) and in 2012 (European sovereign debt crisis).

Finally, the third stage conditions on the correlation intercept parameters allow us to estimate the coefficients governing the dynamics of correlation. The parameters are estimated by the Maximum Likelihood method assuming that the assets returns are conditional Gaussian. As proposed by Engle (2002), the model can be estimated by using the log-likelihood function:

$$L(\theta) = -\frac{1}{2}\sum_{t-1}^{T}[(n\log(2\pi) + 2\log|D_t| + \varepsilon_t^{'}D_t^{-2}\varepsilon_t) + (\log|R_t| + \eta_t^{'}R_t^{-1}\eta_t - \eta_t^{'}\eta_t)] \quad (11)$$

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 R_t is the correlation matrix.

In the AG-DCC-GARCH model, an element of R_t has the form as follows:

$$\rho_{ij,t} = \frac{q_{ij,t}}{\sqrt{q_{ii,t}}\sqrt{q_{jj,t}}} \quad (12)$$

where $i, j = 1, 2, ...$ and $i \neq j$; $\rho_{ij,t}$ is the key to this methodology because it represents the conditional correlation between financial assets.

3. Data and empirical results

3.1. Data description

We use the weekly return index (RI) from Hedge Fund Research Inc. database for 8 styles of hedge funds: Event Driven, Global Macro, Relative Value Arbitrage, Equity Hedge, Absolute Return, Distressed Restructuring, Equity Market Neutral and Merger Arbitrage, from January 2005 to June 2012. The weekly returns of indices (except for hedge fund correlations' explanatory variables) is measured in U.S. dollar and computed as $Y_t = 100 * ln(RI_t/RI_{t-1})$.

The graphical analysis of hedge fund return data[3] shows strong evidence of stationarity, highlights cyclical movements inherent to hedge fund returns and indicates violent correction characterizing most hedge strategies over the last few years, reflecting further subprime effects (Jawadi and Khanniche, 2012). Summary statistics for the weekly returns of hedge-fund style indices are provided in Tables 2. We note that four out of eight hedge fund strategies have positive average returns in the sample period (Event Driven, Global Macro, Relative Value Arbitrage and Merger Arbitrage) and the others have negative ones. Among them, Merger Arbitrage is the most interesting strategy with a largest average return (0.095) and a moderate volatility (0.480). Meanwhile, Distressed Restructuring exhibit the lowest average return (-0.064). In term of volatility, Equity Hedge and Global Macro are the most volatile (1.529 and 1.430, respectively) and Absolute Return, the least (0.185). We also note a leptokurtic and asymmetrical effects, and the rejection of normality for hedge fund strategies. These descriptive statistics are generally consistent with previous studies (Billio et al., 2012; Boyson et al., 2010; Akay et al., 2012).

The unconditional correlations among the hedge fund indexes are given in Table 3. The entries display a great deal of heterogeneity, ranging from 0.139 (between Event Driven and Absolute Return or between Event Driven and Merger Arbitrage) and 0.970 (between Absolute Return and Merger Arbitrage). The correlation among the eight styles of hedge funds are in fact generally high. However, these correlations can vary through time and become lower in tranquil periods as Figures 1 to 5 illustrate.

3.2. Empirical results

3.2.1. Hedge fund market exposures

Regarding risk factors of hedge funds, we consider a set of eight variables that provide a reasonably source of risk exposures for typical hedge fund strategies (Agarwal and Naik, 2004). The hedge fund factor exposures consist of U.S. stock, U.S. Treasury bond, EMU stock, EMU government bond, crude oil, GSCI commodities, S&P500 futures and global income & currency fund.

The estimation of mean equations, reported in Table 4, provides us the risk factor exposures of hedge fund strategies. Firstly, we note that hedge fund strategies, except for Absolute Return, exhibit a significant and positive exposure to GSCI commodities. The positive impact of commodity returns on the performance of hedge fund strategies confirms that managers tend to have a long position on GSCI commodities as their returns are expected to increase. It should be noted that during the period 2005 - 2008, the prices of commodities experienced a considerable increase in line with the demand of growing world economy. However, after the bursting of U.S. subprime industry, the commodity prices suffered a dramatic collapse.

[3]Not reported in the paper.

Regarding EMU stock market, we find a significant exposure for Equity Market Neutral strategies only. This exposure is positive, meaning that Equity Market Neutral' managers take a long position in EMU stocks while minimizing exposure to the systematic risk of the market. However, Equity Market Neutral fund returns are generated by the spread between the longs and the shorts plus the difference between dividends earned on long positions and dividends paid on short positions.

Meanwhile, Event Driven, Global Macro and Distressed Restructuring funds exhibit a negative exposure to U.S. Treasury bond and other strategies do not show a significant relation with this asset. In effect, to mitigate risk in equities, funds managers trade in U.S. Treasury bonds as a natural hedge. Thereby, managers of Event Driven, Global Macro and Distressed Restructuring strategies tend to take a short position on U.S. Treasury bond, selling short risky assets. Thus, profits might be made from negative shock in returns.

Global income and currency fund is also an interesting factor which exhibits the significant and positive exposure of five out of eight hedge fund strategies. The global income and currency fund is designed for investors seeking to diversify their investment portfolio or specifically to gain exposure to the currency market who believe that the fund's investment strategy has the ability to generate positive returns over the investor's time horizon. Thus, hedge fund managers try to earn positive returns by taking long position on this factor.

On the contrary, the exposures of hedge fund strategies to U.S. equity and EMU bond markets are insignificant in all cases. This fact may due to the uncertain condition in U.S. equity market and the sovereign debt in Euro area during the sample period.

3.2.2. Parameter estimates of AG-DCC-GARCH model

The first stage of the AG-DCC estimation process is to fit univariate GARCH specification for each of 8 return series. To account for possible asymmetry in conditional volatility, we estimate GJR-GARCH models in each case. We find evidence of asymmetry in volatility of all hedge fund strategies under investigation. Parameter estimates from the univariate GJR-GARCH models are reported in Table 5. The results highlight the autoregressive conditional heteroscedasticity effects and the persistence of volatility through the significance of variance equations' parameters (α and β). Moreover, the parameter γ is also significant in all cases, indicating evidence of asymmetries in conditional variances. Given existing results in the literature (see, e.g., Glosten et al. (1993) and Nelson (1991)), it is not surprisingly that we find this asymmetric effect in the variance of hedge fund returns.

We also noted that many large jumps are observed in the dynamic correlation between financial assets during turbulent periods. These raise the question of whether the data generating process underwent an unobserved structural shift in the levels of the correlations during financial crises. This is of great importance as failing to model this break would imply that the mean reverting drift is potentially spurious, as convergence would be occurring towards an incorrect long run average. As a result, the DCC specification is modified in order to account for a structural break in the unconditional correlations on this date, as proposed in similar work by Cappiello et al. (2006). The parameter estimates of five DCC specifications are reported in Table 6. Most parameter coefficients are statistically significant at conventional levels. Log-likelihood values (Table 7) suggest that the structural break AGD-DCC-GARCH model achieves the best fit among all specifications. BIC values (Table 7) give us some slight differences[4]. Among models without breaks, AGDC-DCC-GARCH is the best, but among models with breaks, the DCC-GARCH is the most parsimonious and efficient. In other words, the flexibility given by breaks seems to be more important than the flexibility given by asymmetries.

Then, we focus on the asymmetries in covariances. The results show that not only variances, but also covariances exhibit significant effects such as leverage effects. The asymmetric effects for shocks with the same sign seem to be important, as the corresponding estimated coefficients are statistically significant for four out of eight cases in the AGD-DCC-GARCH model and seven out of eight cases in the structural break AGD-DCC-GARCH model. The positive sign of the coefficients indicates that next week's conditional covariance between returns is higher when there are two negative shocks rather than two positive shocks.

The conditional correlations and conditional covariances of hedge fund strategies' returns are plotted in Figures 1 to 5. While correlations indicate the relationship between two returns, the covariance captures the level of comovement between them. Thus it is possible to determine whether changes in comovement are due to a change in the correlation or simply due to volatility. On each plot, the break dates are marked with a vertical line, while the shades areas correspond to the climax stages of the U.S. subprime and the European sovereign debt crises. There is an evidence of considerable variation in correlations and covariances in all cases. Typically the dynamic pattern of correlations is also witnessed in the corresponding covariances, although variation in volatility lead to periods of significantly different behaviors.

The correlations of hedge fund strategy assets show considerable variation. The correlations are generally positive and dynamic. Before the first break in implied volatility index, dated on September 2007, the correlations seem to be more stable. The correlations fluctuate a lot during the period from 2007 to 2012. We remark that, correlations and covariances between hedge fund strategies, without exception, increase abruptly and hit a great peak in July 2011 (week 342, July 2011).

[4] Although there are many information criteria available, in addition to likelihood ratio tests using nested models, the use of the BIC is appropriate as it leads to the correct model specification being selected asymptotically as long as it is a member of the group. The BIC was computed as $-2L + kln(T)$ where L is the maximized log likelihood, k is the number of parameters in the specification and T is number of observations.

This finding strengthen the contagion hypothesis among hedge funds. We are led to believe that the funds belonging to different categories of hedge funds must have common assets or similar positions in portfolio. It comes maybe to the common assets and positions which are poorly described by the risk factors. It is also possible that the high exposure to liquidity risk (Chan et al., 2006) leads these funds to common strategy revisions in times of stress: sales of the most liquid assets and reduced leverage. The introduction of break and the existence of asymmetry in the AG-DCC-GARCH model offers finally a greater flexibility to capture these important changes of correlation.

4. Conclusion

In this study, we investigate whether hedge fund strategy returns and correlations are affected by crises and verify the asymmetries in conditional variances and correlation dynamics for a cross-section hedge funds. As the optimal portfolio of a portfolio manager depends on the predicted covariance between assets, relaxing the symmetric specification may lead to superior investment choices. For this purpose, we use the AG-DCC GARCH model proposed by Cappiello et al. (2006), which generalizes the DCC GARCH model of Engle (2002) allowing for series-specific news impact and conditional asymmetries in correlation dynamics. Then, we explore the dynamics and changes in the correlations of hedge fund strategies.

The main empirical findings can be summarized as follows. As the conditional covariances change substantially over time, the constant covariance hypothesis should be rejected. With respect to asymmetric effects in variances, we find that weekly returns of hedge fund strategy indexes exhibit significant leverage effects. Not only variances, but also correlations between hedge fund returns exhibit significant asymmetries. Especially joint negative shocks in the hedge fund returns are followed by a much higher correlation impacts than joint positive shocks. This means that when bad news hit simultaneously financial markets, the conditional correlations between hedge funds increase more than good news. This finding has important implications for international investors, as the diversification sought by investing in multiple markets is likely to be lowest when it is most desirable. The results indicate that the performance of the structural break AGD-DCC-GARCH of conditional second moments is quite well. Indeed, when compared with symmetric, scalar and asymmetric representations, the structural break AGD-DCC-GARCH model turns out to be superior.

There is also a more economical reading for empirical results obtained in this paper. This rising of correlations affects various style-categories of hedge funds, which are normally weakly correlated with the general evolution of financial markets (see, e.g.,Guesmi et al. (2014)) and weakly correlated between themselves. This is undoubtedly a significant and untapped financial contagion dimension.

Table 1: Structural breaks in Chicago Board Options Exchange Market Volatility Index

Zivot-Andrews Statistics	**-6.998****	**-6.910****	**-8.415****	**-5.272****	**-5.400****	**-6.173*****	**-8.458****	**-7.618****
Break-points	137 (17/09/07)	156 (07/01/08)	190 (01/09/08)	213 (09/02/09)	275 (19/04/10)	290 (02/08/10)	341 (18/07/11)	350 (26/09/11)

Note: ***, **, * statistically significant at 1% and 5%, respectively.

Table 2: Total period data description

Variables		Mean	Variance	Skewness	Kurtosis (Excess)	Jarque-Bera	AR (BIC)	Q(12)	ARCH	
									Q(12)	X^2(12)
Event Driven	**RED**	0.028	0.733	**-1.621*****	**5.317*****	**596.345*****	1	**104.623*****	**146.636*****	**126.413*****
Macro	**RGM**	0.021	1.430	**-1.809*****	**11.878*****	**2370.855*****	1	**104.146*****	**92.319*****	**124.649*****
Relative Value Arbitrage	**RRVA**	0.016	0.743	**-2.962*****	**17.894*****	**2584.360*****	1	**56.581*****	**104.324*****	**94.464*****
Equity Hedge	**REH**	-0.024	1.529	**-1.241*****	**4.005*****	**341.439*****	1	**25.840****	**68.133*****	**66.302*****
Absolute Return	**RAR**	-0.018	0.185	**-0.948*****	**5.271*****	**458.450*****	0	14.352	**125.694*****	**79.603*****
Distressed Restructuring	**RDR**	-0.064	0.574	**-2.247*****	**24.515*****	**9862.144*****	3	**97.707*****	**148.109*****	**145.489*****
Equity Market Neutral	**REMN**	-0.001	0.454	**-0.350*****	**3.302*****	**175.311*****	1	**23.128****	**44.537*****	**37.038*****
Merger Arbitrage	**RMA**	0.095	0.480	**-1.624*****	**15.808*****	**3371.730*****	1	**23.128****	**44.537*****	**37.038*****

Note: Total period: 01/01/2005 – 01/06/2012; Observations = 369; ***, **, * statistically significant at 1%, 5%, and 10%, respectively; Q(12) is the Ljung-Box test for autocorrelation of order 12; ARCH-Q(12) is the McLeod-Li test and X^2(12) is the Engle (1982)'s test for conditional heteroscedasticity of order 12.

Table 3: Unconditional correlations between hedge fund indices

	RED	**RGM**	**RRVA**	**REH**	**RAR**	**RDR**	**REMN**	**RMA**
RED	1.000	0.680	0.954	0.490	0.139	0.954	0.490	0.139
RGM		1.000	0.707	0.558	0.153	0.707	0.558	0.153
RRVA			1.000	0.532	0.214	0.968	0.532	0.214
REH				1.000	0.548	0.532	0.965	0.548
RAR					1.000	0.214	0.548	0.970
RDR						1.000	0.532	0.214
REMN							1.000	0.548
RMA								1.000

Table 4: Parameters of mean equations

	RED	**RGM**	**RRVA**	**REH**	**RAR**	**RDR**	**REMN**	**RMA**
Const	**0.123***** **(0.045)**	**0.111*** **(0.067)**	**0.124**** **(0.050)**	**0.169***** **(0.044)**	**0.085*** **(0.077)**	**0.128***** **(0.046)**	**0.092***** **(0.027)**	**0.156**** **(0.044)**
RUS	-0.038 (0.135)	0.176 (0.199)	-0.104 (0.148)	0.196 (0.130)	-0.009 (0.228)	0.056 (0.138)	0.030 (0.082)	0.352 (0.235)
RUSB	**-0.151**** **(0.065)**	**-0.211**** **(0.096)**	-0.117 (0.072)	0.002 (0.063)	0.043 (0.111)	**-0.172**** **(0.067)**	-0.046 (0.040)	-0.202* (0.114)
REMS	0.028 (0.023)	0.026 (0.034)	0.016 (0.025)	0.028 (0.022)	-0.001 (0.039)	0.028 (0.024)	**0.025*** **(0.014)**	0.022 (0.040)
REMB	0.112 (0.086)	0.138 (0.128)	0.100 (0.095)	0.078 (0.084)	0.133 (0.146)	0.121 (0.089)	0.065 (0.053)	0.174 (0.151)
RCOM	**0.074***** **(0.026)**	**0.099**** **(0.039)**	**0.079***** **(0.029)**	**0.064**** **(0.025)**	0.040 (0.045)	**0.088***** **(0.027)**	**0.039**** **(0.016)**	**0.138***** **(0.046)**
ROIL	-0.021 (0.015)	-0.031 (0.022)	-0.019 (0.017)	-0.015 (0.015)	-0.007 (0.026)	**-0.026*** **(0.015)**	-0.008 (0.009)	-0.040 (0.027)
RGIC	**0.052***** **(0.018)**	**0.101***** **(0.027)**	**0.051**** **(0.020)**	0.022 (0.017)	-0.020 (0.031)	**0.066***** **(0.018)**	**0.023**** **(0.011)**	0.077** (0.032)
RSPF	-0.024 (0.134)	-0.267 (0.198)	0.061 (0.148)	**-0.254*** **(0.130)**	0.038 (0.228)	-0.130 (0.138)	-0.070 (0.082)	**-0.439*** **(-0.439)**

Note: ***, **, * statistically significant at 1%, 5%, and 10%, respectively.

Table 5: Parameters of variance equations

	Const	**α**	**β**	**γ**
RED	**0.145***** **(0.054)**	0.037 (0.028)	**0.561***** **(0.090)**	**0.417**** **(0.197)**
RGM	0.009 (0.012)	**0.247***** **(0.057)**	**0.910***** **(0.016)**	**-0.250***** **(0.058)**
RRVA	**0.071***** **(0.021)**	**0.268***** **(0.084)**	**0.543***** **(0.090)**	**0.149***** **(0.103)**
REH	**0.601***** **(0.124)**	0.132 (0.054)	**0.427***** **(0.107)**	**0.537***** **(0.146)**
RAR	**0.224***** **(0.051)**	**0.069*** **(0.054)**	**0.881***** **(0.157)**	**0.212**** **(0.101)**
RDR	**0.121*** **(0.056)**	**0.475***** **(0.066)**	**0.719***** **(0.043)**	**-0.317***** **(0.109)**
REMN	**0.017***** **(0.008)**	**0.028***** **(0.090)**	**0.909***** **(0.0144)**	**0.009***** **(0.005)**
RMA	**0.073***** **(0.014)**	0.214 (0.033)	**0.658***** **(0.365)**	**0.428***** **(0.220)**

Note: ***, **, * statistically significant at 1%, 5%, and 10%, respectively.

Table 6: Parameters of the dynamic conditional correlations

	DCC-GARCH	ADCC-GARCH	GDDCC-GARCH	AGDDCC-GARCH	AGDDCC-GARCH With breaks
A	**0.159*** (0.019)**	**0.153*** (0.020)**	-	-	-
B	**0.829*** (0.011)**	**0.831*** (0.011)**	-	-	-
G	-	**0.001*** (0.088)**	-	-	-
AQ(1)	-	-	**0.315*** (0.026)**	**0.316*** (0.028)**	**0.144*** (0.019)**
AQ(2)	-	-	**0.204*** (0.040)**	**0.321*** (0.056)**	0. 026 (0.072)
AQ(3)	-	-	**0.123*** (0.020)**	**0.126*** (0.028)**	**0.136*** (0.023)**
AQ(4)	-	-	**0.346*** (0.027)**	**0.332*** (0.035)**	**0.220*** (0.016)**
AQ(5)	-	-	**0.201*** (0.020)**	**0.186*** (0.015)**	**0.150*** (0.019)**
AQ(6)	-	-	**0.192*** (0.033)**	**0.159*** (0.007)**	**0.179*** (0.028)**
AQ(7)	-	-	**0.147*** (0.018)**	**0.182*** (0.037)**	**0.093*** (0.021)**
AQ(8)	-	-	**0.293*** (0.028)**	**0.201*** (0.028)**	**0.044*** (0.015)**
BQ(1)	-	-	**0.863*** (0.042)**	**0.901*** (0.025)**	**0.949*** (0.006)**
BQ(2)	-	-	**0.906*** (0.027)**	**0.877** (0.029)**	**0.890** (0.003)**
BQ(3)	-	-	**0.909*** (0.012)**	**0.902*** (0.008)**	**0.907*** (0.006)**
BQ(4)	-	-	**0.885*** (0.011)**	**0.831*** (0.018)**	**0.926*** (0.006)**
BQ(5)	-	-	**0.902*** (0.018)**	**0.899*** (0.020)**	**0.949*** (0.008)**
BQ(6)	-	-	**0.915*** (0.020)**	**0.892** (0.036)**	**0.922** (0.017)**
BQ(7)	-	-	**0.867*** (0.014)**	**0.907*** (0.009)**	**0.909*** (0.029)**
BQ(8)	-	-	**0.885*** (0.019)**	**0.900*** (0.018)**	**0.892*** (0.003)**
GQ(1)	-	-	-	0.007 (0.125)	**0.193*** (0.030)**
GQ(2)	-	-	-	**-0.119** (0.111)**	0.184 (0.127)
GQ(3)	-	-	-	-0.068 (0.069)	**0.060** (0.024)**
GQ(4)	-	-	-	0.022 (0.115)	**0.143*** (0.036)**
GQ(5)	-	-	-	**0.012* (0.074)**	**0.160*** (0.035)**
GQ(6)	-	-	-	**-0.281* (0.097)**	**0.219*** (0.068)**
GQ(7)	-	-	-	0.055 (0.018)	**0.101** (0.018)**
GQ(8)	-	-	-	**0.038* (0.101)**	**0.089*** (0.032)**
Likelihood	-2399.135	-2398.183	-2351.229	-2332.934	**-2291.154**
BIC	4810.091	4814,098	4797,030	4807,727	**4724,167**

Note: ***, **, * statistically significant at 1%, 5%, and 10%, respectively.

Table 7: Log-likelihood values

	Likelihood	BIC
DCC-GARCH	-2399.135	4810.091
DCC-GARCH with breaks	**-2332.425**	**4676,671**
ADCC-GARCH	-2398.183	4814,098
ADCC-GARCH with breaks	**-2332.420**	**4682,572**
GDDCC-GARCH	-2351.229	4797,030
GDDCC-GARCH with breaks	**-2303.433**	**4701,438**
AGDDCC-GARCH	-2332.934	4807,727
AGDDCC-GARCH with breaks	**-2291.154**	**4724,167**

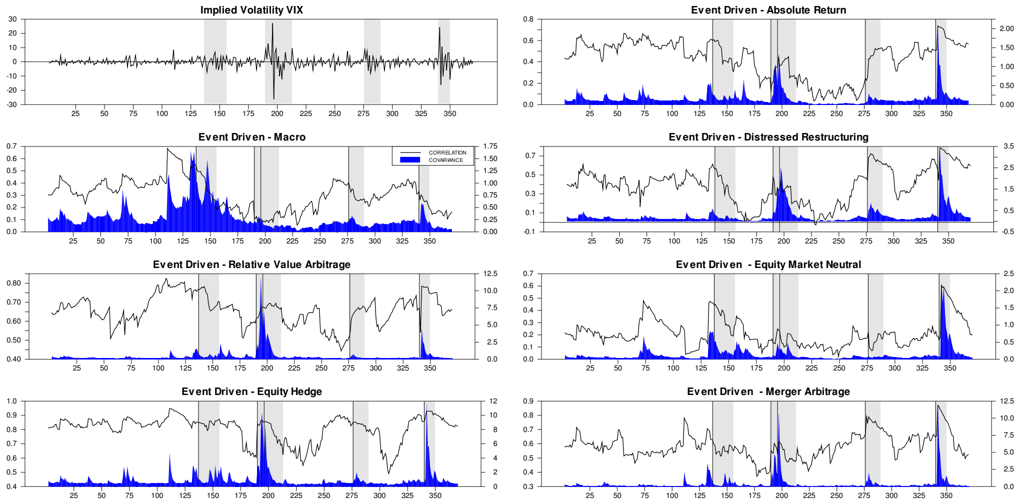

Figure 1: Implied volatility VIX and Conditional Correlations and Covariances between indices - Part 1

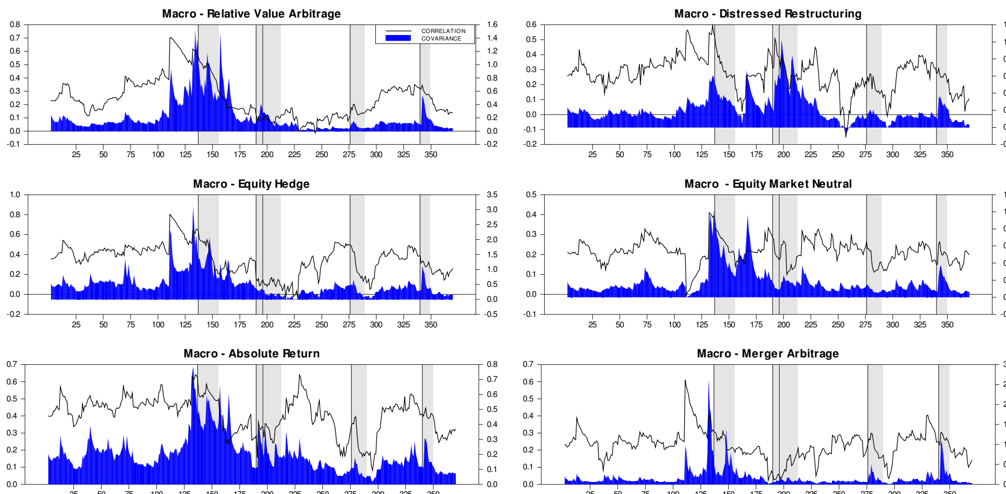

Figure 2: Conditional Correlations and Covariances between indices - Part 2

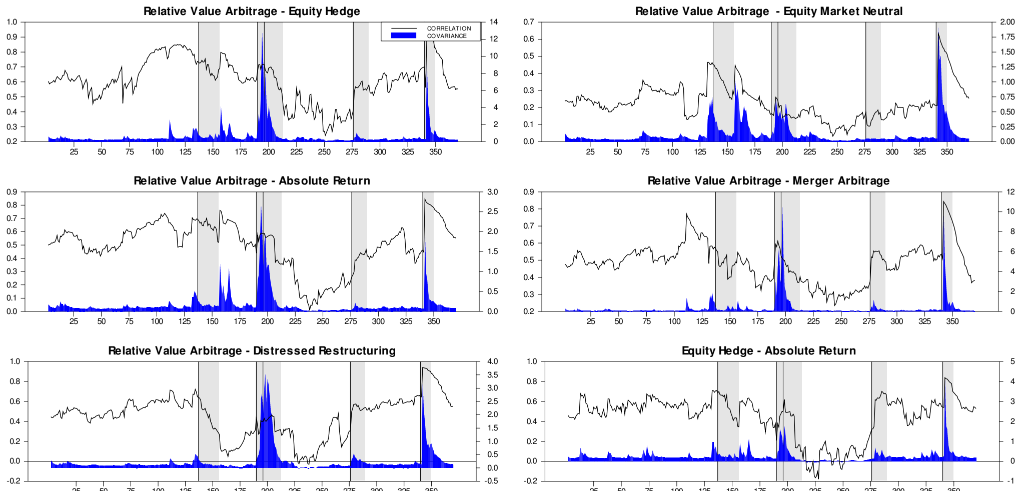

Figure 3: Conditional Correlations and Covariances between indices - Part 3

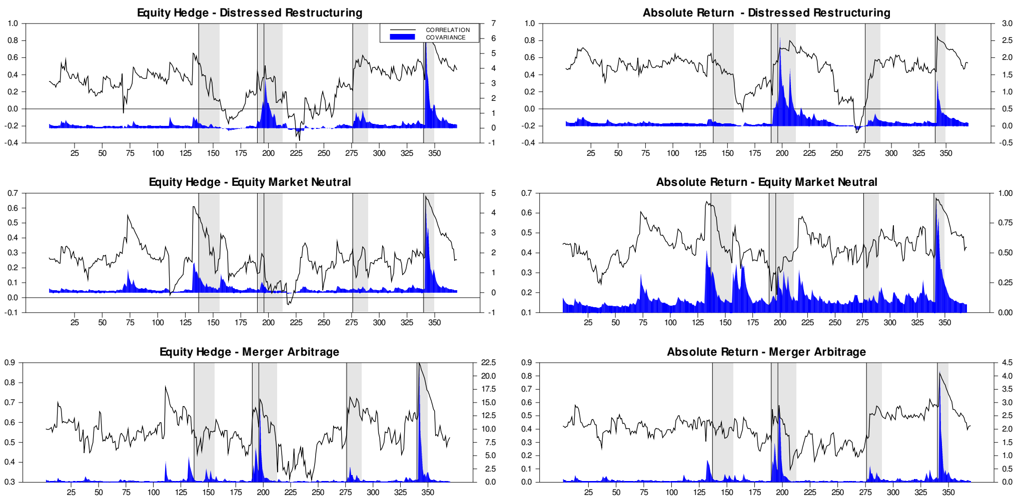

Figure 4: Conditional Correlations and Covariances between indices - Part 4

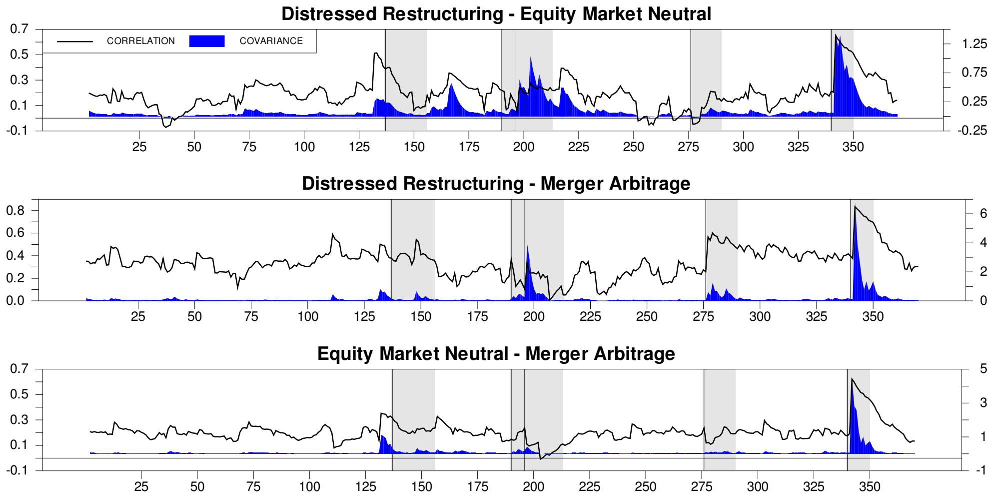

Figure 5: Conditional Correlations and Covariances between indices - Part 5

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