Hedge Fund Returns under Crisis Scenarios: A Holistic Approach

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Abstract

The assets of the hedge fund industry are nearly equivalent to the GDP of the UK. The industry, which claims returns independent of markets conditions and has been blamed for economic crises, has attracted the interest of a wide range of financial and political players and academics. This paper, using monthly series performance data since January 1995, at a fund strategy level and S&P500, and a holistic and a developed dynamic correlation quantitative approach, aims to challenge the allegations and the claims, which have been made on rather incomplete research grounds. Statistically, the results strongly reject the claims of the vast majority of fund strategies, excluding the case of the macro and short strategies, over the crisis periods, suggesting that they cannot protect their investors like S&P500. Regarding the allegations, it is inferred that Hedge Funds are used in most cases as a scapegoat rather than actually being the cause of the crises.

Keywords: Absolute Returns, Carhart's Model, Dynamic Conditional Correlation, Financial Crisis, Hedge Funds, Structural Breaks.

JEL Classification: GO1, G11, G23.

1. Introduction

Hedge funds play a critical role in financial markets by broadening the use of investment strategies, increasing the number of participating investors and enlarging the pools of available capital. For investors, hedge funds serve a risk-management purpose, achieving returns that are often uncorrelated to those in the equity and fixed-income markets. At the same time, hedge funds provide liquidity for mispriced assets –arbitrage opportunities– particularly when large volumes are traded in a thin market which is a volatility reducing activity (Blundell, 2007). For these reasons, hedge funds have gained a great deal of economic and political prominence over the last two decades (Quaglia, 2009). Their assets under management have grown substantially; from $41 billion in 1990 to approximately $3 trillion in 2014, which is almost equal to the real GDP of the UK. Politically, the activity of hedge funds has come to the centre of attention for their alleged role in the Asian financial crisis in 1997, after the collapse of the LTCM fund in 1998, in the burst of the high-tech bubble in 2000, and in the 2008 subprime crisis. These events emphasized the potential systemic impact that can be driven by the behavior of hedge funds and especially by the use of extended leverage.

Within this framework, the issue of the role and the effect of hedge funds on economic crises is frequently raised, with opposing views arising during and after every financial crisis. One argument is well summarized in Stromqvist's (2009) statement that, although hedge fund investments in the price adjustment of incorrectly valued assets, under normal conditions, have a positive impact on the effectiveness of the market, during financial crises they contribute to market instability. The opposing side claims that hedge funds do not drive financial crises on the grounds and that, in most cases, on a broad front, they have been hurt (Brown *et al*., 1999 and 2001, IOSCO 2006 and 2009, Palaskas *et al*., 2013). However, the fact that hedge funds have experienced losses during crises does not rule out the possibility that they may have played a role, together with banks and other institutional investors (ECB, 2008), in the development of the crisis.

The rising divergence in the arguments and the research conducted on the role of hedge funds in financial markets have shed only limited light on the questions which have naturally arisen, bearing in mind the aim of hedge funds, which factors influence the performance of hedge fund investment strategies under economic turmoil, and if and to what extent these factors are able to protect investors in downturns.

To this end, the paper aims to contribute to the existing literature and discussion on two levels. First, the performance of hedge funds, using monthly frequency data from January 1995 to September 2014, a period which witnessed the most important financial turmoil of the last 30 years, will be analysed in order to shed light on the question if and to what extent they managed to generate absolute returns, as they allege. Second, by adopting a holistic approach -Carhart's asset pricing model, dynamic volatility and correlation estimates, structural break and equality of means tests - hedge fund performance across all strategies during crisis and non-crisis periods will be assessed.

The paper, apart from the introduction and the conclusion, unfolds in three sections. The section below provides a brief literature review on hedge funds. Section 3 presents and discusses the quantitative approach adopted to derive the results discussed in section 4, and is followed by section 5 the conclusion.

2. Literature Review

The hedge fund industry has been cloaked in secrecy within the asset management territory until the beginning of the '90s. Till then qualitative and quantitative information about their investment strategies was unavailable to the broader investment community (Makarewicz *et al.,* 2011). Over the last three decades, many aspects of the hedge fund industry have become better known, mainly due to academic studies. On the brink of the last and the current millennium Ackermann *et al.* (1999), Brown *et al.* (1999), Amin and Kat (2003) and Agarwal and Naik (2004) attempted to compare the performance of hedge funds using benchmark indices, while Brown *et al.* (1999) and Liang (2000, 2001) focused on the perseverance of their returns. Fung and Hsieh (1997) and Brown *et al.* (1995, 2001) analysed hedge fund investment style adopting quantitative models. Fung and Hsieh (1997), Liang (1999), Amin and Kat (2003) and Agarwal and Naik (2004) focused on the correlation of hedge funds with other investment products and analysed the power of hedge fund diversification properties. Another group of authors (Schneeweis and Spurgin, 1998, Amenc *et al.,* 2002) turned their interest to the risk to which Hedge Funds are exposed, proving that their returns are exposed, beyond market risk, to volatility risk, default risk and/or liquidity risk.

The available research on the link between hedge fund performance and economic crises, the core question of the present paper, is quite recent, and has been examined employing approaches ranging from the Capital Asset Pricing Model (CAPM), to the models of Fama and French (1993), Carhart (1997), Ackermann *et al.* (1999), Liang (1999), Do *et al.* (2005), Fung and Hsieh (2006), Steri *et al.* (2008), Criton and Scaillet (2011), Jordao and Moura (2011)[1], etc.

The early stage researchers employed the CAPM (Sharpe, 1964) model to specify the return of a high-risk asset portfolio minus the return of the risk-free rate as a function of the market risk premium. Three decades later, Fama and French (1993) with CAPM as a starting point, added two factors to explain the returns of portfolios: the company size effect and the market value effect, Using Fama and Frenchs' (1993) model, Carhart (1997) then added the variable 'momentum effect'[2] (Jordao and Moura, 2011) to explain portfolio returns.

At the same time, while Ackermann *et al.* (1999), using hedge fund performance rates, management fees and age to explain variations in the Sharpe ratio, concluded that hedge funds consistently outperform mutual funds but not standard market indices, Liang (1999), employing an asset class factor model and a mean-variance efficient analysis framework, provided a

[1] For a more extensive analysis of the literature see Jordao and Moura (2011).

[2] It is defined as the difference between the return of a hypothetical portfolio that includes companies with the highest returns over 11 months and the returns of a similar portfolio that comprises companies with the worst returns over the same period.

comprehensive evaluation of hedge fund performance and risk. The applied research initiatives and attempts to understand and quantify the factors determining hedge fund performance, independent of the economic cycle, hold up well today. Fung and Hsieh (2004), performing a modified version of the CUSUM test, identified structural break-points in hedge fund factor loadings with major market events, such as, the collapse of LTCM in September 1998 and the peak of the technology bubble in March 2000. Do *et al.* (2005) concluded, by evaluating the Australian hedge fund market and adopting a modified Sharpe ratio[3], that although hedge funds are ineffective as single investments, the addition of a hedge fund to a portfolio, irrespective of strategy, improves its returns. Three years later, Steri *et al.* (2008) developed a model for Italian hedge funds applying panel analysis to assess the performance of both temporal data of market indices and cross-sectional data of the distinct characteristics of funds. Their findings show that high performance fees and long redemption periods produce a negative effect on the performance of hedge funds.

In 2011, three applied works, Criton and Scaillet (2011), Jordao and Moura (2011) and Boasson *et al*. (2011), using case studies data and different quantitative approaches attempted to shed light on hedge fund performance. The first, Criton and Scaillet (2011), employing structural change tests, identified heterogeneity within each strategy; however at the same time they show that, whatever the strategy, exposures are concentrated on the credit spread and the bond risk factors. Jordao and Moura (2011), using Brazilian data, tested the claim that, under a scenario of high volatility and financial stress, hedge funds can produce abnormal returns with a low correlation to market risk. The results were unfavourable for the Brazilian hedge fund industry since only 3.7% of the funds presented positive and statistically significant alpha coefficients. Finally, Boasson *et al*. (2011), using Carhart's (1997) multi-factor asset-pricing model, examined the risk and return performance of hedge fund investment strategies, which is close to the core question of this paper. Their results indicate that, on average, hedge fund

[3] It takes into account the non-normality of fund returns.

returns have relatively low correlations with the market, implying that investments in hedge funds could potentially offer better opportunities for diversification. More recently, Bussiere *et al*. (2014) measured the commonality in hedge fund returns, identified its main driving factors and found that hedge fund commonality increased significantly from 2003 until 2006 which is attributed to the increase in hedge fund exposure to emerging market equities. They also demonstrated that funds with high commonality were affected disproportionately by illiquidity and exhibited negative returns during the 2008 financial crisis, thereby providing few diversification benefits to the financial system and to investors. Sun *et al*. (2015) provided novel evidence that hedge fund performance persists following periods of relative hedge fund market weakness, but not following periods of relative market strength. Their findings suggest an error-in-measurement problem embedded in the unconditional average historical hedge fund returns, which, in turn, weakens their performance predictability.

To sum up, the literature on hedge fund performance, although relatively extensive since the late nineties, tends to focus on specific indicators and does not, in most cases, take into account the effect of economic and/or financial crises separately. Consequently, the variation in findings may very well depend on the indicators chosen and the timeframe of the analysis. The present paper aims at a twofold contribution to the literature. First, it adopts a holistic approach to assess hedge fund performance under pre and ongoing crisis scenarios. Second, it develops and applies a dynamic conditional correlation framework to investigate whether crises are responsible for the change in the correlation pattern between hedge fund risk adjusted performance and S&P500, the main benchmark indicator.

3. Data and Performance Indicators

The discussion in the literature in conjunction with the set hypothesis under examination prompted the definition of the variables to be used in the quantitative analysis.

Data

The quantitative analysis uses monthly data over the period January 1995 - September 2014 obtained from Hedge Fund Research Inc. (HFRI)[4]. The variables are the monthly performance (see Figure 1) for each of the classified strategies, i.e. Convertible Arbitrage, Distressed, Emerging Markets, Equity Hedge, Equity Neutral, Event Driven, Macro, Merger Arbitrage, Relative Value, Short Selling, Multistrategy and Fund of Funds.

[Insert Figure 1 about here]

Carhart's model

To begin, Carhart's (1997) approach is adopted. Understanding the specific model requires a brief presentation of Sharpe's CAPM, and the preceding Fama-French approach. The CAPM assumes that an asset's excess return is determined by its correlation with excess market return:

$$R_{i,t} - R_{f,t} = a_i + \beta_i\left(R_{M,t} - R_{f,t}\right) + u_{i,t}, \tag{1}$$

where $R_{i,t}$ is the portfolio return of asset *i* in month *t*; $R_{f,t}$ is the return on a risk-free asset, $R_{M,t}$ is the return on market portfolio and $u_{i,t}$ is the error term. In Fama and French's (1993) specification, the CAPM model is augmented by the addition of the difference between portfolio returns on small stocks and portfolio returns on large stocks (SMB) and the return difference of portfolios with high book-to-market equity and returns with low book-to-market equity (HML). Carhart (1997) modified Fama and French's specification by adding to the explanatory variables the *momentum effect* (*PR*1*YR)* to perform the regression of excess return of funds:

$$R_{i,t} - R_{f,t} = a_i + \beta_i\left(R_{M,t} - R_{f,t}\right) + \gamma_i SMB_t + \delta_i HML_t + \zeta_i PR1YR_t + u_{i,t}. \tag{2}$$

The intercept a_i measures the administrator's ability index which quantifies the abnormal returns earned by the fund, since the return obtained by the administrator is not explained by any

[4] Despite its limitations, the HFRI database is one of the largest hedge fund databases available for academic research and is extensively used worldwide to support investors' decisions. For more details see Fung *et al.* (2002).

exposure to risk factors in the models (Jordao and Moura, 2011). The beta index β_i, accounts for the fund's systematic risk.

Structural Breaks and Equality of Means

The next step in our approach is to test, consistently with the paper' questions, for the presence of structural breaks, crisis vs non crisis periods, in the performance of each hedge fund strategy. The tests are applied on the Carhart's specification:

$$\begin{aligned} R_{i,t} - R_{f,t} &= a_{1,i} + \beta_{1,i}\left(R_{M,t} - R_{f,t}\right) + \gamma_{1,i}SMB_t + \delta_{1,i}HML_t + \zeta_{1,i}PR1YR_t + u_{1,i,t} \\ R_{i,t} - R_{f,t} &= a_{2,i} + \beta_{2,i}\left(R_{M,t} - R_{f,t}\right) + \gamma_{2,i}SMB_t + \delta_{2,i}HML_t + \zeta_{2,i}PR1YR_t + u_{2,i,t}. \end{aligned} \tag{3}$$

The null hypothesis asserts that: $a_{1,i} = a_{2,i}$, $\beta_{1,i} = \beta_{2,i}$, $\gamma_{1,i} = \gamma_{2,i}$, $\delta_{1,i} = \delta_{2,i}$ and $\zeta_{1,i} = \zeta_{2,i}$ under the assumption that $u_{j,i,t} \overset{i.i.d.}{\sim} N\left(0, \sigma^2_{u_j}\right)$, where $j = 1$ refers to crisis periods and $j = 2$ to non crisis periods. The analysis of variance and the Kruskal-Wallis test are employed to assess the equality of mean performance for each strategy within and between crisis periods.

Dynamic Estimates of Correlation

Finally, for a number of reasons explained in this section, a multivariate framework is developed and applied to our data for the dynamic estimation of the variance-covariance matrix of monthly returns. This will enable us to investigate the time-varying correlation among the returns of the 13 hedge fund strategies under consideration and the S&P500.[5] The intention is to provide dynamic estimates of the correlations in order to overcome the drawbacks of the static correlation specifications that have been applied to explore hedge fund performance. The dynamic estimation of the correlation matrix provides the exact information that the fund

[5] The S&P500 was chosen as a benchmark because, due to the globalization of the financial markets, it reflects to a large extent all crisis incidents.

managers are interested in: the month to month changes of the time-varying correlation between hedge fund returns and S&P500.[6]

In our case, the $\mathbf{y}_t = \left(HF_{1,t} \quad HF_{2,t} \quad \ldots \quad HF_{13,t} \quad \mathrm{S\&P500}_t\right)'$ vector denotes the returns of the hedge funds $HF_{i,t}$, for $i = 1,\ldots,13$, and the S&P500 index at a monthly frequency t. The vector of the monthly returns is assumed to be decomposed into the predictable component $E_{t-1}(\mathbf{y}_t)$,[7] and the unpredictable component $\boldsymbol{\varepsilon}_t$. The $\boldsymbol{\varepsilon}_t$ has a conditional variance-covariance matrix $\mathbf{H}_t$.The generalized proposed framework is:

$$\begin{aligned} \mathbf{y}_t &= E_{t-1}(\mathbf{y}_t) + \boldsymbol{\varepsilon}_t \\ \boldsymbol{\varepsilon}_t &= \mathbf{H}_t^{1/2}\mathbf{z}_t \\ \mathbf{z}_t &\sim f(\mathbf{z}_t; \mathbf{0}, \mathbf{I}, \nu) \\ \mathbf{H}_t &= \sigma(\mathbf{H}_{t-1}, \mathbf{H}_{t-2}, \ldots, \boldsymbol{\varepsilon}_{t-1}, \boldsymbol{\varepsilon}_{t-2}, \ldots), \end{aligned} \tag{4}$$

where $\mathbf{z}_t$ is a vector process with $E(\mathbf{z}_t) = \mathbf{0}$, $E(\mathbf{z}_t\mathbf{z}_t') = \mathbf{I}$ and multivariate density function $f(\mathbf{z}_t; \mathbf{0}, \mathbf{I}, \nu)$.

However, due to the characteristics of hedge fund data series, the framework of equation (4) is developed as follows: First, due to the autocorrelation pattern of monthly returns, the $E_{t-1}(\mathbf{y}_t)$ is modelled as an autoregressive process[8]. Second, since it has been established that hedge fund returns are non-normally distributed (Leland, 1999; Cotton, 2000), the multivariate Student *t* density function for the standardized residuals $\mathbf{z}_t$ is adopted. Third, the variance-covariance matrix $\mathbf{H}_t$ is constructed according to Engle's (2002) Dynamic Conditional Correlation, or DCC, specification, not only because it has been successively applied for estimating time-varying covariance matrices on a large scale similar to our case of 14 assets but

[6] For more information relating to the construction of the dynamic frameworks of correlation matrices estimation and its advantages, the interested reader is refered to Degiannakis *et al.* (2013) and Degiannakis *et al.* (2016), among others.

[7] $E_{t-1}(\mathbf{y}_t)$ is the expected value of $\mathbf{y}_t$ conditional on the information set available at time $t-1$, I_{t-1}.

[8] The last month's performance elaborates the auto-dependence for all hedge funds.

also because, it requires the estimation of fewer numbers of parameters than other multivariate GARCH models such as Engle and Kroner's (1995) BEKK model, Engle's *et al*. (1986) VECH model, etc. Finally, since the volatility of hedge fund returns exhibits significant asymmetry (see Elyasiani *et al*., 2010), the conditional variance must be modelled asymmetrically with respect to the lagged values of variance and squared residuals. Hence, the Glosten *et al*.'s (1993) Threshold ARCH, or TARCH, specification which models the leverage effect (i.e. good news and bad news to have different effects on the conditional variance) is assumed.

Therefore, the re-specified multivariate dynamic framework, AR-DCC-TARCH-*t*, takes the form:

$$\begin{aligned} \mathbf{y}_t &= (\mathbf{I}-\mathbf{c}_1)\mathbf{c_0} + \mathbf{c}_1\mathbf{y}_{t-1} + \boldsymbol{\varepsilon}_t \\ \boldsymbol{\varepsilon}_t &= \mathbf{H}_t^{1/2}\mathbf{z}_t \\ \mathbf{z}_t &\sim t(\mathbf{z}_t;\mathbf{0},\mathbf{I},\nu) \\ \mathbf{H}_t &= \boldsymbol{\Sigma}_t^{1/2}\mathbf{C}_t\boldsymbol{\Sigma}_t^{1/2}. \end{aligned} \tag{5}$$

The $E_{t-1}(\mathbf{y}_t) \equiv (\mathbf{I}-\mathbf{c}_1)\mathbf{c_0} + \mathbf{c}_1\mathbf{y}_{t-1}$ states the 1st order autoregressive process, and the $t(\mathbf{z}_t;\mathbf{0},\mathbf{I},\nu)$ denotes the multivariate standardized Student *t* density function:

$$t(\mathbf{z}_t;\mathbf{0},\mathbf{I},\nu) = \frac{\Gamma((\nu+n)/2)}{\Gamma(\nu/2)(\pi(\nu-2))^{n/2}}\left(1+\frac{\mathbf{z}_t'\mathbf{z}_t}{\nu-2}\right)^{-\frac{\nu+n}{2}}, \tag{6}$$

where $\Gamma(.)$ is the gamma function and ν (for $\nu > 2$) is the degree of freedoms to be estimated. The Student *t* distribution captures the excess leptokurtosis observed in returns of hedge funds (Leland, 1999; Cotton, 2000). The DCC specification decomposes the covariance matrix $\mathbf{H}_t = \boldsymbol{\Sigma}_t^{1/2}\mathbf{C}_t\boldsymbol{\Sigma}_t^{1/2}$, where $\boldsymbol{\Sigma}_t^{1/2}$ is the diagonal matrix with the conditional standard deviations along the diagonal:

$$\boldsymbol{\Sigma}_t^{1/2} = diag(\sigma_{1,t}, \sigma_{2,t}, ..., \sigma_{14,t}), \tag{7}$$

and $\mathbf{C}_t$ is the matrix of conditional correlations. The $\sigma_{i,t}^2$, for $i = 1,...,14$, are defined as Glosten *et al*.'s (1993) TARCH specification:

$$\sigma_{i,t}^2 = \tilde{a}_{i,0} + \tilde{a}_i \varepsilon_{i,t-1}^2 + \tilde{\gamma}_i d\left(\varepsilon_{i,t-1} < 0\right)\varepsilon_{i,t-1}^2 + \tilde{b}_i \sigma_{i,t-1}^2, \tag{8}$$

where $\tilde{a}_{i,0}, \tilde{a}_i, \tilde{\gamma}_i, \tilde{b}_i$ are parameters to be estimated, $d(\varepsilon_{t-i} < 0) = 1$ if $\varepsilon_{t-i} < 0$, and $d(\varepsilon_{t-i} < 0) = 0$ likewise. The good news $(\varepsilon_{t-i} > 0)$, has an impact of a_i, whereas the bad news $(\varepsilon_{t-i} < 0)$, has an impact of $a_i + \gamma_i$ on the conditional variance (i.e. leverage effect).

The matrix of conditional correlations has the form:

$$\mathbf{C}_t = \mathbf{Q}_t^{*-1/2} \mathbf{Q}_t \mathbf{Q}_t^{*-1/2}, \tag{9}$$

where $\mathbf{Q}_t = (q_{i,j,t})$ is computed as:

$$\mathbf{Q}_t = (1 - a - b)\overline{\mathbf{Q}} + a(\mathbf{z}_{t-1}\mathbf{z}'_{t-1}) + b\mathbf{Q}_{t-1}, \tag{10}$$

for $\mathbf{z}_t \equiv (z_{1,t}, z_{2,t}, ..., z_{14,t})' = (\varepsilon_{1,t}\sigma_{1,t}^{-1}, \varepsilon_{2,t}\sigma_{2,t}^{-1}, ..., \varepsilon_{14,t}\sigma_{14,t}^{-1})'$, $\overline{\mathbf{Q}}$ is the unconditional covariance of $\mathbf{z}_t$ and $\mathbf{Q}_t^{*-1/2}$ is a diagonal matrix that contains the square roots of the inverse of the diagonal elements of $\mathbf{Q}_t$:[9]

$$\mathbf{Q}_t^{*-1/2} = diag\left(q_{1,1,t}^{-1/2}, q_{2,2,t}^{-1/2}, ..., q_{14,14,t}^{-1/2}\right). \tag{11}$$

4. Results and Analysis

In line with the set hypotheses of the paper, the derived results and analysis are referred to six periods: i) the total sample period from January, 1995 to September, 2014; ii) the 1997 Asian crisis; iii) the LTCM crisis in 1998; iv) a period including the worst losses of the S&P500 index given the burst of the dot com bubble in 2000; v) a period including the worst losses of the S&P500 index due to the global financial crisis (subprime crisis) in 2008; and vi) the European debt crisis in 2011.

To illustrate the entire sample involved and the defined sub-periods/crisis data behaviour of each hedge fund strategy, descriptive statistics are quoted (Table 1) and analysed. The

[9] Xekalaki and Degiannakis (2010) provide technical information for the estimation of the model.

calculated average monthly return of 0.75% for the HFRI index is slightly higher than the benchmark stock market index (S&P500) with a substantially lower standard deviation, demonstrating the higher risk of S&P500. Taking fund strategies individually, it is noted that their average performance varies from -0.20 for Short Selling funds to 0.87 for Equity Hedge funds. Standard deviations also vary considerably among the various hedge fund strategies with the Short Selling Funds possessing the highest (5.10) while at the antipode the Equity Neutral funds have the smallest deviations (0.89). In addition, the statistics on skewness and kurtosis confirm that the majority of hedge fund strategies are asymmetrically and leptokurtically distributed; an issue that must be taken into consideration in the following statistical analysis. Finally, the estimated monthly premiums of *SMB* factor and of *HML* factor are 0.17% and 0.24%, respectively (see Table 2).

[Insert Table 1 about here]

[Insert Table 2 about here]

Next, there is a discussions of whether or not the results of each of the adopted approaches is in line with the paper's fundamental question, i.e. whether hedge funds manage to produce returns irrespective of market movements. To start with, the existence of structural breaks for each of the thirteen fund strategies in both crisis and non-crisis[10] sample periods is tested. The results, in Table 3, statistically reject, at a 95% level of significance, excluding Convertible Arbitrage, Equity Neutral, Macro and Short Selling fund strategies, the non-existence of the structural breaks hypothesis between the two periods, suggesting that the majority of hedge fund/strategies managers did not succeed in hedging their way out of the crises.

[Insert Table 3 about here]

Bearing in mind that the involved time series are not normally distributed (see the discussion above), an additional test, the Kruskal-Wallis test, is applied to examine the equality

[10] The returns of the 13 hedge fund strategies were dichotomized between non crisis and crisis periods.

of the coefficients (Table 4). The results[11] overwhelmingly and statistically support (at a 95% level of significance) the findings of managers' failure to hedge over crisis periods, with the only exception the Macro strategy. The ability of the Macro strategy to produce results irrespective of market movements can be attributed to the fact that it *plays* the macro theme meaning that is not driven by the fundamentals of the companies but by a thorough analysis of the macroeconomic developments of the global markets, which are driving market behavior as opposed to company fundamentals.

[Insert Table 4 about here]

For the reasons already discussed, the developed multivariate dynamic framework (AR-DCC-TARCH-*t*) is applied to examine the hypothesis of the existence or not of a dynamic correlation between the 13 fund strategies and the S&P500 index which is used as a benchmark of fund performance. The results of the developed DCC model (Figure 2) show that the dynamic correlations between each of the fund strategies and the S&P500 vary over time with a tendency to increase during crisis periods. More precisely, according to Table 5, it is observed that, over crisis periods that are characterized by co-movement in the volatility of global equity markets, the dynamic correlation coefficient strengthens statistically, a finding confirmed by Forbes and Ribogon (2002)[12] and Guesmi *et al*. (2014)[13]. In only two cases: i) the Macro (it presents an increased correlation with S&P500 over the Asian crisis due to the nature of the particular crisis, i.e. currencies); and ii) the Short Selling (due to negative market exposure) the choice of the dynamic correlation coefficient is not statistically significant, supporting the claim of fund managers and illustrating at the same time the power of diversification in allowing outperformance of markets during downturns.

[11] Refer separately to each of the six periods under consideration.

[12] They found that the correlations between hedge funds and global stocks alter during crisis periods.

[13] Based on a (both unconditionally and conditionally) symmetric DCC model, Guesmi *et al*. (2014) examined the correlations between hedge fund strategy indices and asset classes and revealed correlations between hedge fund strategies and the stock market.

[Insert Figure 2 about here]

[Insert Table 5 about here]

The question of whether hedge funds managed to deliver superior returns over the S&P500 irrespective of market movements and to hedge the systematic market risk is also tested applying the Carhart (1997) model for: i) the whole sample; and ii) for the crisis periods.

The models' derived results, the Jensen's alpha abnormal returns and the beta coefficients, accounting for the systematic market risk and the market timing coefficients, are summarized in Tables 6 and 7. According to the empirical evidence in Table 7 we note that: first, over the whole sample period, nine of the thirteen hedge fund strategies were able to obtain performances statistically superior to the benchmark (i.e. S&P500). The fact that 4 of the hedge fund strategies have statistically non-significant alphas i.e. Convertible Arbitrage, Event Driven, Short Selling and Fund of Funds, was not expected, given that the main aim of hedge funds is to achieve abnormal returns and to outperform the market and the risk-free rate. On the other hand, over the crisis periods, the only hedge fund strategies that managed to outperform the benchmark were Macro, mainly due to its top down nature, and Short Selling, since these funds present their highest performance in bear markets.

Second, analysis of the risk perspective of the hedge fund strategies requires a thorough examination of the null hypothesis of the beta coefficients, which is rejected at a 99% level of significance (Table 7) across all the hedge fund strategies. Statistically, the findings strongly suggest that almost all fund strategies failed, to a large extent, to hedge the systematic market risk[14]. However, running the same model over the crisis periods, the results accept the null hypothesis for two hedge fund strategies, Macro and Short Selling, implying that they were the only strategies, when, under financial turmoil, managed to hedge the market systemic risk.

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[14] With the exception of the Macro strategy that has a 0,07 non-statistically significant coefficient at 95% level of significance.

The administrator's ability to forecast the market, which is implied by the fund managers' claim of hedging, is also estimated using Carhart's specification (eq. 3), by taking advantage of being long on the high return stocks and short on the low return stocks (Jordao and Moura, 2011). To confirm the existence of market timing, the coefficient ζ_i of eq. 3 must be positive and statistically significant. The findings in Tables 6 and 7, indicate that 62% of the hedge fund strategies have market timing ability according to Cahart's model over the total period of analysis and only 1 strategy during crisis period (Equity Neutral).

[Insert Table 6 about here]

[Insert Table 7 about here]

5. Conclusions

Using monthly performance data and adopting a holistic approach through the DCC model framework, the Carhart model and statistical indicators such as structural break and equality of means tests, the paper examined the hedge fund claim of being able to hedge during crisis and non crisis periods versus the widely adopted benchmark, the S&P500 index. To overcome a number of the issues discussed, a dynamic correlation, the DDC approach, is developed and adopted. If indeed the weakly correlation assumption statistically holds under any market circumstances, then their claim holds and investors should turn to hedge funds to protect their assets during bear markets.

In both crisis and non-crisis sample periods, the existence of structural breaks is statistically accepted for the majority of hedge fund/strategies, a result also supported by the equality of the coefficients tests (Kruskal-Wallis) which highlights the failure of hedge fund managers, excluding the Macro fund strategy, to hedge their way out of crises. The findings of the developed AR-DCC-TARCH-*t* model not only strongly statistically support the existence of dynamic correlations between each of the fund strategies and the S&P500 index, but also demonstrate that these correlations also strengthen during crisis periods. Among the fund strategies, in only two cases, those of Macro and Short Selling, the pick in dynamic correlation coefficients is not statistically significant, thus illustrating the power of diversification in allowing outperformance of markets during downturns. Finally, according to the results of the Carhart model, over crisis periods the only hedge fund strategies that managed to outperform the benchmark were Macro and Short Selling. Moreover, a thorough examination of the null hypothesis of beta coefficients shows that it is rejected at a 99% level of significance across all hedge fund strategies. This finding strongly suggests statistically that almost all fund strategies failed to a large extent to hedge the systematic market risk. However, running the same model over the crisis periods, the results do not reject the null hypothesis for the two hedge fund strategies, Macro and Short Selling, implying that they were the only strategies that, under financial turmoil, managed to hedge the systemic market risk.

As discussed above, the Macro and Short Selling funds are the sole exceptions which succeeded in providing protection to their investors under severe financial conditions. This fact that may well be explained by the way in which the two investment strategies are formed. For Macro funds, which are considered the traditional strategy in the alternative space, the investment decision is typically based on forecasts and analysis about interest rates trends, the general flow of funds, political changes, government policies, inter-government relations, and other broad systemic factors. In addition, global macro traders and managers come primarily from the risk side of trading. In the case of Short Selling Funds, in bull markets their investment decisions are driven by companies' fundamentals but in periods of financial and economic turbulence in general and during the subprime crisis in particular, short selling, when not banned, produced returns due to the collapse of the market.

Overall, the present paper concludes that in cases of severe financial stress, hedge funds, excluding the Macro and Short Selling strategies, do not manage to produce absolute returns irrespective of market movements.

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Tables and Figures

Table 1. Hedge Fund Strategies and S&P500 Descriptive Statistics

	Minimum	Maximum	Mean	Std. Deviation	Skewness	Kurtosis
ConvertArb	-16.01	9.74	0.7086	2.78343	-1.473	9.440
Distressed	-8.50	5.55	0.7824	1.77737	-1.629	6.137
EmergingTotal	-21.02	14.80	0.7379	3.93321	-0.988	4.639
EquityHedge	-9.46	10.88	0.8746	2.61197	-0.232	2.446
EquityNeutral	-2.87	3.59	0.4632	0.89372	-0.285	2.377
EventDriven	-8.90	5.70	0.8428	1.91594	-1.314	4.805
HFRI	-8.70	7.65	0.7492	1.99011	-0.667	3.069
Macro	-3.77	6.82	0.6619	1.79642	0.524	0.696
MergerArb	-5.69	2.54	0.5978	1.02609	-1.577	6.270
RelativeVal	-8.03	3.93	0.6922	1.22225	-2.935	16.758
ShortSell	-21.21	22.84	-0.2050	5.10005	0.430	3.502
Multistrategy	-8.40	3.89	0.4486	1.36401	-2.700	13.755
FoF	-7.75	7.73	0.4573	1.75465	-0.537	4.354
S&P500	-16.94	10.77	0.7146	4.39203	-0.727	1.173

Source: HFRI and Estimations.

Table 2. Descriptive Statistics of the Explanatory Variables

	Minimum	Maximum	Mean	Std. Deviation
SMB	-16.40	22.02	0.17	3.49
HML	-12.61	13.88	0.24	3.28
PR1YR	-34.72	18.39	0.45	5.33

Source: HFRI and Estimations.

Table 3. Test Results for Structural Breaks

	F	Sig.
ConvArb	0.7	**0.60**
Distressed	7.3	0.00
EmergingTotal	9.4	0.00
EquityHedge	5.0	0.00
EquityNeutral	0.2	**0.95**
EventDriven	6.5	0.00
HFRI	5.5	0.00
Macro	0.2	**0.94**
MergerArb	4.7	0.00
RelatVal	3.8	0.00
ShortSell	0.3	**0.93**
Multistrategy	18.4	0.00
FoF	5.8	0.00

Source: HFRI and Estimations.

Table 4. Analysis of Equality of Means	
	Sig.
ConvertArb	0.000
Distressed	0.000
EmergingTotal	0.000
EquityHedge	0.000
EquityNeutral	0.000
EventDriven	0.000
HFRI	0.000
Macro	**0.061**
MergerArb	0.000
RelativeVal	0.000
ShortSell	0.000
Multistrategy	0.000
FoF	0.000

Source: HFRI and Estimations.

Table 5. Average Dynamic Correlation Coefficients (Hedge Fund Strategies vs S&P500).

	ConvertArb	Distressed	Emerging	Total EquityHedge	EquityNeutral	EventDriven	HFRI
Total Period	0.56	0.65	0.65	0.78	0.39	0.71	0.77
Crises Periods	0.67	0.73	0.71	0.84	0.49	0.79	0.83
Non-Crisis Periods	0.55	0.64	0.64	0.78	0.38	0.71	0.76
Comparison (sig.)	0.12	0.09	0.10	0.08	0.11	0.08	0.07

	Macro	MergerArb	RelativeVal	ShortSell	Multistrategy	FoF
Total Period	0.39	0.57	0.59	-0.79	0.44	0.69
Crises Periods	0.42	0.64	0.66	-0.84	0.55	0.75
Non-Crisis Periods	0.38	0.56	0.58	-0.78	0.44	0.69
Comparison (sig.)	0.02	0.09	0.10	0.04	0.11	0.07

Source: HFRI and Estimations.

Table 6. Summary of the Models

	R Square		Adjusted R Square		Std. Error of the Estimate	
	Total Period	**Crises**	**Total Period**	**Crises**	**Total Period**	**Crises**
ConvertArb	0.51	0.56	0.26	0.32	2.41	4.43
Distressed	0.54	0.40	0.29	0.16	1.51	2.70
EmergingTotal	0.54	0.49	0.29	0.24	3.33	4.76
EquityHedge	0.77	0.69	0.59	0.47	1.69	2.92
EquityNeutral	0.48	0.40	0.23	0.16	0.74	1.43
EventDriven	0.67	0.53	0.45	0.28	1.42	2.61
HFRI	0.72	0.63	0.51	0.39	1.39	2.35
Macro	0.39	0.59	0.15	0.34	1.65	1.58
MergerArb	0.51	0.47	0.26	0.22	0.85	1.63
RelativeVal	0.48	0.39	0.23	0.15	1.07	2.30
ShortSell	0.81	0.79	0.65	0.63	3.01	4.94
Multistrategy	0.18	0.65	0.03	0.42	0.20	0.19
FoF	0.16	0.65	0.03	0.42	0.20	0.18

Source: HFRI and Estimations.

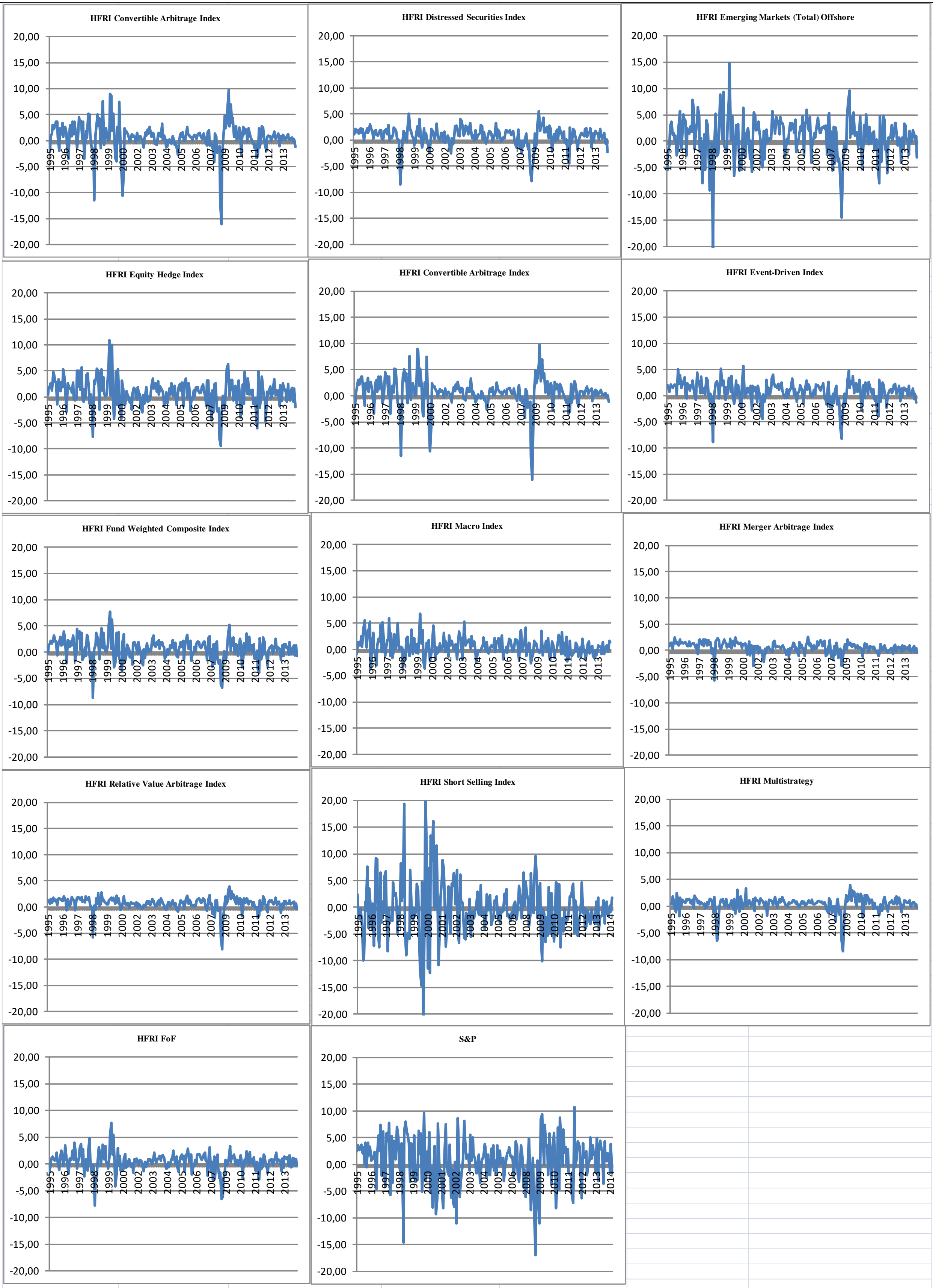
Table 7. Coefficients and Significance

	Alpha				Beta				SMB			
	Total Period		***Crisis***		***Total Period***		***Crisis***		***Total Period***		***Crisis***	
	Coef.	**Sig**	**Coef.**	**Sig**	**Coef.**	**Sig**	**Coef.**	**Sig**	**Coef.**	**Sig**	**Coef.**	**Sig**
ConvertArb	0.300	0.400	-1.320	0.130	0.210	0.004	0.290	0.050	0.156	0.002	0.150	0.530
Distressed	0.390	0.000	-1.350	0.150	0.139	0.000	0.193	0.050	0.177	0.000	0.210	0.110
EmergingTotal	0.180	0.041	-3.640	0.100	0.345	0.000	0.510	0.050	0.254	0.000	0.466	0.051
EquityHedge	0.270	0.020	-1.005	0.185	0.349	0.000	0.437	0.006	0.227	0.000	0.304	0.500
EquityNeutral	0.134	0.080	-0.197	0.477	0.070	0.000	0.149	0.020	0.028	0.050	0.007	0.920
EventDriven	0.406	0.160	-0.922	0.770	0.198	0.000	0.302	0.018	0.198	0.140	0.262	0.470
HFRI	0.293	0.002	-1.108	0.730	0.228	0.000	0.307	0.007	0.175	0.000	0.263	0.270
Macro	0.335	0.003	0.580	0.090	0.070	0.070	0.020	0.665	0.066	0.010	0.057	0.463
MergerArb	0.290	0.000	0.245	0.440	0.082	0.000	0.182	0.020	0.068	0.203	0.132	0.103
RelativeVal	0.371	0.000	0.234	0.602	0.096	0.000	0.173	0.000	0.070	0.420	0.118	0.297
ShortSell	0.064	0.756	-0.410	0.090	-0.548	0.000	-0.640	0.150	-0.495	0.000	-0.570	0.150
Multistrategy	0.507	0.000	-0.210	0.750	0.050	0.000	0.300	0.010	0.040	0.379	-0.050	0.810
FoF	0.410	0.280	-0.540	0.370	0.250	0.000	0.380	0.010	0.080	0.030	0.040	0.800

	HML				MoM					
	Total Period		***Total Period***		***Crisis***		***Total Period***		***Crisis***	
	Coef.	**Sig**	**Coef.**	**Sig**	**Coef.**	**Sig**	**Coef.**	**Sig**	**Coef.**	**Sig**
ConvertArb	0.300	0.400	0.156	0.001	-0.550	0.100	0.041	0.031	-0.128	0.400
Distressed	0.390	0.000	0.036	0.260	-0.270	0.821	-0.300	0.129	-0.004	0.962
EmergingTotal	0.180	0.041	-0.160	0.024	-0.133	0.531	-0.720	0.093	-0.010	0.952
EquityHedge	0.270	0.020	-0.149	0.000	-0.185	0.161	0.033	0.131	0.021	0.831
EquityNeutral	0.134	0.080	0.017	0.286	0.035	0.5833	0.056	0.000	0.089	0.070
EventDriven	0.406	0.160	-0.024	0.428	-0.051	0.663	-0.046	0.012	-0.037	0.680
HFRI	0.293	0.002	-0.130	0.000	-0.135	0.201	0.070	0.010	0.008	0.926
Macro	0.335	0.003	-0.083	0.190	-0.080	0.914	0.048	0.230	0.162	0.600
MergerArb	0.290	0.000	-0.070	0.698	-0.025	0.725	-0.020	0.680	-0.113	0.520
RelativeVal	0.371	0.000	0.002	0.050	0.073	0.480	0.030	0.028	-0.076	0.343
ShortSell	0.064	0.756	0.602	0.000	0.470	0.030	0.052	0.050	0.090	0.500
Multistrategy	0.507	0.000	0.005	0.080	0.160	0.140	0.030	0.300	0.060	0.400
FoF	0.410	0.280	0.000	0.980	0.040	0.670	0.080	0.000	0.080	0.220

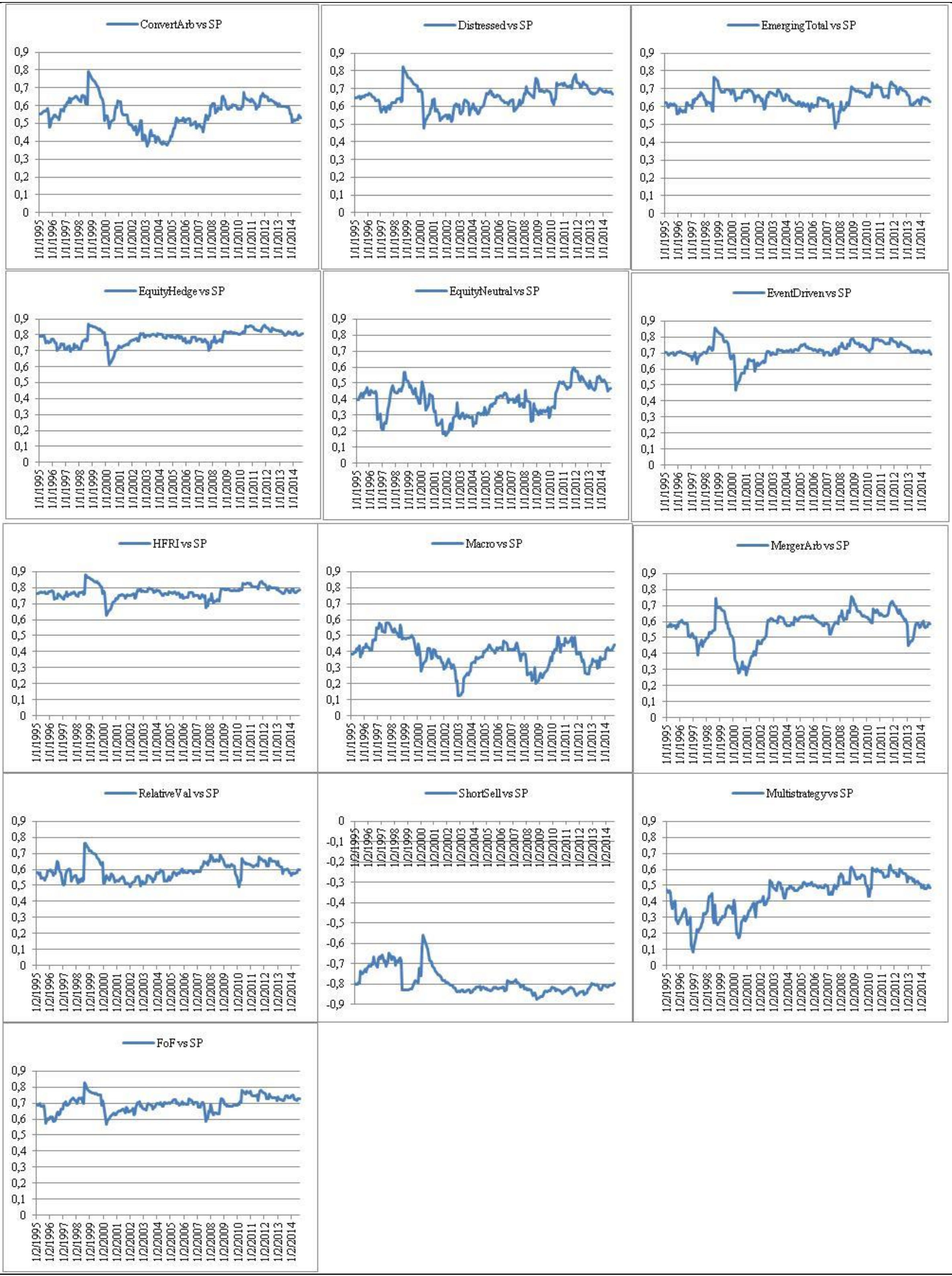
Source: HFRI and Estimations.

Figure 1. Hedge Fund Monthly Performance by Strategy (1995-2014)



Source: HFRI.

Figure 2. Dynamic Correlation Coefficients per Strategy vs S&P500 (1995-2014)



Source: HFRI and Estimations.