Asymmetry in Hedge Fund Return Volatility: An EGARCH Approach

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Abstract

This study examines whether positive and negative innovations in hedge fund (HF) returns have an asymmetric effect on their conditional volatilities. Thirteen different HF strategies are analyzed using the monthly data over the period of January 1994 to August 2009. We estimate the asymmetry of return volatility employing a higher-moment factor-EGARCH (1,1) model. We find strong support (11 out of the 13 strategies studied) for asymmetric risk transmission. Similar to the results based on equity returns, the predictive asymmetry coefficient is found to be negative for the fixed income arbitrage, risk arbitrage and dedicated short strategies, indicating that positive (negative) return shocks decrease (increases) their volatility. For the remaining strategies the results suggest that positive innovations contribute to greater risk taking on the part of the fund managers. For all strategies, we find strong evidence of GARCH effects with persistence of shocks dissipating between 16 to 21 days. The results also reveal distinct effects on the conditional volatility of HFs during the post 1998 Long Term Capital Management (LTCM) crisis, 2007 mortgage crisis and post 2008 credit crisis periods. Additionally, our findings strongly support the application of a higher-moment return generating model as most of the co-skewness and co-kurtosis coefficients are found to be significant. Finally, our results show that the financial crisis of 1998 and the credit crisis of 2008 affected the HF returns in a more significant manner than did the 2007 mortgage crisis.
1.0. INTRODUCTION

Over the past two decades, the hedge fund (HF) industry has witnessed a considerable level of growth and prominence in terms of assets under management, the role it plays in monitoring and intervention in the management of firms in which HFs invest, as institutional investors, and the impact on the stability of the U.S. and the world financial systems. With a modest 610 funds managing approximately 39 billion USD in 1990 (Naik and Tapley, 2007) the industry grew to nearly 8000 funds and around 2.033 trillion USD under management as of November 2009 (www.hedgefund.net). With the current size and asset under management, HFs are among major non-bank financial intermediaries in the U.S. economy.

HFs played a major role in triggering multiple financial crises in the last decade. The most notable ones are the Asian Currency Crisis in 1997 (see, Fung and Hsieh 2000a) and Long Term Capital Management (LTCM) in 1998 (see, Jorion 2000). More recently, the sub-prime mortgage crisis and credit crisis have called into question their claim of superior risk management ability. All fund strategies, with the exception of Managed Futures and Dedicated Short, posted double digit losses in 2008 (www.credit-suisse.com). In addition, 2008 is also marked by a record liquidation of 1,471 HFs (www.hedgefundresearch.com).

While the roles of other major financial institutions are quite well understood, the same is not true for HFs. Issues related to HF activities, investment strategies, impact on financial markets, and their implications for financial stability all remain relatively less apparent. The ongoing concerns about HF vulnerability and its implications on risk of systemic collapse underscore the importance of understanding the volatility patterns of
various HF styles under boom and bust scenarios and their interdependencies in normal and crises conditions. A particular issue of interest is whether HF return volatility demonstrates symmetric or asymmetric patterns of behavior in response to received positive and negative shocks. This issue has a number of significant practical implications for investor and regulator of risk management policies. First, in the area of regulation, the policymakers should understand the volatility trends and craft regulations accordingly in order to avoid sharp fluctuations in the industry and crises in the financial system. Otherwise, the industry’s rapidly changing structure, and technological and financial innovations may render the prevailing regulations redundant and stifle further industry developments. Along the same line, given the level of losses sustained by investors in the past two years, an understanding of HF volatility can assist regulatory bodies in crafting better rules regarding the net worth requirement for accredited investors.¹

Second, an analysis of HF return volatility, and whether volatility shock is asymmetric in response to received shocks, will allow investors to assess at least two prominent sources of risk, i.e., valuation risk and over-the-counter derivative transaction risk. The HF managers may improve their risk management challenges by providing greater transparency in their operations.²

Third, Fung and Hsieh (2000a) have found evidence of “style convergence” through which funds can arrive at similar trades. A key

¹ The SEC in December 2006 proposed a rule for eligibility to be an accredited investor. To be an accredited investor, one must meet the existing requirements and additionally own $2,500,000 of “investable assets”. This proposed requirement will limit participation by individual households. This action is quite contrary to the general global trends. For example, Australia imposes virtually no restriction on investment in HF's registered with the Australian SEC. Similarly, Canada and United Kingdom and several other European countries are moving toward opening HF's to a larger investment community.

² Of course, there is a limit how transparent a HF can be without revealing its valuable trading strategies. The economic theory dictates that HF will disclose information only to the point where the marginal benefit of disclosure is equal to the marginal cost. Too much disclosure for some funds would invariably lower their returns.
determinant of HF risk is the degree of similarity between the trading strategies of different funds. In the extant literature, the similarity of trading strategies is characterized by the level of co-movements in returns. What is more important, however, is an understanding of co-movements among conditional volatilities of different funds because it will significantly enhance our understanding of style convergence in HFs.

The primary objective of this study is to determine whether the positive and negative innovations in HF returns have an asymmetric effect on the conditional volatility of returns. In the equity return literature, there is strong evidence that suggests that negative shocks to stock returns generate more volatility than positive shocks of equal magnitude (see for example, Christie (1982), Pagan and Schwert (1990), Nelson (1991), Engle and Ng (1993)). We attempt to ascertain whether the same relationship holds for HF volatility, despite the idiosyncratic risks that are inherent in each HF style. Additionally, we examine the effect of changes in volatility pattern of various strategies during the post 1998 LTCM crisis, post 2007 mortgage crisis and post 2008 credit crisis along with the effect of these crises on HF returns. For return generating model, we propose a higher moment factor models that include factors for co-skewness and co-kurtosis along with various strategy specific economic factors.

The main contributions of this study are as follows. We model the return behavior of HFs within an EGARCH framework, allowing for asymmetric volatility responses to positive and negative shocks. We find strong support (11 of 13 strategies studied) for the asymmetric risk transmission. Similar to the results based on equity returns, the predictive asymmetry coefficient in the EGARCH specification is found to be negative for the fixed income arbitrage, risk arbitrage and dedicated short strategies indicating
that, for these strategies, positive (negative) return shocks decrease (increases) their volatility. For the remaining strategies the predictive asymmetry coefficient is found to be positive which suggest that positive innovations contribute to greater risk taking on the part of the fund managers. Our results strongly support significant volatility clustering for all strategies, with the exception of equity market neutral. For all strategies, we find strong evidence of GARCH effect with persistence of shock, measured by the Half Life of Volatility Shocks (HLS) being between 16 to 21 days. The results also reveal that the conditional volatility of HFs is affected during the post 1998 LTCM crisis, post 2007 mortgage crisis and post 2008 credit crisis periods and the direction of affect is found to be strategy dependent. Additionally, our findings strongly support the application of a higher moment return generating models as most of co-skewness and co-kurtosis coefficients are found to be significant. Finally, the financial crisis of 1998 and the credit crisis of 2008 is found to have affected the HF returns in a more significant manner than did the 2007 mortgage crisis.

The rest of the paper is organized as follows: Section 2 presents a description of data and methodology. Empirical results are given in Section 3, followed by Conclusions in Section 4.

2.0. DATA AND METHODOLOGY

2.1. Data Sources and Properties

The data used in this study are Credit Swiss First Boston (CSFB)/Tremont indices and are obtained form www.credit-suisse.com. These data are of monthly frequency and run from January 1994 to August 2009 (188 observations). Monthly returns are calculated as log(NAV_t/NAV_{t-1}). Fung and Hsieh (1997) stress the importance of
considering “styles” in studying HF performance. The style factors are represented by HF indices and are published by Credit Suisse First Boston (CSFB/Tremont index). Thirteen HF styles are analyzed. The fund categories include: Convertible Arbitrage (CA), Dedicated Short (DS), Distressed (DST), Emerging Markets (EM), Equity market Neutral (EMN), Event Driven (ED), Event Driven Multi Strategy (EDMS), Fixed Income Arbitrage (FIA), Global Macro (GM), Long Short Equity (LSE), Managed Futures (MF), Multi Strategy (MS) and Risk Arbitrage (RA).

The CSFB/Tremont indices have two noteworthy features. First, these indices are asset-weighted values of funds with a minimum of $10 million of assets under management and a minimum of one-year track record. The indices are computed and rebalanced every month and the universe of funds is redefined on a quarterly basis. Second, the CSFB database is constructed so as to account for survivorship bias in HFs (Fung and Hsieh, 2000b, 2002). Agarwal and Naik (2004) find that the Hedge Fund Research (HFR) and CSFB indices exhibit similar risk exposures that are consistent with the trading strategies followed by the HFs.

Panel A of Table 1 contains the descriptive statistics of net-of-fee monthly excess returns (in excess of six month LIBOR rate) of the CSFB/Tremont indices. For each fund category, the mean, the maximum, the minimum excess returns along with the respective standard deviation, skewness and kurtosis are reported. In addition, the

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3 In the extant literature, various definitions of risk free rate are used to determine the HF excess returns. The rates include LIBOR (Billio et al. 2006), 90 day T-bill rates (Billio et al. 2009), and 30 day T-bill rates by Ding et al. (2009), to name a few.

4 There is no standard classification system of HF exist in the industry. Since every HF embarks on its own proprietary strategy, this leads to a very heterogeneous class of HFs. Most HF index providers have their own classification definitions; however, these funds can be classified into a broader category depending on the main type of strategy followed. Agarwal and Naik (2000) classify funds, based on market exposure of traditional asset classes, into directional and non-directional. Ineichen (2003) categorizes funds into arbitrage, event driven and directional. We follow the classifications provided by these authors and for the
results on the Jarque-Bera joint normality test, the Ljung-Box tests \( Q(n) \), \( |Q(n)| \) and \( Q^2(n) \) for the 12th order serial correlation in excess returns, absolute excess returns and squared excess returns are also presented. Descriptive statistics for the explanatory variables are contained in Panel B.

According to the figures in Table 1, the best performing HF category in terms of returns is Global Macro with 0.519 percent average monthly excess return (6.228 percent annualized) for the sample period, while the poorest performing category is Dedicated Short with –0.6237 percent monthly (-7.476 percent annualized) return. A comparison of the HF returns with the S&P500 index reveals that only five HF categories namely, event distressed driven, event driven multi strategy, global macro, and long-short equity, outperformed the broader market index for that time period. The most risky HF category, as measured by standard deviation, is dedicated short (SD=0.048) closely followed by emerging markets (SD=0.046) while the least risky category is risk arbitrage (SD=0.012). In all but one instance (dedicated short) the skewness statistics are negative and with the exception of managed futures, the values are statistically significant. The range of skewness is from 0.528 for dedicated short to -12.49 for equity market neutral, demonstrating a wide range of statistical distributions.\(^5\)

The presence of significant skewness is an indication of asymmetry of the HF return distribution around its mean caused by the nature of investment strategies employed by HFs. For a non-symmetric distribution, the skewness statistic is negative

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\(^5\) The dramatically high skewness and kurtosis for equity market neutral is caused by its performance since November 2008. The estimated skewness and kurtosis during the period of January 1994-September 2008 is -0.069 and 0.7975, respectively.
when the lower tail is thicker. The negative skewness is an indication that extreme negative returns are more likely than sharp positive returns. This suggests a high level of risk for the investors. The figures on the magnitude of skewness indicate that there is a high probability of extreme price changes (skewness greater than 2.0) in all styles under Relative Value and Event Driven (with the exception of risk arbitrage) and less so for the remaining styles.

A more direct measure of tail-risk is represented by kurtosis. The results presented in Table 1 show the excess kurtosis for each HF style. With the exception of managed futures, the excess kurtosis values are statistically significant and the magnitude of excess kurtosis is directly proportionate to that of skewness (in absolute term). In particular, the equity market neutral style with the highest level of skewness also possesses the largest level of excess kurtosis. The range of kurtosis is from 0.21 to 165.68. The kurtosis values strongly indicate the presence of fat tails in the HF return distribution. The findings above are consistent with Chan et al. (2005), Ranaldo and Favre (2005) and Billio et al. (2009).

The Jarque-Bera (1981) test for joint normal kurtosis (zero-excess kurtosis) and skewness (zero skewness) reject normality for all return series with the exception of managed futures.6 The Ljung-Box (1978) test statistics of 12 lags reveal that the null hypothesis of no autocorrelation can be rejected for the return series of global macro, multi strategy and risk arbitrage. The ARCH(1) test results, reported in Table 1, reveal the presence of first order ARCH effects in the return series of convertible arbitrage,

\[ J - B = T \left( s^2 / 6 + k^2 / 24 \right) - s^2 / 2, \]  

where \( s \) is the coefficient of skewness, \( k \) is the coefficient of kurtosis, and \( T \) is the sample size. The J-B test statistic asymptotically follows a \( \chi^2 \) distribution under the null hypothesis that the distribution is symmetric (zero skewness) and mesokurtic (zero-excess kurtosis).

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6 The Jarque-Bera (1981) test statistic is defined as: \( J - B = T \left( s^2 / 6 + k^2 / 24 \right) - s^2 / 2 \), where \( s \) is the coefficient of skewness, \( k \) is the coefficient of kurtosis, and \( T \) is the sample size. The J-B test statistic asymptotically follows a \( \chi^2 \) distribution under the null hypothesis that the distribution is symmetric (zero skewness) and mesokurtic (zero-excess kurtosis).
event driven multi strategy, fixed income arbitrage, global macro, and multi strategy. No evidence of higher order ARCH effects, represented by $Q^2(n)$, is found to be present. This evidence of limited ARCH effects in monthly data series is also supported by Li and Kazemi (2006).

In order to avoid spurious conclusions due to model misspecification, a number of stationarity tests are performed to identify whether the time series of HF excess returns are stationary. The test procedures include the Augmented Dickey-Fuller (ADF) test (Dickey and Fuller, 1979, 1981), and the Phillips-Perron test (Perron, 1988; Phillips and Perron, 1988). The findings indicate that all return series follow an integrated process of order zero (I (0)), and, thus, are considered to be stationary.

The explanatory factors used in this study are determined along the lines discussed in Agarwal and Naik (2004), Chan et al. (2005) and Billio et al. (2006), and are presented below:

- **S&P 500 index (RM):** monthly return of S&P500 index including dividends;
- **Lehman Brothers US Government Credit Index (LGC):** monthly return of the Lehman U.S. Aggregate Government Credit Index;
- **Large minus Small (LS):** monthly return difference between Russell 1000 and Russell 2000 indexes;
- **Credit Spread (CS):** monthly yield difference between seasoned BAA and AAA corporate provided by Moody’s;
- **Value minus Growth (VG):** difference in monthly return between Russell 1000 Value index and Russell Growth index;
- **Term Spread (TS):** difference between 10 year Treasury bond redemption yield and the 6 month LIBOR rate;
- **USD Exchange rate (USD):** monthly return on Bank of England Trade Weighted Index;
• **Emerging Market Bond Index (EMB)**: monthly return on JPMorgan EMBI Global Index. This index tracks total returns for traded external debt instruments (i.e., foreign currency denominated fixed income) in the emerging markets;

• **Emerging Market Equity Index (EMS)**: monthly return on MSCI Emerging Market Stock Index;

• **Momentum (MU)**: the momentum factor is based on six value-weighted portfolios formed using independent sort on size and prior returns of NYSE, AMEX, and NASDAQ stocks. This variable is downloaded from Ken French’s website (http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html);

• **GOLD**: monthly return on gold spot price (US dollar per Troy Ounce) index;

• **VIX**: monthly first difference in the VIX implied volatility index based on the Chicago Board of Options Exchange’s (CBOE) OEX options.

Additionally, several financial crises event dummies, as well as the non-overlapping pre-and post event period dummy variables are used. The event dummy variables are defined as follows:

• **Financial Crisis of 1998 (D98)**: this event dummy variable assumes the value of one for the months of August and September 1998, and zero otherwise. Two major events, the default of Russian government debt in August 1998 and the events surrounding the Long Term Capital management (LTCM) in September 1998, contributed to an increase in “systemic risk” of HF s (see, Chan et al. (2005));

• **Mortgage Crisis of 2007 (D07)**: a value of one is assigned to October 2007, and zero otherwise for this event. Although it is difficult to perfectly ascertain the start of the subprime mortgage crisis, the signs for a major crisis were visible in October 2007. According to Mortgage Bankers Association, in the third quarter of 2007, the sub-prime Adjustable Rate Mortgage (ARM) represented the third largest type of mortgage outstanding at 6.8%, but represented the highest level of foreclosures at 43% during that time period. Additionally, compared to the third quarter 2006, the seriously delinquent rate for subprime loans was 460 basis points higher in the third quarter of 2007. (http://www.mbaa.org/NewsandMedia/PressCenter/58758.htm);

• **Credit Crisis of 2008 (D08)**: a value of one is assigned to the months of September and October 2008, and zero otherwise. As is the case with mortgage crisis, it is also difficult to perfectly pinpoint the start of credit crisis in 2008.
However, the government takeover of Fannie Mae and Freddie Mac, the merger of Merrill Lynch with Bank America, the collapse of Lehman Brothers and bailout of AIG in September and consequent uncertainty in October are characterized as the credit crisis event dummy in this study.\footnote{In the extant literature, different length of event windows has been tried out for the financial crisis of 1998 (Rigobon, 2003) and for mortgage crisis of 2007 and credit crisis of 2008 (Billio et al., 2009). In this study, we also used shorter / longer windows for event and non-overlapping dummy variables. The results are identical to what have been presented in Table 2. The results can are available from the author.}

Three non-overlapping pre and post even dummy variables are defined as:

- \( D_{98\_07} \): this variable assumes the value of one during the period of August 1998 to September 2007, and zero otherwise;
- \( D_{07\_08} \): the period of October 2007 to August 2008 set to one and zero otherwise; and
- \( D_{08\_09} \): assumes the value of one for the period of September 2008 to August 2009 and zero otherwise.

The motivations for using the ARCH type model and in particular Exponential GARCH are as follows. First, the rejection of the normality assumption is inconsistent with linearity and constancy of the conditional variance that is fundamental to the existing models of HFs returns. Second, the nature of HF investment along with the fact that the returns of most underlying assets and in some cases the return variance of such assets are time varying. Third, to determine whether the dynamic trading strategies, the use of leverage and derivatives that are often attributed to creating asymmetric returns also contribute to asymmetric risk transmission. Finally, the non-linear dependence and the excess kurtosis exhibited by the HF return series suggest that the appropriate framework for analyzing returns and risk is the ARCH type modeling strategy.

### 2.2. The Higher-Moment Multi-Factor Return Model

In this study, the HF return generating process is considered to be a higher-moment multi-factor model. The most prevalent models in the theoretical and empirical
asset pricing literature are linear factor models such as the Capital Asset Pricing Model
(CAPM) and the Arbitrage Pricing Theory (APT). One shortcoming of these asset pricing
approaches is that they limit the risk-return trade-off to a simple mean-variance
framework, rendering the assets with non-linear payoffs difficult to price. Additionally,
the maintained assumption of normal distribution for the APT and CAPM return
generating processes has been repeatedly rejected for various asset classes including the
HF returns. Gibbons et al. (1989) document that skewness and kurtosis risk cannot be
diversified away by increasing the number of assets in the portfolio. Thus, the non-
diversifiable risk associated with skewness and kurtosis become important consideration
in asset valuation. The mean-variance framework, however, fails to price the skewness
and kurtosis risk.

Research addressing the skewness and kurtosis is presented within the framework
of three-moment or four-moment CAPM models. The theoretical foundation for the
three-moment CAPM is presented by Ingersoll (1975) and Kraus and Litzenberger
(1976). In this framework, a greater covariance of asset returns with the squared market
returns indicates a stronger correlation of asset returns and the systematic skewness
resulting, in turn, in a greater degree of positive skewness of the market being captured
by the asset. If the market portfolio is positively (negatively) skewed, the value of the
asset will increase (decrease). Consequently, the expected asset return will decline
(increase).

Barone-Adesi (1985) using a quadratic market model finds support for the Kraus
and Litzenberger hypothesis that investors are willing to pay a premium to hold assets
with positive market co-skewness. While addressing the importance of non-linearities
arising from conditional skewness, Harvey and Siddique (2000) develop an extension of the CAPM in which the pricing kernel is a function of the market return and the squared market return. In their model, coskewness measures the degree to which an asset’s returns increase due to an increase in squared market returns. They find that systematic skewness is priced and requires an average risk premium of 3.6 percent for U.S. stocks. More recently, Barone-Adesi, et al. (2004) provide an arbitrage based approach to test the restrictions imposed by the APT on the system of multivariate quadratic model. They consider coskewness and its implications for testing asset pricing models by using a quadratic market model. Their return generating process includes a market returns and the square of market returns as the two factors. Their findings confirm the significance of coskewness coefficients which, implying that the quadratic market model is a valuable extension of the market model.

Extension to the three-moment CAPM has been done by Fang and Lai (1997) and Dittmar (2002) who include a cubic market returns to the pricing kernel equation. The introduction of the cubic market return allows the exploration whether the cokurtosis is also a priced factor in determining asset returns. Cokurtosis is positive if the asset returns move in the same direction as the cubic market return. Since cokurtosis measures the likelihood that extreme returns jointly occurring in the asset and in the market, and these extreme returns cannot be diversified, the investors require a premium for assets with positive cokurtosis. On the other hand, an asset with low systematic kurtosis

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8 The mean-variance-skewness-kurtosis preferences imply a fourth degree polynomial utility function. Scott and Horvath (1980) showed that under fairly general assumptions of investor utility functions, investors have a positive preference for higher first and third moments (mean and skewness) but dislike for the second and fourth moments (variance and kurtosis). However, it should be noted that the higher–moment market models used by Ranaldo and Favre (2005) and others, the definition of co-skew and cokurtosis is not consistent with the definition of the third and fourth statistical moments used by Scott and Horvath. In the higher-moment market models, the skew and kurtosis are normalized by dividing the third and fourth statistical moment by the standard deviation raised to the third and fourth power respectively.
provides a better diversification opportunity which in turn reduces the portfolio risk and expected returns. Therefore, the expected return is positively related to systematic kurtosis risk. A rational investor dislikes (prefers) positive (negative) co-kurtosis; therefore, the rate of return is expected to increase (decrease) for those HFs with significantly positive (negative) cokurtosis coefficient. Fang and Lai (1997) find that the portfolio excess returns are not only related to systematic variance but also to systematic skewness and systematic kurtosis. Their results show that investors are compensated positively for bearing systematic variance and systematic kurtosis and are penalized for accepting systematic skewness. Using return on aggregated wealth, they find that the quadratic and cubic pricing kernel are able to price the cross-section of returns substantially better than the Fama and French (1993) three-factor model. Finally, Chan et al. (2005) apply polynomial market returns along with other linear risk factors to assess non-linearities in HF returns and find statistical significance of squared and cubic market returns in all HF strategies along with the over-all HF index.9

2.3. A Factor Model of HF Returns

This study adopts the explanatory factors used in the extant literature to describe the HF returns. Several existing studies have employed the stepwise regression procedure to identify the appropriate factors (e.g., Agarwal and Naik (1999), Liang (1999), Agarwal and Naik (2004) and Chan et al. (2005), Billio et al. (2006)). This methodology involves adding and/or deleting variables sequentially depending on the estimated F-test values. As pointed out by Agarwal and Naik (2004) the advantage of this procedure is that it allows parsimonious selection of the factors. The drawbacks of this procedure include

9 Chan et al. (2005) use various combinations of $\text{RM}_t^2, \text{RM}_{t-1}^2, \text{RM}_{t-2}^2, \text{RM}_{t-1}^3, \text{RM}_{t-2}^3$ and $\text{RM}_{t-1}^3$ in their return model and find both the contemporaneous and lagged squared and cubic returns are significant.
breakdown of standard statistical inferences and inability to incorporate typical stylized facts of financial asset returns, such as excess kurtosis and heteroskedasticity. Nevertheless, by using this methodology Agarwal and Naik (2004) are able to extract factors that produce within sample results that are consistent with other findings and can replicate accurate out-of-sample performance for various HF styles. Hence, we adopt the factors so selected by these authors and address the issue of fat tails of HF returns by adopting a four-moment CAPM model. In addition to the market return (RM), squared market return (RM^2), cubic market return (RM^3) and three event dummy variables (D98, D07, D08) stated above, the list of factors used in each HF strategy is presented below.

- **Convertible Arbitrage**: LGC, LS, CS, VG, VIX.
- **Dedicated Short**: LS, CS, VG, EMB.
- **Distressed**: LGC, LS, CS, VG, VIX.
- **Emerging Markets**: LGC, LS, TS, USD, EMS, MU, GOL.
- **Event Driven**: LGC, LS, VG, TS, USD, EMB, EMS, MU, GOL.
- **Event Driven Multi Strategy**: LS, CS, VG, EMB, EMS, MU, VIX.
- **Equity Market Neutral**: LGC, EMS.
- **Fixed Income Arbitrage**: LGC, LS, CS, VG, TS, USD.
- **Global Macro**: LGC, LS, VG, USD, EMB, EMS, MU, VIX.
- **Long Sort Equity**: LGC, LS, CS, TS, MU, VIX.
- **Managed Futures**: LGC, LS, TS, USD, MU, GOL, VIX.
- **Multi Strategy**: LS, VG, USD, GOL.
- **Risk Arbitrage**: LS, VG.

### 2.4. Modeling HF Volatility

With more than 2.03 trillion dollars invested in HFs, specification issues that affect estimates of potentially time-varying, asymmetric, higher-order central moments have significant practical implications for HF risk management. We extend the literature by identifying whether the HF return volatility changes in response to positive and negative shocks are asymmetric. In the equity return literature, there is strong evidence suggesting that a negative shock to stock returns will generate more volatility than a
positive shock of equal magnitude (see for example, Christie (1982), Pagan and Schwert (1990), Nelson (1991), Engle and Ng (1993)). The linear GARCH model used heretofore in the HF literature (see, Li and Kamzemi, 2006; Fung and Hsieh, 2004) fails to capture the asymmetric second moment often referred to as the leverage effect. This is due to the fact that the conditional variance of a GARCH (1,1) process is defined as the past conditional variance and squared innovations, and as such prohibits an asymmetric response in the conditional variance to positive and negative errors (Christie, 1982; French et al., 1987).

It is important for HF investors to fully understand the impact of asymmetric risk transmission for a number of reasons. First, if an investor fails to incorporate asymmetry in his/her portfolio decision, the investor may overstate the diversification benefits offered by HFs. As demonstrated by Ang and Chen (2002), and Hong et al. (2007), the utility loss from the resulting suboptimal portfolio choice becomes more substantial as the magnitude of asymmetry increases. Second, failure to account for the appropriate level of risk after a positive or negative shock will distort the underlying risk return trade off and thus the pricing mechanism of HFs.

We address this problem by applying a non-linear Exponential GARCH (EGARCH) model, developed by Nelson (1991), to HF returns. The EGARCH specification allows asymmetric behavior of HF returns as an asymmetric, non-linear specification of the conditional variance process. In particular, the specification presented below accommodates a leverage effect, volatility clustering, and leptokurtosis with an underlying distribution assumed to follow a Student-\(t\). It has been shown (see, Bollerslev, 1987; Baillie and Bollerslev, 1989; Baillie and DeGennaro, 1990) that GARCH models
with conditionally normal distribution generally fail to sufficiently capture the 
leptokurtosis present in asset returns. To capture the fat tails property of the return 
distribution Bollerslev (1987), and Bollerslev et al. (1994) and others recommend 
consideration of non-normal conditional error distributions such as the Student-t.\(^{10}\)

2.5. The Model

The mathematical presentation of higher moment factor EGARCH (1,1) model is 
described by the system of equations (1) – (4) below:

\[
R_{k,t} = b_0 + \sum_{j=1}^{3} b_j R^{j}_t + \sum_{m=1}^{n} f_m F_{m,t} + d_1 D98 + d_2 D07 + d_3 D08 + \varepsilon_t \tag{1}
\]

\[
\varepsilon_t = z_t \sqrt{h_t}; \quad z_t \sim t(0, h_t, \nu), \quad z_t \sim iid(0,1) \tag{2}
\]

\[
\log(h_t) = \omega + \alpha g(z_{t-1}) + \beta \log(h_{t-1}) + \varphi_1 D98_{-07} + \varphi_2 D07_{-08} + \varphi_3 D08_{-09} \tag{3}
\]

\[
g(z_t) = [z_t - E(|z_t|)] + \gamma z_t \tag{4}
\]

where \( R_{k,t} \) is the excess return on HF strategy \( k \) (\( k = 1, 2, \ldots, 13 \)) at time \( t \), \( R^{j}_t \) (\( j=1,2 \) and 3) is the market premium, squared market premium and cubic market premium at 
time \( t \), \( F_{m,t} \) represent the risk factors used in each strategy at time \( t \), and the remaining 
dummy variables are as defined previously.\(^{11}\) All HF returns are in excess of six month 
LIBOR rate. In equation (1), \( \varepsilon_t \) represent the market innovation or shock and has the 
following properties- \( E(\varepsilon_t) = 0 \) and \( E(\varepsilon_t \varepsilon_s) = 0, \forall t \neq s \). The standardized residual is

\(^{10}\) Although the Student-t distribution is symmetric and does not permit skewness, it models thicker tails of 
distribution better than the normal distribution. We address this limitation by introducing \( RM^2 \) in the return 
equation. As has been pointed out by Wang et al.(2001) that accommodating skewness in the conditional 
first moment seems more important than accommodating it in the conditional second moment.

\(^{11}\) To avoid repetition, the subscript \( k \) is deleted from subsequent notation.
represented by $z_t = \frac{\varepsilon_t}{\sqrt{h_t}}$ and $g(z_t)$ is an asymmetric function of $z_t$. The conditional variance, $h_t$, is specified as an exponential function of past standardized innovation and past conditional variances. In addition, $h_t$ is assumed to be time-varying, positive and a measurable function conditional on information set at $t-1$.

The Exponential GARCH model presented by Equation (3) has several elements. As Nelson (1991) points out, in order to accommodate the asymmetric relation between returns and volatility changes, the conditional volatility must be a function of both the magnitude and the sign of $z_t$. In the above specification \[ \alpha \left| z_{t-1} \right| - E_{t-1} \] is considered as the “magnitude effect” while $\alpha \gamma z_{t-1}$ as the “sign effect”. The coefficient $\alpha$, pertaining to absolute value of the standardized residual, is the parameter for the magnitude effect. Due to volatility clustering, it is expected that the coefficient $\alpha$ to be positive in value. If $\alpha$ is positive, a larger shock, regardless of whether it is positive or negative, has a greater impact on HF volatility than a smaller shock. On the other hand, the coefficient $\gamma$ is the parameter for “sign effect” or asymmetric response. If $\gamma \neq 0 (\gamma = 0)$ and statistically significant, the impact is considered asymmetric (symmetric). Provided that $\alpha > 0$, a negative $\gamma, (\gamma < 0)$ implies that positive return shocks are expected to generate less volatility than negative return shocks. On the other hand, a positive $\gamma, (\gamma > 0)$ suggests that HF volatility being positively related to its return shocks. The GARCH coefficient $\beta$ determines the influence of the past conditional volatility on the current conditional volatility. Finally, in order to ascertain how the HF volatility changed after each financial crisis, three non-overlapping pre-post event dummy variables are used as exogenous
variable in the conditional variance equation. A positive (negative) $\phi_i$ is associated with increased (decreased) level of risk during the post event period.

There are several advantages to modeling the HF return volatility using an Exponential GARCH specification. For linear GARCH models, strict positivity restrictions on the coefficients in the conditional variance equation have to be imposed during estimation to ensure a non-negative $h_t$ at all times. In this regard, EGARCH modeling approach parameterizes the logarithm of the conditional variance and relax the non-negativity restrictions of the signs of the coefficients. All coefficients in the volatility equation are allowed to be negative without risking violation of the non-negative variance condition. In fact, if $|\beta| < 1$ the EGARCH (1,1) process is considered to be stationary (see, Nelson 1991). Additionally, a negative coefficient for an exogenous variable suggests a fall in the conditional variance in response to a movement in the underlying variable. Finally, EGARCH specification has the flexibility to allow for asymmetric effects as well as magnitude effects of shocks to the HF volatility.

The underlying distribution is assumed to follow a student-$t$. The student-$t$ distribution with variance $h_t$ and $\nu$ degrees of freedom ($2 < \nu \leq \infty$), the EGARCH-t log-likelihood function takes the following form:

$$\ln L = T \left[ \ln \left( \frac{v+1}{2} \right) \ln \Gamma \left( \frac{v}{2} \right) \frac{1}{2} \ln(\pi(v-2)) - 0.5 \ln(h_t) + (v+1) \ln(1+\frac{\varepsilon^2}{h_t}) \right]$$

where $\Gamma(.)$ denotes the gamma function. As $\nu$ approaches infinity, the $t$-distribution converges to standardize normal distribution.\(^{12}\) The parameter vector

\(^{12}\) We also estimated the EGARCH model with the Generalized Error Distribution proposed by Nelson (1991). Convergence for four HF styles was difficult to reach using the GED distribution. Among the
\( \Theta = [b_h, b_j, f_m, d_i, \omega, \alpha, \beta, \gamma, \text{and } \phi] \) is estimated simultaneously by using the maximum likelihood estimation technique.

3.0. EMPIRICAL RESULTS

3.1 Excess Return, Market, Co-skewness and Co-kurtosis

Table 2 presents the higher-moment factor EGARCH (1,1) results. Excess returns for each style is highly significant and, with the exception of long-short equity and managed futures, positive. Aside from equity market neutral and emerging markets, the sensitivity to S&P 500 (b_1) is statistically significant. As expected, the equity market neutral strategy is designed to be market beta neutral; however, the emerging market strategy that involves investing in both stock and fixed income securities around the world appears to have properly hedged their market exposure. All market beta coefficients, with the exception of dedicated short, are positive. The negative market exposure is due to the fact that the dedicated short biased strategy maintains a net short position at all times and takes short positions in mostly equities and derivatives. In terms of the magnitude of S&P500 exposure, the long-short equity, considered to be a part of directional strategy, has the highest exposure (0.56) while convertible arbitrage, a part of relative value (or non-directional) has the lowest (0.04). Unlike directional strategy that is characterized by significant market exposure, the relative value strategy tries to take advantage of temporary mispricing between different financial instruments and attempts to maintain a very low exposure to market.

The coefficient of systematic skewness (b_2) is found to be significant for nine of the thirteen strategies. As stated previously, this coefficient has the opposite sign of models that did converge, the results are qualitatively the same as the ones presented in this study. In all cases, the shape parameters are greater than unity which indicates fat tailed density functions. In the case of t-distribution, the shape parameters are all around 4 and in three cases it is greater than 6.
market skewness. With the market skewness computed to be -0.75, all coefficients, with the exception of dedicated short and managed futures, are positive.

The evidence of significant systematic kurtosis for 11 HF styles is presented by statistically significant ($b_3$) coefficient. The two insignificant styles are risk arbitrage and long-short equity. Contrary to the findings by Ranaldo and Favre (2005), our results suggest that the systematic kurtosis plays an even greater role than systematic skewness (nine vs. eleven strategies with significant coefficients) in pricing the risk profile of HFs. Six of the HF styles show positive while the five remaining styles show negative cokurtosis relationship with the market. The negative cokurtosis coefficient suggests that the investors in these HFs are not compensated for bearing systematic kurtosis risk.13

Since adding an asset with negative cokurtosis to a portfolio makes the resulting portfolio’s kurtosis smaller, the asset with negative cokurtosis is expected to have lower returns than assets with similar risk characteristics but with zero cokurtosis. It is interesting to note that all funds with negative cokurtosis (dedicated short, global macro, managed futures, multi strategy), with the exception of fixed income arbitrage, belong to the directional strategy. Funds under directional strategy have exposure to broad equity market, bond market, currency market, etc., where the risk exposures often follow both linear and non-linear trends. Thus, with negative cokurtosis, insertion of these funds into

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13 Analogous to this discussion is the relationship between the HF returns and the conditional volatility of returns. To identify this intertemporal relationship, we ran EGARCH(1,1)-M with the identical specification as outlined in equations (1)-(4). For all HF styles, with the exception of multi-strategy and risk arbitrage, the M coefficient that captures the risk-return tradeoff is found to be statistically significantly and in all cases the coefficient is negative. The findings in the extant literature about the relationship between the conditional mean and the conditional variance of excess return is non conclusive. Glosten et al. (1993) offer two reasons why the intertemporal tradeoff between risk and return may be negative. First, it is possible that the riskier periods in the market may coincide with periods when investors are better able to bear risk. Second, due to uncertainty in the market, investors may elect to save more during riskier times; since all assets are risky, competition may raise asset prices and lower risk premia.
the market portfolio has the potential to weaken the likelihood of extreme outcomes. For HF styles convertible arbitrage, equity market neutral, distressed, event driven, event driven multi strategy, and emerging markets, the sign pertaining to cokurtosis \( (b_3) \) is as expected. As pointed out previously, for these funds, although the investors are not compensated for the variance risk but are compensated for the kurtosis risk. With positive cokurtosis, combining these funds with the market portfolio will increase the likelihood of obtaining extreme returns.

3.2. HF Risk Factors

3.2.1. Relative Value Strategy

The HFs under the relative value strategy attempt to take advantage of temporary mispricing of financial instruments and try to expose their investors to a minimal market risk. The convertible arbitrage style exploits the difference in the value between a company’s convertible bond and the underlying common stock. This is accomplished by investing in a convertible bond while shorting the common stock of the same company. If a convertible bond appears to be undervalued, then the manager may purchase the bond in an effort to hedge out of risks such as equity risk, credit risk, interest rate risk, etc. Clearly, this style is designed to perform well when the fixed income security does well. As a result, the return on convertible arbitrage is positively related to the Lehman Government bond index returns. This style is also positively affected by the performance in small cap stocks, value stocks and a change in the VIX index. These findings are similar to those obtained by Billio et al. (2006). However, contrary to Billio et al. (2006),
we find the coefficient pertaining to credit spread to be positive (0.11). 14 When the credit spread increases, the liquidity in the market decrease; this results in lower demand for low credit securities. At the same time, brokers demand higher fee to obtain more leverage. As a result, the cost of funding goes up which puts a downward pressure on return. On the other hand, wider credit spread creates more opportunities in the convertible markets. First, a wider credit spread (and high level of equity volatility) attracts corporations to issue convertible securities as opposed to traditional funding. Second, a wider spread also induces corporations to opportunistically buy back their convertible bonds in order to improve their balance sheets. These activities collectively lead to an increased number of opportunities in the convertible arbitrage space which, in turn, lead to increased profitability for convertible arbitrage strategy.

The equity market neutral style is designed to be market beta neutral and is accomplished by taking advantage of short term pricing anomalies between stocks which usually behave identically. The return on equity market neutral is positively affected by the Lehman Government bond index return and the MSCI emerging market index return.

The fixed income arbitrageur attempts to profit from price differences between related interest rate securities. The fund invests in interest rate swap arbitrage, U.S. and non-U.S. government bond arbitrage, forward yield curve arbitrage, and mortgage-backed securities arbitrage. The performance of fixed income arbitrage style is positively affected by the performance of Lehman Government bond index. The negative coefficient of credit spread is consistent with the findings in the extant literature and is

14 In the extant literature, there is a wide range of magnitude and direction documented for this coefficient. While Billio et al. (2006), using January 1994 to March 2005, find the coefficient to be -1.77, Chan (2005) on the other hand, using January 1994 to August 2004 data report the coefficient to be 0.20.
attributed to “flight to quality” (Fung and Hsieh 2002). The fund performance is positively related to the performance of value stocks and steepening of the yield curve.

3.2.2. Event Driven Strategy

The event driven strategy attempts to exploit the price anomalies triggered by “special opportunities” such as corporate restructuring, mergers, liquidation, etc. The distressed securities investors focus mostly on bank debt, bonds, trade claims and equity of companies in financial distress and generally in bankruptcy. The active form of this style involves buying substantial portion of the outstanding security of a distressed company and attempting to exert influence on the restructuring process. The return on distressed securities fund is found to be negatively affected by an increase in Lehman bond index. The low interest environment is positive for this style. As interest rate decreases, it is easier and less expensive for companies under distress to reorganize and refinance their debt at a lower cost. As a result, they have more funds available to create value for the company. Additionally, lower interest rate increases the present value of distressed assets. There is positive equity premium, especially when the small cap stocks outperform the large cap stocks. In addition there is a positive exposure to credit risk and emerging market bonds.

Similar to distressed, in the event driven universe, managers seek to generate returns by capturing price movements due to significant corporate events such as mergers, bankruptcy, corporate restructuring, liquidation and reorganization. Rising equity market, especially performance of small cap stocks is positive for this style. Additionally, a flatter yield curve benefits this style. Finally, the return on event driven
strategy is positively affected by the performance of emerging market bonds and emerging market stocks.

The event driven multi-strategy funds draw from multiple themes that include risk arbitrage, distressed, and investments in micro and small cap companies. The results are similar to those of event driven style; however, the additional drivers are the credit spread, momentum and the change in the VIX index. As expected, this strategy performs better in an environment when the credit spread is tighter.

The focus of risk arbitrage is on securities of companies involved in mergers and takeovers, both of the acquirer and acquired firms. The investors typically long the stock of the company being acquired and short the acquiring company. Rising equity markets with small cap outperforming large cap and value stock outperforming growth stocks are positive for this strategy as the acquired firms are typically smaller than the acquiring firms.

3.2.3. Directional Strategy

In contrast to non-directional funds, directional funds have considerable exposure to the broader market, in particular, to small cap stocks. Some managers make long-term investments while others constantly move in and out of opportunities which make the underlying volatility of this strategy little higher than absolute return funds. The dedicated short sellers maintain net short position at all times and seek to profit from declining security prices. As expected, a better performance in small cap stocks and growth stocks negatively affects the return of this style. The coefficient of credit spread is found to be negative. As credit spread increases, the cost of shorting a stock also goes
up, which adversely affects the return of this strategy. Additionally, the performance of emerging market bond index has an adverse relationship with this style.

Global macro managers invest in a wide variety of strategies and instruments and carry long and short positions in global markets. The portfolios of these funds include currencies, stocks, bonds, interest rates and commodities, usually assuming a directional position based on market trends as influenced by major events. Rising fixed income markets and equity market, especially value stocks, are positive for this style. Strengthening U.S. dollar is also found to be positive for this strategy. Similarly, emerging market bond, emerging market equity, momentum and equity market volatility as measured by the VIX index are all positive drivers for this strategy.

The long-short strategy takes long and short positions in equity securities which are believed to be under or over valued. This strategy attempts to maintain either a net long or a net short position instead of being market neutral. On average, managers maintain a net long exposure between 10% to 40% of their total assets. Thus, equity market performance, especially of small cap stocks, positively affects the return of this strategy as does the bond market performance as represented by Lehman Government bond index. This strategy has positive exposure to credit spread and negative exposure to term spread. Generally, this strategy performs well when the yield curve is flat. Thus, a change in long and/or short rates adversely affects the performance. Similar to global macro, this style is also positively affected by performance in momentum and the VIX index.

Managed futures managers invest in listed financial and commodity futures and currency markets around the world and attempts to exploit short term price anomalies in
futures markets. Two broad investment approaches are often utilized. They are i) systematic trend following which are mostly computer driven and relies on technical analysis, and ii) discretionary where trading decision relies on personal experience and judgment. Managers typically achieve diversification by investing in a broad range of sectors, instruments and markets. Thus, the performance of this strategy is positively affected by the performance in the bond market, relatively better performance of small cap vs. large cap stocks, and value stocks compared to growth stocks. When the U.S. dollar appreciates, the values of long and short positions of various contracts move in opposite direction. The net gain or loss is determined by the relative performance of the long and short contracts. Our finding suggests that appreciation of U.S. dollar contributes to losses for this strategy. This strategy also benefits from increase in momentum an increase in gold prices.

Multi-strategy funds use several strategies within the same asset pool. Strategies adopted may include, but are not limited to, convertible bond arbitrage, equity long-short, statistical arbitrage and merger arbitrage. Funds may be allocated into a certain strategy in response to market trends that allows the manager to more easily capitalize on favorable market conditions. This strategy is found to be positively affected by relatively better performance of small cap stocks compared to large cap stocks which can be attributed to liquidity premium. Stronger U.S. dollar increases demand for foreign goods and at the same time lowers the demand for U.S. goods. The net effect of dollar appreciation is found to adversely affect the return of this strategy.
Finally, the emerging markets funds invest in equities or fixed income securities in emerging markets around the world. These funds are defined mainly by the markets they operate in and not the strategies they follow. Thus, these funds are quite heterogeneous and adopt a variety of strategies such as equity long/short, event driven, global macro and fixed income arbitrage. Since these funds invest in fixed income securities, the relationship with Lehman bond index is found to be positive. Steeper yield curve benefits this strategy as seen by a positive and significant coefficient of term spread. U.S. dollar appreciation also benefits the emerging market funds. Stronger U.D. dollar increases demand for foreign goods which benefits the economics of emerging markets. Momentum and gold are also positive drivers for this strategy. Emerging economies are often suppliers of gold and commodities; thus increase in the value of gold positively affects these economies.

3.2.4. Financial Crises Dummy Variables

The Russian debt crisis and the Long Term Capital Management debacle in the third quarter of 1998 materially affected HF returns. All coefficients pertaining to D98, with the exception of dedicated short, are found to be highly significant (equity market neutral and long-short equity at 10% level). All strategies sustained losses except managed futures. Emerging markets sustained the greatest loss with a coefficient of -0.106 while equity market neutral sustained the lowest loss with a coefficient of -0.005. Managed futures, on the other hand, enjoyed a gain as represented by a coefficient value of 0.034. It appears that at times of market distress, managed futures due to their
investments in wide range of markets and instruments have the ability to provide valuable diversification.\textsuperscript{15}

Our findings suggest that credit crisis of 2008 (D08) affected the HF industry in a more significant manner than did the 2007 mortgage crisis (D07). Ten of 13 HF strategies are adversely affected by credit crisis (D08). This finding is also supported by Billio et al. (2009). They utilized a methodology that identified the presence of a common idiosyncratic risk factor and concluded that, for the whole HF industry a latent factor exposure was present during the 1998 and 2008 crises though not for the 2007 crisis. Similar to our finding, they also conclude that the subprime mortgage crisis affected only a select number of HF strategies. The results presented in Table 2 show that the coefficient for the dummy variable for the mortgage crisis (D07) is significant and positive for convertible arbitrage, fixed income arbitrage, risk arbitrage, and managed futures strategies. These strategies appeared to have bet against low quality U.S. home loans and profited from their decision.\textsuperscript{16}

Since the beginning of subprime crisis in September 2007, financial institutions started deleveraging their positions. This unwinding of positions resulted in a cascading effect across all financial markets. As asset prices fell, the resulting margin calls forced

\textsuperscript{15} It appears that a number of HF strategies rebounded by June 1999. The strategies such as equity market neutral, long-short equity and managed futures posted returns greater than 15\% and somewhat lesser extent by event driven and multi strategy. However, dedicated short, emerging markets and global macro strategies remained at the negative territory. (http://www.hedgeindex.com/hedgeindex/documents/Analyzing_Turmoil_Outcome.pdf).

\textsuperscript{16} There is additional evidence that a number of HFs posted substantial gains by placing bets against subprime mortgage securities. The California-based Lahde Capital Management LLC’s US Residential Real Estate Hedge V Class A posted a 1000\% return in 2007, making it one of the best performing funds of all time. Similarly, the New York based Paulson & Co. managed to double assets to $24 billion in 2007. Paulson has outperformed most peers in 2007 as the housing market weakened. Its $5 billion Credit Opportunities Fund has soared more than fivefold this year. (www.Bloomberg.com).
HFs to offload their liquid assets, in turn triggering further selling pressure and further decline in asset values. In this context, the fact that financial leverage has the ability to magnify a small profit opportunity into a large one and a small loss into a colossal one played a significant role. As the decline in asset price reduced the value of the collaterals, credit was withdrawn quickly; resulting in forced liquidation of large positions over a short period of time resulting in a widespread financial panic. Thus, the coefficients for the dummy variable for the 2008 credit crisis (D08) are uniformly negative and with the exception of event driven, event driven multi strategy and emerging markets, they are statistically significant. Two strategies, convertible arbitrage and dedicated short sustained the most negative effect (coefficient around -0.13) while equity market neutral suffered the least (coefficient = -0.015). Over 81% of convertible arbitrage managers generated positive returns in 2007; however, none could remain in positive territory faced with the events of September and October 2008. 17

The events surrounding nationalization of Fannie Mea and Freddie Mac, the bankruptcy of Lehman Brothers and implementation of short sale ban globally contributed to much of the losses sustained by HF following these strategies. Fannie Mea, Freddie Mac and Lehman Brothers were each significant issuers and holders of convertible preferred stocks. With government takeover of Fannie Mae, Freddie Mac and the collapse of Lehman Brothers, financial convertibles were rendered untradeable, resulting in significant losses for this HF strategy. A number of other strategies such as, multi strategy, global macro, and fixed income arbitrage also sustained a considerable decline in returns (coefficients -0.07 or greater) during this time period. Although it is difficult to identify exact strategy-specific market events that led to reduction in returns,

it can be concluded while the financial market turbulence has affected HFs, the flight to quality has accentuated the crisis with investors pulling out funds in panic.\(^{18}\)

### 3.3 Hedge Fund Volatility

#### 3.3.1. The GARCH Affect

Panel B of Table 2 presents the parameters of the conditional variance equation (3). The parameter \(\omega\) represents the logarithm of the unconditional variance of the return process and is found to be uniformly significant. The GARCH coefficient, \(\beta\), determines the influence of the past conditional volatility on the current conditional variance. For the conditional volatility process to be stationary it is required that \(|\beta| < 1\). The results presented in Table 2 strongly support that the stationary condition is met for all strategies. The magnitude \(\beta\) is approximately 0.3 for all strategies with the largest being 0.375 for long-short strategy and smallest being 0.28 for global macro strategy. In EGARCH specification, persistence of volatility is captured by the \(\beta\) coefficient alone. The persistence of volatility may also be quantified by examining the half-life of a volatility shock (HLS) as: \(^{19}\)

\[
HLS = \frac{Ln(0.5)}{Ln(\beta)}
\]  

The half-life of a volatility shock, defined by Engle and Bollerslev (1986) as the time it takes for the volatility to move halfway back towards its unconditional variance. The volatility process is considered to be “mean reverting” to its long run level and the

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\(^{18}\) It is important to note that although various strategies reacted negatively to the events surrounding September and October 2008, a number of strategies during the January – December 2008 period produced positive returns. These strategies include dedicated short (14.9%) and managed futures (18.3%). (www.credit-suiss.com).

\(^{19}\) See, Nelson (1991) for a discussion on half life volatility shock within EGARCH framework.
magnitude of \( \beta \) controls the speed of mean reversion. For example, for convertible arbitrage with a \( \beta \) of 0.345, the half-life of a volatility shock implied by this mean reverting rate is \( \ln(0.5)/\ln(0.345) = 0.65 \) or approximately 19 days. Utilizing the same approach, the persistence of volatility is calculated for each strategy.\(^{20}\) Overall, the length of persistency is between 16 to 21 days. For global macro, the shock appears to mean-revert the fastest (16 days) while for equity market neutral and long short equity takes the longest (21 days). The fitted EGARCH models strongly suggest that the persistence of volatility shocks of HF returns is relatively short lived compared to their equity counterparts (see, Bollerslev et al. (1992)).

3.3.2. Volatility Clustering

One of the advantages of estimating HF volatility within the framework of EGARCH specification is its ability to disaggregate the changes in volatility into volatility clustering and asymmetric effects. The coefficient \( \alpha \) in the conditional volatility process specified by equation (3) accounts for the volatility clustering observed in volatility behavior following exogenous shocks. Also known as the “magnitude effect”, the parameter \( \alpha \) captures the magnitude of volatility clustering by linking the current volatility and past shocks under the context of an asymmetric function. If the coefficient \( \alpha \) is positive, larger shocks, whether positive or negative in direction, are followed by larger changes in volatility. The results strongly support significant volatility clustering for all strategies, with the exception of equity market neutral, as the estimated parameter \( \alpha \) is positive and significantly different from zero. The highest and lowest

\(^{20}\) The results, in days, are: CA -19, EMN-21, FIA -19, DST -17, ED -18, EDMS-17, RA -17, DS-19, GM-16, LSE-21, MFU -17, MS -17 and EM -18.
\( \alpha \) value pertains to long-short equity (0.345) and event driven multi strategy (0.124), respectively.

HF data generally reveals the unique feature of volatility clustering which is often measured by the magnitude of autocorrelation of squared returns. There is a substantial body of literature that addresses the HF return clustering. Boyson et al. (2008) provide an extensive analysis of whether negative return clustering is due to exogenous common shocks that pervade across all HF styles or from contagion. Their findings suggest that large adverse shocks to credit spreads, prime broker stock prices, stock market liquidity, repo volume, and HF flows contribute to clustering of worst returns. Additionally, they find mixed support for contagion as an explanation for return clustering.

This is the first study that establishes the effects of volatility clustering and asymmetry on HF volatility. It is important for investors and managers alike to understand the effect of volatility clustering on volatility patterns and the subsequent effect on asset pricing. In the aftermath of LTCM crisis, there has been a growing demand on the part of the HF managers for instruments to hedge shifts in volatility. Bondarenko (2006) finds that on average, the HF industry earns about 6.5% annually by short selling the variance risk. The largest sellers of the variance risk are Distressed Securities, Emerging Markets, Equity Non-Hedge, Event-Driven, and Fixed Income. Thus, the ability to predict volatility plays a crucial role in determining the value of the underlying assets and the fund itself. The timing and duration of volatility clusters can significantly alter the value of derivative instruments and consequently affect the HF’s ability to manage the shifts in volatility risk. \(^{21}\)

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\(^{21}\) Two instruments, namely variance swap and volatility swap are particularly well suited to hedge shifts in volatility risk. A variance or volatility swap allows one to hedge risk associated with the magnitude of
3.3.4 Asymmetric Effect

A main contribution of this study is to identify whether the HF volatility is asymmetric, i.e., whether the HF volatility is affected by its return shocks and if so, whether the magnitude of such effects are identical for positive and negative shocks. The asymmetry in effect is often referred to as the leverage effect in the extant literature and is determined by the autocorrelation of today’s squared returns and last period’s returns where the autocorrelation coefficient can be positive or negative in value. The relationship between stock returns and stock return volatility is at the center of derivative asset valuation and portfolio management. As stated previously, within the EGARCH specification, the coefficient $\gamma$ permits us to capture the magnitude and direction of asymmetric effect on volatility by linking the current volatility and past return shocks under the context of an asymmetric function.

The results, presented in Table 2, panel B, suggest that for 11 of the 13 strategies studied, the $\gamma$ coefficient is highly significant indicating the prevalence of asymmetry. Two strategies that did not exhibit statistically significant relationship between price innovation and volatility are convertible arbitrage and emerging markets. A statistically significant $\gamma$ coefficient points to HF volatility being affected in an asymmetric manner due to its return shocks. In the equity return literature, considered as the leverage effect, the coefficient $\gamma$ is typically found to be negative which suggests that positive return shocks $\varepsilon_t > 0$ (an unexpected increase in price) generate less volatility than negative

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Volatility without the influence of its price. Both variance and volatility swaps are sold over-the-counter. Volatility is defined as the square root of variance and serves as the basis for a volatility swap. In a variance swap, two parties agree on a figure for realized variance over the life of the swap agreement and the payoff is equal to the difference between the realized variance and the contract variance. The timing and duration of volatility clusters can significantly change the value of a volatility swap.
return shocks $\epsilon_t < 0$ (an unexpected decrease in price) all else being equal (see, Engle and Ng (1993)). However, Braun et al. (1995) report that this predictive asymmetry of volatility rising strongly in response to bad news and falling in response to good news occurs mainly at the level of the market. They find very limited evidence of this predictive asymmetry (insignificant or positive $\gamma$) for idiosyncratic sources of risk for industry portfolios.

Consistent with the equity return literature, the coefficient of asymmetry, $\gamma$, is negative ($\gamma < 0$) for the fixed income arbitrage, risk arbitrage and dedicated short strategies. For these strategies, positive return shocks, i.e., unexpectedly good performance, decrease their volatility while negative return shocks, i.e., unexpectedly poor performance, increase their volatility.

There are several possible explanations for this negative relationship between returns and return volatility to hold. First, In line with the leverage effect, when the values of these funds drop due to poor performance, their equity, in general, becomes more leveraged, this causes the volatility of returns to increase. The second set of explanation is in line with the time-varying risk premium hypothesis as discussed by French, Schwert and Stambaugh (1987). In this context, an anticipated increase in HF volatility will raise its required rate of return which will lead to an immediate decline in the value of HF assets. A similar explanation is also proposed by Bekaert and Wu (2000) within the framework of volatility feedback which suggests that if volatility is priced, an anticipated increase in volatility raises the required return on assets, which leads to an immediate decline in asset price. Finally, if more assets flow into the fund due to
unanticipated better performance, fund managers may selectively invest in securities that are not priced on a daily basis and therefore lower the volatility of the fund.

For the remaining strategies, the coefficient $\gamma$ is found to be positive, a finding similar to that obtained by Braun et al. (1995) at the portfolio level. For these strategies, a positive innovation in the previous period leads to a higher conditional volatility in the current period while a negative innovation exhibits the opposite affect. There are several plausible scenarios for this relationship to exist. HFs, in general, utilize various strategies to control liquidity and down-side risk. These strategies include lock-ups, side pockets, spin outs, various gate provisions, redemptions-in-kind and finally suspension of redemptions. Faced with negative innovations, funds utilizing these strategies can effectively control the asset flows and manage the down-side risk. On the other hand, positive innovations can contribute to greater risk taking for the following reason. It is well-established in the literature that performance persistence of HFs is short lived typically from one quarter up to one year (Agarwal and Naik 2000). This suggests that additional assets may lead to a decline in fund performance if superior performance in the past solely attracts more flows into the fund (see, Ding et al. (2007)). This is due to the fact that assets with the previous risk-return trade-offs are difficult to attain. Thus, in an effort to maintain higher returns, the fund manager will seek out assets with greater risk.

3.3.5. Pre-post Event Dummy Variables

Results pertaining to three pre-post event dummy variables are also presented in Table 2, panel B. There is considerable evidence that after major drawdown in 1998 LTCM crisis, the HF performance was up by 13% in a year by 34% after a two year period (www.credit-suisse.com). Given the fact that the HF returns stabilized after a
certain period of time, the purpose of the pre-post event dummy variables is to capture whether the post event periods after each major crisis was characterized by increased or decreased level of volatility for each strategy. Our results show that for seven strategies, the post 1998 period (D98_07) coefficient is statistically different from zero. Of which, for five strategies (equity market neutral, event driven multi strategy, global macro, multi strategy, and emerging markets) the conditional volatility decreased during the post 1998 event period.

The post mortgage crisis dummy variable (D07_08) is found to have a significant impact on the volatility of HF returns. The conditional volatilities of ten out of the thirteen strategies considered are affected by the post October 2007 events. For four strategies (equity market neutral, global macro, managed futures, and emerging markets) the coefficient is found to be negative. A perusal of unconditional risk during this time period (reported in Panel B, Table 1) also confirms that these strategies did see a reduction of risk during the post mortgage crisis period.

Similar to the affect of credit crisis event dummy (D08) on HF returns, post credit crisis dummy variable (D08) also has a significant effect on the volatility of HF returns. With the exception of risk arbitrage and dedicated short strategies, all strategies are affected by the market conditions in the post September 2008 period. Similar to the previous periods, the conditional volatility of global macro, managed futures, and emerging markets strategies decreased during this time period.

3.3.6. Model Diagnostic Statistics

The data pertaining to model diagnostic statistics are contained in Table 2. They include log likelihood value (LL), skewness and kurtosis based on $\frac{\varepsilon_t}{\sqrt{h_t}}$, the Ljung-Box
Q statistics of 12 month lags for the standardized errors (Q(12)) and the squared of the standardized errors (Q^2(12)). The results suggest that the higher-moment factor EGARCH (1,1) specification utilized in this study adequately models the return generating process of HF strategies. For risk arbitrage, dedicated short and managed futures strategies, the conditional skewness and kurtosis are statistically insignificant; additionally the conditional skewness is also found to be insignificant for long-short equity and equity market neutral strategies. For the remaining strategies, with the exception of global macro and multi-strategy funds, the conditional skewness (in absolute term) is smaller than their unconditional counterparts. A similar finding is also true for kurtosis. With the exception of convertible arbitrage, the statistically insignificant Ljung-Box Q statistics confirms that the standardized errors are serially uncorrelated. Similarly, the standardized errors are free of ARCH effect as represented by statistically insignificant Q^2(12) for all strategies aside from emerging markets.

4.0. CONCLUSIONS

This paper examines the risk-return behavior of thirteen different styles of HFs using a higher-moment factor EGARCH (1,1) model. This is the first study to our knowledge that attempts to model the conditional volatility of HF return using an EGARCH (1,1) methodology. Unlike linear GARCH (1,1) methodology, modeling conditional volatility using the EGARCH(1,1) approach has several advantages. First, the estimation of linear GARCH models is very restrictive as it imposes strict positivity constraints on the coefficients in the conditional variance equation to ensure a non-negative conditional volatility (h_t) at all times. In this regard, EGARCH modeling
approach relaxes the non-negativity restrictions of the signs of the coefficients. This is due to the fact that EGARCH parameterizes the logarithm of the conditional variance, thus all coefficients in the volatility equation may be negative without risking violation of the non-negative variance condition. Second, unlike the linear GARCH approach, the EGARCH specification has the flexibility to disaggregate the effect of volatility into asymmetric effect as well as magnitude effect. In doing so, this approach permits us to determine the extent of volatility clustering as well as asymmetric affect due to a shock to HF volatility.

Our results strongly support significant volatility clustering for all strategies, with the exception of equity market neutral. This finding has serious implication for HF managers. Thus, the ability to predict volatility plays a crucial role in determining the value of the underlying assets and the fund itself. The timing and duration of volatility clusters can significantly alter the value of derivative instruments and consequently affect the HF’s ability to manage shift in volatility risk.

We find strong support (11 of 13 strategies studied) for the asymmetric coefficient ($\gamma$) to be statistically significant. The results are quite unique and revealing for the HF industry. Similar to the results based on equity returns, the predictive asymmetry coefficient is found to be negative ($\gamma < 0$) for the fixed income arbitrage, risk arbitrage and dedicated short strategies. For these strategies, positive (negative) return shocks decrease (increases) their volatility. For the remaining strategies the predictive asymmetry coefficient is found to be positive ($\gamma > 0$), which suggest that positive innovations contribute to greater risk taking on the part of the fund managers. Future
research should attempt to identify the unique characteristics and other idiosyncratic sources of risk that contribute to such behavior.

For all strategies, we find strong evidence of GARCH effect as exhibited by statistically significant $\beta$; additionally the magnitude of $\beta (\approx 0.3)$ strongly support that the stationary condition is met for all strategies. The persistence of shock as given by Half Life of Volatility Shock (HLS) is between 16 to 21 days. The results also reveal that the conditional volatility of HFs was significantly affected during the post 2007 mortgage crisis and post 2008 credit crisis periods. Additionally, we revisit the post 1998 crisis and find that for seven thirteen strategies, post 1998 period coefficient is statistically different from zero.

Finally, to model HF return, our findings strongly support the application of a higher moment return generating model as most of co-skewness and co-kurtosis coefficients are found to be significant. Our findings pertaining to macro factors are consistent with those of the extant studies. Additionally, our findings suggest that the financial crisis of 1998 and the credit crisis of 2008 affected the HF returns in a more significant manner than did the 2007 mortgage crisis.
References:


## Table 1

Hedge Fund Excess Return Data Diagnostics

<table>
<thead>
<tr>
<th>Relative Value</th>
<th>Event Driven</th>
<th>Directional</th>
<th>Market</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Convertible Arbitrage</td>
<td>Event Driven</td>
<td>Risk Arbitrage</td>
</tr>
<tr>
<td></td>
<td>ERCA EREMN ERFIA</td>
<td>ERDST</td>
<td>ERER</td>
</tr>
<tr>
<td>No. of Observations</td>
<td>188</td>
<td>188</td>
<td>188</td>
</tr>
<tr>
<td>Mean</td>
<td>1.34E-03</td>
<td>3.93E-03</td>
<td>-8.76E-03</td>
</tr>
<tr>
<td>Std.dev</td>
<td>0.022</td>
<td>0.039</td>
<td>0.018</td>
</tr>
<tr>
<td>Max</td>
<td>0.055</td>
<td>0.034</td>
<td>0.041</td>
</tr>
<tr>
<td>Min</td>
<td>-0.140</td>
<td>-0.522</td>
<td>-0.156</td>
</tr>
<tr>
<td>Skew</td>
<td>-2.964</td>
<td>-12.495</td>
<td>-4.475</td>
</tr>
<tr>
<td>p value - Skewness</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>Excess Kurtosis</td>
<td>17.735</td>
<td>165.682</td>
<td>30.635</td>
</tr>
<tr>
<td>p value - Kurtosis</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>p value - JB</td>
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<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>ARCH(1)</td>
<td>43.43</td>
<td>0.00</td>
<td>19.82</td>
</tr>
<tr>
<td>p value - ARCH</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>p value - ADF(4)</td>
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<tr>
<td>p value - PP(0)</td>
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### Panel B

Comparisons of Standard Deviations Between Entire Period and Sub Periods

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<thead>
<tr>
<th></th>
<th>0.0144</th>
<th>0.0636</th>
<th>0.0117</th>
<th>0.0191</th>
<th>0.0197</th>
<th>0.0191</th>
<th>0.0126</th>
<th>0.0498</th>
<th>0.0235</th>
<th>0.0299</th>
<th>0.0355</th>
<th>0.0109</th>
<th>0.0420</th>
<th>0.0434</th>
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<tbody>
<tr>
<td>SD(8/98-8/07)-SD ALL</td>
<td>-0.0073</td>
<td>-0.0332</td>
<td>-0.0067</td>
<td>-0.0007</td>
<td>-0.0001</td>
<td>0.0001</td>
<td>0.0003</td>
<td>0.0015</td>
<td>-0.0062</td>
<td>0.0009</td>
<td>0.0007</td>
<td>-0.0042</td>
<td>-0.0042</td>
<td>-0.0016</td>
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<tr>
<td>STANDARD DEV(8/98-8/08)</td>
<td>0.0224</td>
<td>0.0600</td>
<td>0.0225</td>
<td>0.0127</td>
<td>0.0175</td>
<td>0.0210</td>
<td>0.0132</td>
<td>0.0550</td>
<td>0.0250</td>
<td>0.0276</td>
<td>0.0348</td>
<td>0.0163</td>
<td>0.0314</td>
<td>0.0393</td>
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<tr>
<td>SD(8/98-8/08)-SD ALL</td>
<td>0.0007</td>
<td>-0.0355</td>
<td>0.0041</td>
<td>-0.0071</td>
<td>-0.0005</td>
<td>0.0019</td>
<td>0.0009</td>
<td>0.0067</td>
<td>-0.0047</td>
<td>-0.0014</td>
<td>0.0011</td>
<td>0.0002</td>
<td>-0.0148</td>
<td>-0.0056</td>
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<tr>
<td>STANDARD DEV(9/07-8/09)</td>
<td>0.0688</td>
<td>0.1523</td>
<td>0.0577</td>
<td>0.0347</td>
<td>0.0323</td>
<td>0.0319</td>
<td>0.0190</td>
<td>0.0545</td>
<td>0.0298</td>
<td>0.0409</td>
<td>0.0230</td>
<td>0.0418</td>
<td>0.0613</td>
<td>0.0889</td>
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<tr>
<td>SD(9/08-9/09)-SD ALL</td>
<td>0.0471</td>
<td>0.1128</td>
<td>0.0393</td>
<td>0.0149</td>
<td>0.0143</td>
<td>0.0129</td>
<td>0.0067</td>
<td>0.0063</td>
<td>0.0001</td>
<td>0.0018</td>
<td>-0.0017</td>
<td>0.0257</td>
<td>0.0151</td>
<td>0.0440</td>
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</table>
The t-values are presented below each coefficient. The critical values are 1.64, 1.96, and 2.57 at the .10, .05 and .01 level, respectively. LL refers to the log of the likelihood function.

<table>
<thead>
<tr>
<th>Variables</th>
<th>Coefficient</th>
<th>Relative Value</th>
<th>Event Driven</th>
<th>Directional</th>
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<tr>
<td></td>
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<td>ERCA</td>
<td>EREMN</td>
<td>ERFA</td>
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<tr>
<td>Constant</td>
<td>b_0</td>
<td>0.003</td>
<td>0.002</td>
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<tr>
<td>RM</td>
<td>b_1</td>
<td>0.040</td>
<td>0.008</td>
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<tr>
<td>RM²</td>
<td>b_2</td>
<td>0.781</td>
<td>0.692</td>
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<td>11.105</td>
<td>3.858</td>
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<tr>
<td>Lehman Gov't Bond (ELGC) f</td>
<td>0.117</td>
<td>0.052</td>
<td>0.127</td>
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<td>Large-Small (LS) f_5</td>
<td>-0.075</td>
<td>-0.004</td>
<td>0.000</td>
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<tr>
<td>Credit Spread (CS) f_6</td>
<td>-7.241</td>
<td>-0.810</td>
<td>-9.625</td>
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<tr>
<td>Value - Growth (VG) f_8</td>
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<td>-0.102</td>
<td>0.242</td>
<td>-0.158</td>
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<td>Term Spread (TS) f_9</td>
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<td>0.320</td>
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<td>USD Exchange Rate (USD) f_6</td>
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<td>Emerg. Market Bond (EMB) f_6</td>
<td>0.117</td>
<td>0.065</td>
<td>0.059</td>
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<td>Emerg. Market Equity (EMS) f_6</td>
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<td>Momentum (MU) f_8</td>
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<td>Gold (GOL) f_10</td>
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<td>Variables</td>
<td>Relative Value</td>
<td>Event Driven</td>
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<td>1998 Crisis (D98)</td>
<td>(d_1)</td>
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<td>-12.58</td>
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<td>Mortgage Crisis (D07)</td>
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<td>4.528</td>
<td>1.324</td>
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<tr>
<td>Credit Crisis (D08)</td>
<td>(d_3)</td>
<td>-0.139</td>
<td>-0.015</td>
<td>-0.070</td>
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**PANEL B - VOLATILITY EQUATION**

<table>
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<th>Variables</th>
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<tbody>
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<td>Log (Constant)</td>
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<td>Volatility Cluster</td>
<td>(\alpha)</td>
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<tr>
<td>GARCH</td>
<td>(\beta)</td>
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<tr>
<td>Asymmetric Effect</td>
<td>(\gamma)</td>
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<td></td>
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<tr>
<td>D98_07</td>
<td>(\phi_1)</td>
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<td></td>
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<tr>
<td>D07_08</td>
<td>(\phi_2)</td>
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<tr>
<td>D08</td>
<td>(\phi_3)</td>
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**PANEL C - MODEL DIAGNOSTIC STATISTICS**

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<th>Variables</th>
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<td>LL VALUE</td>
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<td>Based on (\varepsilon_t/\sqrt{h_t})</td>
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<td>Skewness</td>
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<td>Kurtosis</td>
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<td>Unconditional Skewness</td>
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<td></td>
<td>17.7352</td>
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<tr>
<td>Q^2 (12) [Crit. Value 21.02 at 0.05]</td>
<td>0.988</td>
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</table>