Hedge Funds Returns and Deviation from Normality during Crises

François Desmoulins-Lebeault*
†

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Abstract

In classical financial theory, the marginal distribution of returns is supposed idiosyncratic and should have no relation with expected returns. However, in certain cases the deviations from normality of the returns on an asset or portfolio may signal properties associated with a risk premium. On a large and diverse database we show that, in time of crises, a negative premium is associated with deviations from normality in hedge funds returns. We postulate that this can be explained by the fact that non-Gaussian distributions tend to signal funds which make large use of derivatives. These funds will therefore present a non linear dependence structure with the market, allowing them to benefit from bull periods and resist well bear markets.

1 Introduction

Some early literature on the hedge funds have proposed to treat them, as most classes of primary assets or portfolios, through mean-variance models. For example, Fung and Hsieh (1999) propose the use of such mean-variance models for evaluating hedge funds, while remarking that the variance may not be an appropriate risk measure. As the popularity of these investment funds and the amount of scrutiny from academia increased, it soon became clear that mean-variance was poorly suited to understanding hedge funds returns.

Numerous authors and studies have shown that, even if it is impossible to define a “characteristic hedge fund returns distribution” as the funds are

*Assistant Professor of Finance, GRENOBLE ÉCOLE DE MANAGEMENT
†e-mail: francois.desmoulins-lebeault@grenoble-em.com
very diverse, departures from normality are crucial in understanding the performances and returns on hedge funds. The non-normality of hedge funds returns are cited by Kat (2003) among the “10 Things Investors Should Know About Hedge Funds”, and a key element of the properties of these funds by many papers, such as Mitchell and Pulvino (2001), Fung and Hsieh (2001), Brooks and Kat (2002), Kouwenberg (2003), Amin and Kat (2003), Capocci (2004), Agarwal and Naik (2004) and Ranaldo (2005), many noting that the degree of non-normality of the funds and indices is very variable. Malkiel and Saha (2005) insist that many hedge funds or hedge funds indices exhibit large kurtosis values (thick tails) and relatively low skewness, excepted “global macro” and “managed futures” funds. Kosowskia et al. (2007) or Kouwenberg and Ziemba (2007) highlight that these elements are relevant when judging the performance of a fund.

Hedge funds, being largely unrestricted in their use of derivatives and dynamic trading strategies, present themselves as “alternative investment funds” and are the object of some scrutiny because of the supposed properties of their returns. Their name stems from the “hedged investments” they frequently provide, i.e. investments protected by the use of attached derivatives. This distinguishing characteristic is probably linked to the non-normality of their returns, most probably the former causing the latter. However, it is probable that the relative importance of both dynamic trading and use and exercise of derivative securities by hedge funds increases in uncertain times while it should be low or at least constant when markets are steady and bullish.

The departures from normality are of little importance if they only concern marginal distributions, as these elements could be diversified by constructing a well crafted portfolio. This point has been abundantly studied and proved by the multi-moment (or non-gaussian) portfolio theory. Many authors, like Kraus and Litzenberger (1976); Friend and Westerfield (1980); Sears and Wei (1985); Lim (1989); Bonsal and Viswanathan (1993); Harvey and Siddique (2000); Perez-Quiros and Timmermann (2000); Kan and Wang (2001); Dittmar (2002); Hung et al. (2004); Fang and Lai (1997); Desmoulins-Lebeault (2006) or Malvergne and Sornette (2006) have shown that co-skewness, co-kurtosis or higher co-moments should, depending on the preferences of investors, correspond to non-zero risk premia. On the other hand, this literature on higher
moments asset pricing indicates that marginal moments, corresponding to idiosyncratic risks, should, and do indeed not, command any premium at all.

However, the hedged nature of many hedge funds is supposed to limit the covariance between their returns and the market’s. This property has been studied by Asness (1998) or Asness et al. (2001). The consequence of the limited or even null correlation that should exist between the hedge funds and the market portfolio is that, more than the covariance (or more generally the dependence structure), statistics of the marginal distribution of returns could in part explain the cross section of hedge fund performances. This constitutes “non-normality risks”, as called by Kat and Miffre (2006). However, the average level of correlation between hedge funds and the leading indices is in general significant, reducing the validity of that approach.

The mean returns of hedge funds (taken as proxies for the expected returns) should therefore be unrelated to their degree of non-normality in quiet market times, while a degree of relation should be observable in times of shocks to the market, mostly negative. We will try to determine empirically if this relation can be observed in hedge funds returns, and to quantify the amount and timing of such relation. To this end we will explore the properties of various samples of hedge fund indices returns.

The remainder of the paper will be organized as follows: first we will describe normality statistics, their properties and how they relate to risk in our specific context, a second section will then be dedicated to describing the hedge fund data and its sample properties. In the third section we will evaluate the relation between returns and normality, and factors that may allow to predict the intensity of said relation before giving some concluding remarks in a forth section.

2 Measures of divergence from normality and risk

When dealing with the risk of a marginal investment, the first approach is to look at the variance. However, this measure of dispersion of the returns is not a complete description of the variability if the distribution differs from a
Gaussian. Indeed, a Gaussian distribution is fully characterized by its mean and variance, respectively indicating location and dispersion. However, for other distributions, the full characterization requires more parameters. If one admits that moments of odd orders are related to location elements and even order moments are related to dispersion, characterizing and measuring the risk attached to returns distributed non-normally requires taking into account moments of higher order, or other elements.

Scott and Horvath (1980) have shown that, under very weak assumptions, investors with usual utility functions will always prefer more of the odd order moments and be averse to even order moments. In this sense, positive skewness can be viewed as a positive element, while negative skewness is to be avoided. Variance, kurtosis or moments of order 6, 8 etc. being constituents of the “risk” to which agents are supposed to be averse. In this sense, the degree of divergence between a given distribution and a Gaussian distribution shows by how much the use of simple variance mis-estimated the actual level of risk.

Moreover, if the investors make their decisions under uncertainty using a set of rules which differ from these of the standard “maximum expected utility” of Von Neumann and Morgenstern (1953), and behave like predicted by Tversky and Kahneman (1974) or Kahneman and Tversky (1979), or exhibit loss aversion in their behaviors, the level of asymmetry and the thickness of the negative tail of the distribution will be important risk factors. Therefore, departures from normality could well be crucial elements explaining the variation of returns across hedge funds, as long as they are de-correlated from the market and their specific risk matter.

Tests of normality are generally used in order to answer the question: “at this given confidence level can we accept the hypothesis that this sample is drawn from a Gaussian population?” However, in order to answer this question, most tests make use of a statistic which measures the distance between the hypothesized Gaussian and a theoretical distribution with the properties of the sample. Therefore the test statistics of most tests of normality are statistics of the deviation from normality of a theoretical parent population for the observed sample.

Among the very many tests of normality, none can be recognized as dominating the others as the alternative hypothesis (“not normal”) is quite vague.
However, a certain number of tests are celebrated in the literature as having a very high power against a very large set of possible alternatives, being real omnibus tests. Among them, the test proposed by Shapiro and Wilk (1965), especially in its version modified by Stephens (1974) and Royston (1993) seems to be quite interesting. Indeed, this test is based on the analysis of the diverse possible estimates of the variance on the sample, and therefore measures elements linked to the risk metric usually selected in finance. The statistic can be seen as the relative degree of adjustment between the qq-plot and the line representing the normal distribution. In this sense, it takes into account all deviations from normality in a context of linearity. Moreover, many comprehensive studies, like Mardia (1980) or D’Agostino and Stephens (1986) have found it to be among the most efficient tests in detecting asymmetry and tail thickness for unbound, continuous alternatives.

The test statistic takes the following form:

$$W = \frac{K \hat{\sigma}^2}{(n - 1)s^2}$$

with

$$K = \frac{m'V^{-1}m}{m'V^{-1}V^{-1}m}.$$

where $s^2$ is the usual symmetric estimate of the variance regardless of the distribution of the sample, $\hat{\sigma}$ is the best linear unbiased estimator of the slope of the qq-plot (i.e. best estimate of the standard deviation if the sample is drawn from a Gaussian distribution), $V$ is the covariance matrix between the observations and $m$ the corresponding expected values of standard normal order statistics. This statistic measuring the linear correspondence between the sample and a Normal distribution should provide us with a good tool for appreciating the impact of marginal distributions on the performances of hedge funds.

To gain additional insights on this relation, we will also make use of the Lilliefors version of the Kolmogorov-Smirnov statistic. This is the supremum of the distance observed between the Empirical Distribution Function $F_n(x(i)) = \frac{i}{n}$, and the hypothesized normal distribution, $Z_i$. This statistic takes the following form:
\[ K = \max(D^+, D^-) \]

where

\[ D^+ = \sup \left( i/n - Z_i \right) \quad \text{and} \quad D^- = \sup \left( Z_i - (i - 1)/n \right). \]

It is known to have less power than most usual tests of normality, yet a large number of finance researchers still use it, so we thought that its inclusion was required. This second statistic also seems to have less economic meaning as it depends only on the single largest deviation from normality of the distribution and therefore fails to capture the full span of risks involved.

3 The Data

Empirically testing any hypothesis on hedge funds is relatively difficult. By nature these funds scarcely disclose information to the public. As they do not have to register with any authority, even their number is not precisely known. It is estimated that there are roughly 10,000 active funds at the end of 2009, managing nearly $2 trillion.

Moreover, the data about these funds suffer from a certain number of biases that make analysis difficult. Certain firms, consultancies etc. gather information on the hedge fund industry from voluntary disclosure of information of a certain number of funds. From these information they usually compute various indices representing as best as possible the performances of funds of a given management style. These data providers supposedly use index building methodologies designed to reduce the main biases affecting hedge funds data, mainly survivorship and backfilling.

Survivorship bias arise from the exclusion of the index, for a given period, of the funds which “died” during this period. These funds can either have ceased to report their data or disappeared altogether. In both cases, it is only logical to suppose that they have performed badly before this event, and excluding them thus generates an upward bias in index performances. The backfilling bias is more specific to the hedge fund industry and arises when past performances of a fund that newly discloses its information are included in the database. It is sometimes called “instant history” and its selectivity also
generates an upward bias. The survivorship bias could have an effect of about 3%, while backfilling could be 1.4%, both per annum, according to Brown et al. (1999) or Fung and Hsieh (2000, 2002). All hedge funds data providers have different ways of dealing with these issues when creating their indices. To enhance the robustness of our results we will conduct our analysis on 4 sets of indices provided by 3 different data providers: Hedge Fund Research, Inc. (HFR), Crédit Suisse/Tremont and the Center for International Securities and Derivatives Markets (CISDM).

Each data provider includes new indices when they have enough data to cover a given sub-universe of hedge funds. As most funds are only included in one index, this means that the universe covered by the indices increases over time. In order to be able to compare the results at different points in time, we need our data to be equivalent at any given date. Therefore, we can only include indices that have observations at all dates of our observation period. This leads us to a dilemma. Indeed, we would like to have a long history of hedge funds indices returns, which implies a very limited number of different indices, and yet to have many indices to observe, which would require a very short observation period. We decided to select two different samples to address this problem. The first one goes from the 30th of April 1994 to the 30th of November 2009. The starting date was selected to maximize the total number of observations in the global sample, comprising all four data sets. 66 indices exist for this entire period, with 187 monthly returns each. A second subsample goes from the 1st of January 2005 to the 30th of November 2009, in order to contain as many indices as possible while having at least 50 observations per index. 176 indices are included in this shorter time period subsample, with 58 monthly returns.

Indices from the same data provider do not overlap; however, there is no reason for the indices from different providers not to contain the same hedge funds. To avoid issues of redundancy, we will conduct our tests on the set of indices that contains most data, and use the other data sets as robustness checks.

1 HFR © 2009, www.hedgefundresearch.com
2 www.hedgeindex.com
3 http://cisdm.som.umass.edu and http://www.casamhedge.com
The HFRX data set is provided by HFR and contains from 11 indices in March 2003, to 71 indices, in November 2009. They are based on simulation and multiple weighting strategies applied to sub-indices which are supposed to be "pure representatives" of given underlying strategies. This construction of indices aims at providing the most accurate vision of the hedge fund industry while avoiding the biases usually attached to classical index building. HFR also provides more classical indices, based on baskets of hedge funds. These indices are the HFRI data set, which contains from 24 indices in December 1989 to 33 indices in November 2009. These indices are equally weighted, giving no advantages to the strategies of larger funds, and thus aim at representing as best as possible the returns available to an hedge fund investor in all their diversity. Crédit Suisse/Tremont provide from 13 indices, in December 1993, to 42 indices in November 2009. This includes the whole range of indices calculated by Tremont, which weight the contributing funds by their assets under management size. Thus, these indices give more weight to the strategies that attract most investors than to the relatively underground strategies. The indices set is computed by CISDM include indices on Commodity Trading Advisors (CTA) funds and Commodity Pool Operators (CPO) funds, as they also make use of derivatives and dynamic trading. CISDM provides from 19 indices, in December 1989, date at which they started reporting hedge funds per se, to 37 in November 2009. These indices are median performance indices from the pool of funds reporting to CISDM or managed by Credit Agricole Structured Asset Management. This offers again a slightly different view of the hedge fund industry by the use of a median instead of an average.

These many indices cover a large number of styles and funds, allowing us to obtain a rather representative view of the industry, even if the individual funds do represent a much wider yet variety of styles and, therefore, of returns distributions. In our “long” sample (1994-2009), HFRX indices are not represented, there are 22 CISDM indices, 30 HFRI indices and 14 Tremont indices. Therefore we will consider HFRI as our primary sample and use the other indices to confirm the robustness of our findings. In the “short” sample (2005-2009), we find 36 CISDM indices, 33 HFRI indices, 65 HFRX indices and 42 Tremont indices. For this sub-sample, the main analysis will therefore be conducted based on HFRX indices while the other data will be used for
tests of robustness.

As a reference index to represent “the market”, we will make use of the MSCI world index as many funds comprised in the indices include investments in equity from different countries, and certain indices are even specifically dedicated to hedge funds invested in Europe or Asia.

Observing the some statistical properties of these returns series yields interesting information. The average monthly mean return over the “long” observation period, for the primary sample, HFRI indices\(^4\) is 0.7573\% (ranging from 0.1906\% to 1.7503\%, while it is 0.4331\% for the MSCI world index. The average standard deviation for the indices is 0.0267 (from 0.0094 to 0.0832) and 0.0443 for the MSCI world index, thus giving the impression that the latter is at the same time riskier and offers less performances than the average of our hedge funds indices. Looking at higher order moments, the average skewness of the indices returns is -1.0233 (going from -3.3885 to 0.4226), slightly better than the -0.9148 of the MSCI world index. however, kurtosis is slightly less favorable for the hedge funds, at 9.0574 (with a minimum of 2.8208 and a maximum of 29.7351) when the market has a kurtosis of 5.0424.

Let us consider some of the statistical properties of these returns series. Table \(\text{[1]}\) presents information on the first moments of the distributions, over the 1994-2009 observation period, of the HFRI indices\(^5\). It can be seen that there is a certain degree of diversity in the hedge funds returns structures, yet some general traits can be noticed. The average hedge fund index has, over the period, offered higher mean returns for a lower standard deviation and quite comparable negative asymmetry. The main difference resides in the kurtosis, which is, in average, noticeably larger for hedge funds indices than for the MSCI world (equity) index. Moreover, decomposing the kurtosis into two components allows us to see that most of the large deviations from the mean concern negative returns. The negative extreme events are, for both

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\(^{4}\)The statistical properties of the returns distributions for the two other data sets, CISDM and Tremont are very similar, with Tremont being slightly off, mostly because of their "Tremont Hedge Fund Index Equity Market Neutral" which has a skewness of -11.80 and a kurtosis of 155.89.

\(^{5}\)The statistical properties of the returns distributions for the two other data sets, CISDM and Tremont are very similar, with Tremont being slightly off, mostly because of their "Tremont Hedge Fund Index Equity Market Neutral" which has a skewness of -11.64 and a kurtosis of 150.99.
the average hedge fund and the MSCI world index, far more frequent than it would be the case in a Gaussian setting (values would be $3/2$ for both $K^-$ and $K^+$), while positive extreme events are quite rarer. This asymmetry in extreme values constitutes a risk. Moreover, the correlation coefficients between hedge funds indices and the equity market are very diverse, from $90\%$ to negative values. The mean value being $55.6\%$ for the HFRI set of indices.

Table 1: Moments of the HFRI Indices and MSCI world monthly returns, Long sample

<table>
<thead>
<tr>
<th></th>
<th>mean</th>
<th>Std</th>
<th>skewness</th>
<th>kurtosis</th>
<th>$K^-$</th>
<th>$K^+$</th>
</tr>
</thead>
<tbody>
<tr>
<td>average</td>
<td>0.7573%</td>
<td>0.0267</td>
<td>-1.0096</td>
<td>8.8176</td>
<td>7.2867</td>
<td>1.5309</td>
</tr>
<tr>
<td>Std</td>
<td>0.2800%</td>
<td>0.0166</td>
<td>1.0925</td>
<td>6.4477</td>
<td>6.7791</td>
<td>0.8310</td>
</tr>
<tr>
<td>min</td>
<td>0.1906%</td>
<td>0.0094</td>
<td>-3.3434</td>
<td>2.7787</td>
<td>1.0925</td>
<td>0.4220</td>
</tr>
<tr>
<td>max</td>
<td>1.7503%</td>
<td>0.0832</td>
<td>0.4169</td>
<td>28.8395</td>
<td>26.3771</td>
<td>3.5883</td>
</tr>
<tr>
<td>MSCI</td>
<td>0.4331%</td>
<td>0.0443</td>
<td>-0.9026</td>
<td>4.9299</td>
<td>4.1421</td>
<td>0.7878</td>
</tr>
</tbody>
</table>

In this table we present in columns some of the statistical properties of the monthly returns distributions, over the long observation period (1994 to 2009) for both the indices of the HFRI subset and the MSCI world index. Std denote the unbiased estimate of the standard deviation, $K^-$ is the contribution of the observations below the mean to the kurtosis, while $K^+$ is the contribution of observations above the mean to the kurtosis. Rows give additional information on the distribution of these statistical moments over the sample of HFRI indices, while the last row is the value of said moments for the distribution of MSCI world returns.

On the “short” observation period the statistical properties of the returns series on our primary sample, HFRX indices\(^6\), are rather similar. The average monthly mean return is of 0.5285\% (going from -0.6858\% to 2.1251\%), when the MSCI world index offered 0.1449\%. In terms of standard deviation, the mean value is 0.0289 (with a minimum of 0.01063 and a maximum of 0.0731) when the returns on the market index have a standard deviation of 0.0512, again seeming more risky while having a lower rate of return. In terms of skewness, the mean level over the HFRX indices is at -1.0313 (minimum: -4.2892, maximum: 1.0018) when it is -1.2019 for the MSCI world index. The average kurtosis of the returns distributions is 6.6307 (2.2714 to 26.4068) on our sample, as opposed to a slightly more modest 5.9813 for the market. For

\(^6\)This time again the properties of returns distributions for the other indices sets are strikingly similar to those on the primary sample, with once again a slight difference on the Tremont set. This difference disappears when one restricts it self to the classical hedge funds indices and forgets the Blue Chip and Sector Invest indices.
both our observation periods, the hedge funds indices seem to offer better performances than the reference index while being slightly less risky, even when taking asymmetry (skewness) and tail thickness (kurtosis) into account.

On the “short” observation period the statistical properties, presented in table 2 of the returns series on our primary sample, HFRX indices[7] and world index are rather similar. The average return is reduced, probably since the subprimes crises represents a much larger portion of the sample, and both skewness and kurtosis are slightly reduced for the hedge funds, while the equity market on the contrary presents values that are somewhat less favorable. Correlation coefficients are still quite diverse, yet the average absolute level is quite reduced at -10.39% for HFRX indices[8].

Table 2: Moments of the HFRX Indices and MSCI world monthly returns, Short sample

<table>
<thead>
<tr>
<th></th>
<th>mean</th>
<th>Std</th>
<th>skewness</th>
<th>kurtosis</th>
<th>$K^-$</th>
<th>$K^+$</th>
</tr>
</thead>
<tbody>
<tr>
<td>average</td>
<td>0.5285%</td>
<td>0.0289</td>
<td>-0.9874</td>
<td>6.1180</td>
<td>5.1206</td>
<td>0.9975</td>
</tr>
<tr>
<td>Std</td>
<td>0.5035%</td>
<td>0.0139</td>
<td>1.0459</td>
<td>4.2690</td>
<td>4.6716</td>
<td>0.9250</td>
</tr>
<tr>
<td>min</td>
<td>-0.6858%</td>
<td>0.0106</td>
<td>-4.1066</td>
<td>2.1932</td>
<td>0.3825</td>
<td>0.1189</td>
</tr>
<tr>
<td>max</td>
<td>2.1251%</td>
<td>0.0731</td>
<td>0.9591</td>
<td>23.9229</td>
<td>23.8040</td>
<td>4.5217</td>
</tr>
<tr>
<td>MSCI</td>
<td>0.1449%</td>
<td>0.0512</td>
<td>-1.1507</td>
<td>5.5333</td>
<td>4.8064</td>
<td>0.7270</td>
</tr>
</tbody>
</table>

In this table we present in columns some of the statistical properties of the monthly returns distributions, over the short observation period (2005 to 2009) for both the indices of the HFRX subset and the MSCI world index. Std denote the unbiased standard deviation, $K^-$ is the contribution of the observations below the mean to the kurtosis, while $K^+$ is the contribution of observations above the mean to the kurtosis. Rows give additional information on the distribution of these statistical moments over the sample of HFRX indices, while the last row is the value of said moments for the distribution of MSCI world returns.

The impact of these characteristics can be seen in the statistics of the tests of normality that we apply to the data. These statistics are presented in table 3. The rejection rate is rather strong for both periods, yet seems rather lower for the shorter period, confirming the impression we had from the observation of moments. A second visible element is that the Shapiro-Wilk test is more

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7This time again the properties of returns distributions for the other indices sets are strikingly similar to those on the primary sample, with once again a slight difference on the Tremont set. This difference disappears when one restricts it self to the classical hedge funds indices and forgets the Blue Chip and Sector Invest indices.

8the same reduction in absolute level is true for all data subsets, yet HFRX is the only one offering an negative average correlation.
powerful than the Lilliefors test (as expected from the literature). In any case, many hedge fund indices have returns distributions which strongly deviate from the Gaussian. The MSCI world equity index shares this characteristic, although with less important departures from normality. One may suspect that the reduction of the percentage of rejection of normality comes from the fact that certain indices have quite Gaussian returns over different shorter periods of time and see the parameters of that Gaussian change when market conditions change, yielding a mixture (and therefore non-normal) distribution for longer periods.

Table 3: Statistics of the tests of normality at 5%, applied to hedge funds indices and MSCI

<table>
<thead>
<tr>
<th></th>
<th>SW long</th>
<th>L long</th>
<th>SW short</th>
<th>L short</th>
</tr>
</thead>
<tbody>
<tr>
<td>min p-value for hedge funds</td>
<td>4.44e-16</td>
<td>1.00e-4</td>
<td>4.01e-10</td>
<td>1.00e-4</td>
</tr>
<tr>
<td>max p-value for hedge funds</td>
<td>0.6891</td>
<td>0.6920</td>
<td>0.9634</td>
<td>0.9980</td>
</tr>
<tr>
<td>mean p-value for hedge funds</td>
<td>0.0396</td>
<td>0.0598</td>
<td>0.1706</td>
<td>0.1831</td>
</tr>
<tr>
<td>rejection rate over hedge funds</td>
<td>0.90</td>
<td>0.8333</td>
<td>0.6615</td>
<td>0.4769</td>
</tr>
<tr>
<td>p-value for MSCI World</td>
<td>7.257e-5</td>
<td>0.0086</td>
<td>0.0012</td>
<td>0.1155</td>
</tr>
</tbody>
</table>

In this table we present the p-values of the tests of normality used in this paper, the Shapiro-Wilk test (SW) and the Lilliefors (L) version of the Kolmogorov-Smirnov test. They are applied to the hedge fund indices of the primary samples for both our observation period: 1994-2009 (Long) and 2005-2009 (Short). The p-value indicates, in this instance, the probability of making an error when rejecting the null hypothesis that the sample follows a Gaussian distribution. A p-value of less than 5% leads to a rejection of normality, since we apply the test with a 5% size.

Splitting the observation period into shorter time spans, coherent with the market conditions, may well reduce yet again the rejection rate for the normality hypothesis for returns distributions. However, it is clear that many hedge fund indices present distributions that are very distant from a Gaussian, exhibiting quite a large asymmetry and thick tails. This type of distribution seems like an exaggerated version of the equity returns distribution. The question is then to know if the different situation of these distributions relative to the normal distribution may explain, in times of crisis when the hedging component of hedge funds is supposed to be put to use, the differences in returns that exist between funds indices.
4 Explaining Hedge Fund Returns with Non-Normality in the Crisis

A first approach in testing the fact that hedge funds returns may cease to be explained by their co-movements with the markets in times of shocks on the market, and henceforth be in part explained by deviation from normality, we may contrast the observations of the recent periods. From the month of April 2007 until at least the end of 2009, the markets and the world economy have experienced the so called “subprime and mortgage crisis”. It is a period of instability and adverse movements, and a time when most information sources highlighted the risk and negative dimension of financial investment. One may surmise that it was a period when most hedges came into use to protect the funds, at least in part. On the other hand, the remaining of our “short” observation period was a period of quiet rise in the markets, when hedge funds were probably in majority exposed to the markets.

Opposing the results on these two (February 2005 to March 2007 and April 2007 to November 2009) sub periods may already give information on the relevance of distances to normality, especially combined with standard deviation, as a tool to understand returns in times of strong negative market movements.

Following the classical approaches to asset valuation, we propose explaining the expected returns with the betas between the given fund index and the MSCI world index. These betas draw from the CAPM theory of Sharpe (1964) and Lintner (1965). They are computed over the entire period as $\beta_i = \frac{\text{cov}(R_i, R_{MSCI})}{\sigma_{MSCI}^2}$ where $R_i$ is the returns on index $i$, $R_{MSCI}$ the returns on the MSCI world index, and $\sigma_{MSCI}^2$, the variance of the returns on this latter index. We estimate the following equation:

$$E(R_i) = \alpha + \beta \cdot \beta_i + \gamma \cdot \text{Norm}(R_i),$$

(1)

Where $\text{Norm}(R_i)$ is the statistic of a test of normality applied to returns $R_i$, and $E(\cdot)$ denotes the mathematical expectation. In order to really distinguish between the expected effects of the beta and the normality statistic, we also

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9To maintain the coherence of our results, we use the test statistic for the Lilliefors test and 1 minus the test statistic for the Sharpiro-Wilk test, since for this test a larger statistic corresponds to a distribution closer to the Gaussian.
estimate the two following sub-equations:

\[ R_i = \alpha_1 + \beta_1 \cdot \text{beta}_i, \]  
(2)

and

\[ R_i = \alpha_2 + \beta_2 \cdot \text{Norm}(R_i). \]  
(3)

These equations are all estimated over the entire period and over two different sub-samples, February 2005 to March 2007, and from April 2007 to November 2009. The results are provided in tables 4, 6 and 5.

Table 4: Linear explanation of the hedge funds returns, entire period

<table>
<thead>
<tr>
<th>Equation</th>
<th>( R^2 )</th>
<th>DW</th>
<th>Constant</th>
<th>( \beta_i )</th>
<th>\text{Norm}(R_i)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Eq. 1 with SW</td>
<td>0.5410</td>
<td>1.7203</td>
<td>0.005732</td>
<td>0.008907</td>
<td>-0.033291</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(0.000)</td>
<td>(0.000001)</td>
<td>(0.000)</td>
</tr>
<tr>
<td>Eq. 1 with L</td>
<td>0.4285</td>
<td>1.7195</td>
<td>0.010142</td>
<td>0.007536</td>
<td>-0.059654</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(0.000)</td>
<td>(0.000126)</td>
<td>(0.000)</td>
</tr>
<tr>
<td>Eq. 2</td>
<td>0.1461</td>
<td>2.0477</td>
<td>0.002789</td>
<td>0.007448</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(0.004946)</td>
<td>(0.001678)</td>
<td></td>
</tr>
<tr>
<td>Eq. 3 with SW</td>
<td>0.3493</td>
<td>1.7403</td>
<td>0.008434</td>
<td></td>
<td>-0.030545</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(0.000)</td>
<td>(0.000)</td>
<td></td>
</tr>
<tr>
<td>Eq. 3 with L</td>
<td>0.2968</td>
<td>1.6595</td>
<td>0.012625</td>
<td></td>
<td>-0.059311</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(0.000652)</td>
<td>(0.000003)</td>
<td></td>
</tr>
</tbody>
</table>

In this table are presented the coefficients of equations 2, 3 and 1 in various cases, estimated by the generalized least squares method. The normality test statistics used are the Lilliefors test statistic when L is indicated and one minus the Shapiro-Wilk statistic when SW is noted. The statistics for the least square estimation of the equations are also provided. The numbers presented between parenthesis and below the value of any coefficient are the corresponding t-probability. When this t-probability is zero to the sixth decimal place, we simply write (0.000).

Over the entire period, the full model achieves a quite good explanatory power at 54.10% or 42.85%, depending on the normality statistic included. The beta, which theoretically should be the only factor explaining the variability of the returns across the sample of hedge fund indices, is the less significant factor in the complete model, and has a rather low explanatory power (14.61%) when used alone. The statistics of the two normality tests are always fully significant and have, alone, fairly good explanatory powers, at 34.93% and 29.68%. Furthermore, the Shapiro-Wilk test statistic allows systematically a better explanation, and has a smaller t-probability, than the Lilliefors statistic.
The reason could be that the latter is less powerful and captures less of the smaller deviations from normality, or that due to its construction it does not capture the full span of said deviations.

It is to be noted that the coefficient of the normality statistic is negative, and significantly so, for all tests. This result seems a little counter intuitive, as distance from normality can be perceived as a risk, and should therefore correspond to higher premia, hence higher returns. However, we need to bear in mind that half of the observation period corresponds to the 2007-2009 financial crisis, that is to say a period of realized risks more than premia. Moreover, most models of risk and asset management tend to rely on an assumption of normality, like the CAPM.

Table 5: Linear explanation of the hedge funds returns, April 2007 to August 2009

<table>
<thead>
<tr>
<th>Equation</th>
<th>$R^2$</th>
<th>DW</th>
<th>Constant</th>
<th>$\beta_i$</th>
<th>Norm($R_i$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Eq. 1 with SW</td>
<td>0.3048</td>
<td>1.7902</td>
<td>0.004915</td>
<td>0.000004</td>
<td>-0.029245</td>
</tr>
<tr>
<td></td>
<td>(0.000028)</td>
<td>(0.998674)</td>
<td>(0.000001)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Eq. 1 with L</td>
<td>0.2487</td>
<td>1.8677</td>
<td>0.010563</td>
<td>-0.002018</td>
<td>-0.063951</td>
</tr>
<tr>
<td></td>
<td>(0.000004)</td>
<td>(0.409396)</td>
<td>(0.000012)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Eq. 2</td>
<td>0.0058</td>
<td>2.0949</td>
<td>0.001740</td>
<td>-0.001713</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.120112)</td>
<td>(0.545135)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Eq. 3 with SW</td>
<td>0.3265</td>
<td>1.7902</td>
<td>0.004916</td>
<td>-0.039632</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.000001)</td>
<td></td>
<td>(0.000001)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Eq. 3 with L</td>
<td>0.2641</td>
<td>1.8618</td>
<td>0.009908</td>
<td>-0.063658</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.000003)</td>
<td></td>
<td>(0.000012)</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

In this table are presented the coefficients of equations 2, 3 and 1 in various cases, estimated by the generalized least squares method. The normality test statistics used are the Lilliefors test statistic when L is indicated and one minus the Shapiro-Wilk statistic when SW is noted. The statistics for the least square estimation of the equations are also provided. The numbers presented between parenthesis and below the value of any coefficient are the corresponding t-probability. When this t-probability is zero to the sixth decimal place, we simply write (0.000).

The results concerning the financial crisis period, from April 2007 to the end of the sample, August 2009, are presented in table 5. During this period, the complete model does perform less satisfactorily than over the entire period. One possible explanation is that the number of observation used to computed normality statistics or betas is shorter en hence the precision of these estimate values less. More probably the crisis and its aftermath have created a lot of
financing constraints leading to behaviors that often cannot be described usual models. Nevertheless, it is striking to see that in the two variants of the total model, the beta is un-significant even at 40%. The model using solely the beta has almost no explanatory power at all. However, the two normality statistics remain highly significant in all cases, with a constantly negative coefficient, of similar values to what is obtained for the entire period, only slightly larger in absolute value. The deviation from normality seems to command a negative premium for this period, which seems quite logical considering that the stronger the exposure to risks, the more violent the impact of the crisis, in general. Lastly, the superior performances of the Sharpiro-Wilk over the Lilliefors test statistics are confirmed on this sub-sample.

Table 6: Linear explanation of the hedge funds returns, January 2005 to March 2007

<table>
<thead>
<tr>
<th>Eq.</th>
<th>SW</th>
<th>L</th>
<th>$R^2$</th>
<th>DW</th>
<th>Constant</th>
<th>$\beta_i$</th>
<th>Norm($R_i$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.6902</td>
<td>1.4133</td>
<td>0.002756</td>
<td>0.011067</td>
<td>0.007795</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(0.010794)</td>
<td>(0.000000)</td>
<td>(0.393586)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>0.6871</td>
<td>1.3726</td>
<td>0.002721</td>
<td>0.010911</td>
<td>0.004613</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(0.000004)</td>
<td>(0.000000)</td>
<td>(0.728316)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>0.6963</td>
<td>1.3534</td>
<td>0.003394</td>
<td>0.010790</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(0.000021)</td>
<td>(0.000000)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>0.0504</td>
<td>1.4814</td>
<td>0.011922</td>
<td>-0.027560</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(0.000000)</td>
<td>(0.072288)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>0.0759</td>
<td>1.4980</td>
<td>0.016575</td>
<td>-0.048640</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(0.000000)</td>
<td>(0.026349)</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

In this table are presented the coefficients of equations 2, 3 and 1 in various cases, estimated by the generalized least squares method. The normality test statistics used are the Lilliefors test statistic when L is indicated and one minus the Shapiro-Wilk statistic when SW is noted. The statistics for the least square estimation of the equations are also provided. The numbers presented between parenthesis and below the value of any coefficient are the corresponding t-probability. When this t-probability is zero to the sixth decimal place, we simply write (0.000).

The results in table [6] computed for the period preceding the crisis, from January 2005 to March 2007, is actually contrasting strongly the previous observations. Indeed, this is a relatively quiet period, a period that could be considered as “standard”, and hence the standard financial theory describes the returns far more accurately than during the crisis. The beta does indeed explain a large part of the variation of hedge funds indices returns and statistics.
of the deviation from normality are either not significant at all or just barely significant. When used in conjunction with the beta, normality statistics do not have any significance. However, when used in isolation the two statistics of normality remain significant at 10%, and Lilliefors statistic even at 5%. These statistics still negative coefficients, implying that the result observed for the other subperiod may not be only caused to the fact that crises caused a realization of risks. It is to be noticed that the Durbin-Watson statistics seem to indicate, for all the models on this period, that the residuals are on the verge of being serially correlated. However, as the order in which our indices are presented has no real economic significance, being alphabetical, this can only be interpreted as a sign that possibly some elements are missing in these models.

A negative premium attached to the distance from normality signals that this characteristic is considered desirable by investors and funds managers. However, it is clear that, ceteris paribus, more deviation seems like more risks, and in terms of moments, generally corresponds to more kurtosis and more negative skewness. Investors being averse to both, this negative premium can probably be explained by the fact that, at least in the hedge fund industry case, deviation from normality signals a sought after property. As we have noted, the relation between normality and returns being caused in the first place by the use of hedging that causes local decorrelation between funds and the market in “bad times”, one may think that larger deviations from normality correspond to a more hedged structure, and therefore a better protection against market instability while maintaining exposure to the market in good times. Such a characteristic would generate non linear dependence between the hedge fund indices returns and the market returns.

In order to verify this hypothesis, we propose testing the relation between the distance from normality and the degree by which dependence structures are non linear. A statistic indicating non linear dependence and measuring it would be the difference between the standard Pearson correlation coefficient and the Spearman rank correlation. Indeed, the rank correlation is not susceptible to non linear relations, while linear correlation only perceives, as it name says,
linear relations. The relation to be estimated is as follows:

\[(r_i - \rho_i) = \alpha + \gamma \cdot \text{Norm}(R_i),\]  

(4)

where \(\text{Norm}(R_i)\) is one of our two non-normality statistic for a given test of the returns on the \(i^{th}\) of the 65 hedge fund indices, over the entire sample period, January 2005 to August 2009, \(r_i\) is Pearson’s correlation between the returns on index \(i\) and the MSCI world index, and \(\rho_i\) is the Spearman’s rank correlation between the returns on index \(i\) and the MSCI world index.

Therefore, the difference between Pearson and Spearman correlations is a proxy measure of the degree of non-linearity of the dependence structure. It is an element that the traditional beta fails to capture. The results are presented in table 7 again using \(1 - W\) as the Shapiro-Wilk statistic.

Table 7: Relation between non linearity in correlation and statistics of normality

<table>
<thead>
<tr>
<th></th>
<th>adjusted (R^2)</th>
<th>Durbin-Watson</th>
<th>Constant</th>
<th>(\text{Norm}(R_i))</th>
</tr>
</thead>
<tbody>
<tr>
<td>Shapiro-Wilk</td>
<td>0.3125</td>
<td>1.8887</td>
<td>0.034447</td>
<td>-0.550592</td>
</tr>
<tr>
<td></td>
<td>(0.020916)</td>
<td>(0.000001)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Lilliefors</td>
<td>0.3399</td>
<td>1.9052</td>
<td>0.127365</td>
<td>-1.209491</td>
</tr>
<tr>
<td></td>
<td>(0.000026)</td>
<td>(0.000)</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

In this table are presented the coefficients of equation 4. These coefficients were estimated over the February 2005 - November 2009 period by the least squares method. The statistics for said estimation are also provided. The numbers presented between parenthesis and below the value of any coefficient are the corresponding t-probability. When this t-probability is zero to the sixth decimal place, we simply write (0.000).

It appears that indeed there is a certain degree of association between distances from normality and non-linearity of the dependence with the market over the period considered (February 2005 - November 2009). Moreover, the larger the deviation from normality over the period, the more non-linearity there is in the dependence structure. This makes sense, especially if the large deviations from normality are caused by the strong use of derivatives and dynamic trading strategies. Indeed, the funds resorting to these strategies are the funds who will be best able to change their dependence with the market in bad times, thus generating non-linear relations. The results obtained for the three other data sets were rather similar. However, the relation was much...
stronger (adjusted $R^2$ of 60.11%) for the CISDM indices, and quite weak for the Tremont indices (adjusted $R^2$ of 2.08%, becoming 19.12% when only “classical hedge funds indices” are taken into account).

5 The dynamic of the relations between normality and hedge funds returns

We have observed in the previous section that the average returns on hedge funds indices, over the last 5 years, can be explained to some extend by the distance from normality. Moreover, we have noticed that this relation is much stronger during the April 2007 - November 2009, covering the “subprimes crisis”, than during the more quiet February 2005 - March 2007 period. These findings, as well as the fact that deviations from normality are associated with a non-linear dependence structure with the market and commend a negative premium, seem to support our hypothesis that deviation from normality are in part a signal of the use of derivatives or dynamic strategies in order to “hedge the hedge fund”, and constitute an element of the risk to which a fund is exposed, especially in times of market turmoil.

To get a more detailed perception of the relations that may cause the emergence of deviation from normality as a factor of hedge funds returns at certain periods of time, and the interaction between non-normality and the risk taken by investors when selecting a hedge fund, we will now make use of the full length sample, ranging from April 1994 to November 2009. This time the primary sample will be the 30 HFRI indices that exist over the period.

Since the relation between the deviation from normality and the mean returns of the hedge funds indices could be a sign of disconnection between many of the funds and the market by the use of dynamic trading strategies or derivative securities, the intensity of this relation evolves over time. We have seen already that over the April 2007- November 2009 period, this relation was quite stronger than over the February 2005 - March 2007 period. It would make sense that funds manager exercise their derivatives or initiate a change of strategy when they foresee adverse times while they would maintain a degree of connection with the market (maybe amplifying its movements) when they
anticipate quiet times. Therefore, it would be very interesting to study how
the association between deviation from normality and mean returns evolve
over time and if it really corresponds to the shocks happening on the market
or some other factors.

To judge of market conditions and have estimates of the elements hedge
funds managers possibly use to anticipate the market evolution and decide
whether they need to separate their performances from the market, we use
two different set of data. The first one is the VIX volatility index. This
index, traded on the Chicago Board Options Exchange (CBOE), is a measure
of market expectations of near-term volatility conveyed by S&P 500 stock
index option prices. It makes use of the implied volatility extracted from the
prices of highly traded options. This index will proxy the perception market
participants have of future uncertainty on equity prices. A second indicator is
the dollar price of an ounce of gold, which, as gold is often perceived as a refuge
against adverse equity market times, proxies for the anticipated direction of
the market. A rise in gold prices being the signal that many participants
anticipate a decrease in equity valuation.

Even with the “long sample” going from May 1994 to November 2009, we
only have 187 observations. To obtain a reliable estimate of the average return
or the deviation from normality, we need at least 20 observations, ideally 30
or more. Therefore, we decided to make use of moving a moving window
approach in order to retain enough observation while still having consistent
estimated for both the deviations from normality and the mean returns over a
given period. This allows us to study a new time series containing 157 points.
Obviously, due to the very nature of the method used for obtaining this series,
serial autocorrelation will be quite present, especially in the residuals of any
least square model estimation. Moreover, any shock or rapid change of a
relation happening at a given date will start affecting our results 30 month
before its occurrence, and may still affect it for 30 months after. Therefore we
will consider the moving period going from date $t$ to date $t + 30$ as being the
relation “at date $t + 30$”.

Within this framework we estimate equation 3 for each of the 157 windows
of 30 months, over the 30 indices of the HFRI sub-sample. The coefficient
of determination of the least square estimations are plotted in figure 1, along
with the monthly maxima of the VIX index.

Figure 1: Time Evolution of the Returns/Normality Relation

Plotted in this figure are the time evolution of the volatility index VIX on top, and the time series of the evolution of the $R^2$ of the estimation of equation 3 at the bottom. The scale of the two trajectories is quite different in reality, with the VIX ranging between 12.44 and 89.53 and the $R^2$ between 0 and 41.36%. The only commonality is the time scale.

It can be observed from this figure that the general shape of both curves are quite similar. Starting at a rather low point in November 1996, they increase slowly, albeit with rather strong variability, up until 2000-2001. From then on a slow decrease takes place, initially with a large degree of variability, and then, from July 2003 to the end of 2006, with very little variability. November 2006 marks a low point for the market volatility but sees a rather brusque increase in the relation between returns and normality. It is possible that at this point, the more savvy market analysts, many of them working for or being listened to by hedge funds, start perceiving the disequilibria in debt markets and anticipate a crash. Sometimes later the level of the volatility index also rises suddenly and experiences again some variance. In September 2008 both the volatility of the market and the intensity of the relation between distance
from normality and mean returns jump up at the time when Lehman-Brothers filled for Chapter 11 bankruptcy protection (on the 15th of the month). Then, after having remained at historically high levels for some times, both the index and the relation between normality and returns fall sharply but still remain at significant levels.

For a more precise estimation of the fitting of the changes in the relation between returns and deviation from normality and the forecasted market conditions, we estimate with least squares regression the following models:

\[ R^2_{r,N} = \alpha + \beta \cdot VIX \]  
(5)

and

\[ R^2_{r,N} = \alpha + \beta \cdot VIX + \gamma \cdot GOLD, \]  
(6)

where \( R^2_{r,N} \) is the series of coefficients of determination from the estimations of equation 3 for the 157 thirty month subperiods, VIX is the corresponding monthly high of the CBOE volatility index and GOLD is the dollar price of an ounce of gold.

<table>
<thead>
<tr>
<th></th>
<th>( R^2 )</th>
<th>DW</th>
<th>Constant</th>
<th>GOLD</th>
<th>VIX</th>
</tr>
</thead>
<tbody>
<tr>
<td>Eq. 6 with SW</td>
<td>0.7250</td>
<td>0.6070</td>
<td>-0.151078</td>
<td>0.00233</td>
<td>0.003815</td>
</tr>
<tr>
<td></td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
</tr>
<tr>
<td>Eq. 6 with L</td>
<td>0.3919</td>
<td>0.4898</td>
<td>-0.051760</td>
<td>0.00145</td>
<td>0.001736</td>
</tr>
<tr>
<td></td>
<td>(0.000051)</td>
<td>(0.000)</td>
<td>(0.000004)</td>
<td>(0.000)</td>
<td>(0.000)</td>
</tr>
<tr>
<td>Eq. 5 with SW</td>
<td>0.3907</td>
<td>0.3422</td>
<td>-0.067529</td>
<td>0.000208</td>
<td>0.002324</td>
</tr>
<tr>
<td></td>
<td>(0.00003)</td>
<td>(0.986522)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
</tr>
<tr>
<td>Eq. 5 with L</td>
<td>0.1663</td>
<td>0.3588</td>
<td>0.000208</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.986522)</td>
<td>(0.000)</td>
<td></td>
<td></td>
<td>(0.000)</td>
</tr>
</tbody>
</table>

In this table are presented the coefficients of equations 6 and 5 in various cases, estimated by the generalized least squares method. The normality test statistics used are the Lilliefors test statistic when L is indicated and one minus the Shapiro-Wilk statistic when SW is noted. GOLD denotes the price of an ounce of gold, while VIX is the CBOE index of market volatility. The statistics for the least square estimation of the equations are also provided. The numbers presented between parenthesis and below the value of any coefficient are the corresponding t-probability. When this t-probability is zero to the sixth decimal place, we simply write (0.000).

The results, presented in table 8, manifest a very strong association between the intensity of the role of departures from normality in explaining hedge funds
returns and both the VIX index and gold prices. The quality of the relation seems to be quite weaker when the statistic used to measure deviations from normality is Lilliefors'. However, it has to be noted that even if it always performs less convincingly than the Shapiro-Wilk statistic on all sets of indices, it is only with the HFRI indices that the relation is so weak, as the adjusted $R^2$ for equation 6 with Lilliefors test statistic are 42.11% and 72.26% on the CISDM and Tremont data sets, respectively.

Moreover, the direction of the relation seems quite clear, with highly significant coefficients. The higher the VIX, the more expensive the ounce of gold, the better mean returns for hedge funds indices are explained by deviations from normality. As the VIX is a measure of the expectations about market volatility and gold price a inverse proxy for the anticipations of equity price growth, it seems that the relation between hedge funds returns is stronger when there is expectation of “bad times”, which can usually be defined as periods where the market suffers downward shocks and hectic movements...

Having more observations per index in this “long sample”, we can also look more closely at the relation between normality and the dependence structure between hedge funds and equity market returns. Indeed, it now seems clear that a significant relation between returns and departure from normality does exist, particularly when bad times are expected by market participants. This seems to confirm that the relation appears at the time hedge funds managers modify their dynamic trading strategies or exercises their derivatives in order to real get hedged from the markets. However, the fact that the deviations from normality correspond generally to a negative risk premium remains to analyse more deeply. We saw that a significant, albeit not overwhelming relation exists between deviations from normality and the importance of non-linear dependencies between hedge fund and market portfolio returns. This seems to indicate that the negative risk premium attached to non normality could be paid in expectation of non linear relation between the performances of the market and that of the hedge fund, allowing the latter to benefit from the good times of the former while remaining largely unaffected by its bad times.

We therefore propose to check again for the relation between normality and non-linearity in the dependence structure over this longer period by re-estimating equation 4. Then, making use of the larger size of our observation...
period, we look at the relation that may exist between deviation from normality computed over all the observations and the difference between Spearman’s \( \rho \) and Pearson’s correlation, computed only for the months when the return on the MSCI world index is negative. The idea is that, if indeed the deviations from normality signal the use of dynamic trading and derivatives, the non-linearities in the dependence structure that are linked to these deviations from normality will be concentrated at negative times.

Table 9: Relation between non-linearity in correlation and statistics of normality

<table>
<thead>
<tr>
<th></th>
<th>adjusted ( R^2 )</th>
<th>Durbin-Watson</th>
<th>Constant</th>
<th>( Norm(R_i) )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Shapiro-Wilk</td>
<td>0.3040</td>
<td>1.8256</td>
<td>0.017493</td>
<td>-0.435673</td>
</tr>
<tr>
<td></td>
<td>(0.039150)</td>
<td>(0.001589)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Lilliefors</td>
<td>0.2695</td>
<td>2.0799</td>
<td>0.061049</td>
<td>-0.903169</td>
</tr>
<tr>
<td></td>
<td>(0.000026)</td>
<td>(0.003290)</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

In this table are presented the coefficients of equation 4. These coefficients were estimated over the May 1994 - November 2009 period by the least squares method. The statistics for said estimation are also provided. Again we use one minus the Shapiro-Wilk statistic to maintain the relation “larger statistic equals more distance from normality”. The numbers presented between parenthesis and below the value of any coefficient are the corresponding t-probability.

Table 9 presents the results of the estimation of equation 4 over the May 1994 - November 2009 period, computing the correlations on the full sample. The results are strikingly similar to those observed for the HFRX indices over the 2005-2009 period. The only small difference being that the Shapiro-Wilk statistic recovers its usual position of best performing measure of deviation from normality. Therefore, even for this large period of time and for these different indices, approximately 30% of the variability between indices in terms of non-linearity of the dependence structure with the equity market can be explained by the variability of their deviations from normality.

We present the results of the estimation of equation 4 on the 1994-2009 period, with dependence structure evaluated only on the months where the market presented negative returns, in table 10. As expected, the intensity of the relation increases noticeably compared to what it is when all observations are included in the dependence estimation. The more the Spearman \( \rho \) is smaller
Table 10: Relation between non-linearity in correlation at “bad times” and statistics of normality

<table>
<thead>
<tr>
<th></th>
<th>adjusted $R^2$</th>
<th>Durbin-Watson</th>
<th>Constant</th>
<th>Norm($R_t$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Shapiro-Wilk</td>
<td>0.5617</td>
<td>1.7522</td>
<td>-0.056810</td>
<td>-1.278848</td>
</tr>
<tr>
<td></td>
<td>(0.042760)</td>
<td>(0.000002)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Lilliefors</td>
<td>0.5094</td>
<td>2.0511</td>
<td>0.073855</td>
<td>-2.681451</td>
</tr>
<tr>
<td></td>
<td>(0.150183)</td>
<td>(0.000010)</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

In this table are presented the coefficients of equation 4, when evaluating the non-linearity of the dependence structure only at months where the market index exhibits negative returns. These coefficients were estimated over the May 1994 - November 2009 period by the least squares method. The statistics for said estimation are also provided. Again we use one minus the Shapiro-Wilk statistic to maintain the relation “larger statistic equals more distance from normality”. The numbers presented between parenthesis and below the value of any coefficient are the corresponding t-probability.

relative to the Pearson correlation, the less linear the dependence structure between the hedge fund and the market indices. This increase in non-linearity corresponds as well to an increase in distance from normality thus indicating that indeed the deviation from normality signals, at least in the hedge funds industry, larger degrees of non-linear relation with the market when the market performs negatively. Being able to react differently from the market when it looses, and similarly to market when it gains, may indeed be a rather attractive feature for an investor.

In the specific case of hedge funds, which make heavy use of derivatives and dynamic trading strategies, said possibility to have different types of relation with the market in negative times is certainly linked to a proportion of hedging, which is attractive as it means being protected when it really matters while possibly benefiting from good market performances.

6 Concluding Remarks

Portfolio and assets managers make an increasing use of both dynamic rebalancing and derivatives, in order to hedge against certain risks, increase their exposure to others and try to optimize their risk/return relation. Thus, they follow a path that has already largely been used by hedge funds. Therefore, it is interesting to understand how hedge funds relate to the market, and how the
returns and risk of these alternative investment vehicles evolve through time.

More precisely, we suppose that hedge funds use these advanced financial techniques and securities in order to benefit from the market during bullish times, while they try to have inverse exposure to the market in bearish periods. To transition between these two attitudes, funds managers must change their dynamic trading strategies or exercise derivatives. These elements contribute to both strongly non-Gaussian returns distributions and change in the dependence structure between the fund and the market. Therefore the deviation from normality of the returns distributions should be a factor contributing to explaining the returns at the times when funds disconnect themselves from the market, change their exposure to systematic risk or simply put, exercise their derivatives in order to hedge their investments.

We show that, indeed, the level of deviations from normality in hedge funds indices returns, measured by either a Shapiro-Wilk or a Lilliefors test of normality statistic, explains a significant part of the returns dispersion, particularly during the recent “subprimes” crisis. When deviation from normality has a significant relation with returns it commands a negative risk premium. Moreover, we have seen that at the moment of Lehman Brothers bankruptcy and during some times after, the classical beta almost totally stopped having any explanatory power on funds returns. However, during the period preceding the crisis, beta had a clear explanatory power, while deviation from normality could explain very little.

Analyzing the relations between normality statistics and hedge funds returns over a larger period of time showed us that the intensity of said relations was much increasing with anticipations of volatility and bearish equity markets. This indicated further that, as a fact, deviations from normality in hedge funds returns indicate, just before adverse changes in market conditions, a modification of their dependence with the market. An estimation of the relation between statistics of the deviation from normality and the degree of non-linearity in the dependence between hedge funds and the MSCI world equity index further showed that a large deviation from the Gaussian distribution is strongly associated, for hedge fund indices, with highly non-linear dependence between indices and the market returns, particularly at times when the market exhibit negative returns.
It is rather interesting to see that, in the case of hedge funds, the fact that returns deviate from the Gaussian distribution is not considered as a risk, even if most alternative models of choice under uncertainty say that it should. We believe it is so because deviation from normality simultaneously indicates that more extreme losses may take place (high kurtosis), or that the probability of a given loss is larger than that of the equivalent gain (negative skewness), and that dynamic trading and derivatives may be used to alter in a desirable way the dependence with the market. This second property, especially in volatile, uncertain market conditions, seems to clearly outweigh the first for hedge funds investors.

References


