Dedicated Short Bias Hedge Funds – Just a one trick pony?

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Abstract

During the recent period of significant market unrest in 2007 and 2008 dedicated short bias (DSB) hedge funds exhibited extremely strong results while many other hedge fund strategies suffered badly. This study, prompted by this recent episode, investigates the DSB hedge funds performance over an extended sample period, from January 1994 to December 2008. Performance evaluation is carried out both initially at the individual fund level and then on an equally weighted dedicated short bias hedge fund portfolio using three different factor model specifications and both linear and nonlinear estimation techniques. We conclude that DSB hedge funds are indeed more than a one trick pony. They are a significant source of diversification for investors and produce statistically significant levels of alpha. Our findings are robust to the specification of traditional and alternative risk factors, nonlinearity and the omission of the flattering credit crisis period.

Dedicated Short Bias Hedge Funds – Just a one trick pony?

The period between early 2007 and late 2008 is one which most hedge fund managers would prefer to forget. Market participants witnessed unprecedented events over this period; the collapse of Lehman Brothers, rapidly falling prices in asset markets, and investors rushing to withdraw funds from investments. One hedge fund investment strategy, dedicated short bias, (hereafter DSB) revelled in these conditions. DSB hedge funds are pooled investment vehicles which focus their energy on short selling as the main source of their returns. As such they make money when the markets fall in value, the perfect vehicle to capitalise on the market conditions of 2007 and 2008. Some critics may argue that DSB hedge funds strong performance during the "Credit Crisis" was just a product of the times. A period when all forces conspired to provide DSB funds with ideal conditions in which to prosper and that DSB is a trading strategy which is flattered by such periods. However following an in-depth investigation of the performance of these hedge funds we find that DSB hedge funds are much more than just a one trick pony. Our results suggest that not only do DSB funds provide excellent diversification benefits and protection in market down turns but they also are an investment strategy which provides significant levels of alpha - the holy grail of hedge fund investment.

There is significant debate on the classification of alpha and whether hedge funds really produce "superior returns" due to hedge fund manager's skill, or whether the superior returns reported as alpha in the literature are simply the misspecification of "alternative beta"(Jaeger and Wagner [2005]). During our research we examine four distinct but complementary performance measurement models. Our first model consists of traditional risk factors and as such decomposes hedge fund returns into alpha and "traditional beta". Our second model consists of an alternative risk factor which is designed to capture the specific risk return features of DSB hedge funds, as such it decomposes the returns of the DSB hedge fund strategy into alpha and "alternative beta". Our third model consists of traditional and alternative risk factors and as such decomposes the returns of the DSB hedge fund strategy into alpha, traditional beta and alternative beta. Results from estimating the two models which include a risk factor designed specifically to capture the nonlinear profile of DSB hedge funds suggest the strategy exhibits statistically significant levels of alpha. Further, when we estimate our final linear model across two distinct time periods, before and after the current financial crisis we find alpha to be statistically significant during the less favourable pre credit crisis period. Finally, in our fourth specification, to allow for time variation in risk exposure, we model the returns of DSB hedge fund managers using a nonlinear logistic smooth transition regression specification. Results from estimating this model find further evidence of hedge fund manager alpha.

So what does all this talk of alpha mean for investors? Well it means that DSB hedge funds may be an extremely useful and complementary asset for investors to add to their portfolio. Firstly, DSB hedge funds have the ability to earn positive returns during market downturns (favourable trading conditions) which will act as a hedge against losses suffered by other assets in the investor's portfolio over the same time period. Secondly if these claims of "alpha" production during periods of unfavourable trading conditions are substantiated then investors gain a second time, as despite the fact trading conditions are unfavourable the manager's skill at implementing a DSB trading strategy will make it an efficient hedge against future falls in asset prices.

Hedge fund data and difficulties developing performance measures

It has been well documented that various hedge fund strategies exhibit a number of unusual statistical characteristics (See Brooks and Kat [2002], Fung and Hsieh [2001] and Mitchell and Pulvino [2001] for examples). These characteristics usually fall under three main headings; non-normality, nonlinearity and autocorrelation. These statistical characteristics make hedge funds performance difficult to measure and/or benchmark. Not only are the returns series of hedge funds distinct from those of traditional asset classes such as stocks and bonds, they are also often extremely different from each other on an individual level. Therefore it is important to analyse the performance of any hedge fund strategy in isolation to gain a true understanding of its performance. We therefore examine the performance of DSB hedge funds in isolation to determine the statistical characteristics associated with this specific strategy, and correct for these when developing performance measures for DSB hedge funds. The layout of the rest of the paper is as follows; the next three sections identify DSB hedge funds main statistical characteristics. Having identified these, we then examine the performance of the DSB funds against three distinct linear models and over two time periods, before estimating a nonlinear specification. Finally we conclude with a discussion of our main findings.

Non-normality

Non-normality is a statistical characteristic associated with most hedge fund strategies (See Fung and Hsieh [1997], Mitchell and Pulvino [2001], Agarwal and Naik [2004], and Getmansky et al [2004] for examples). This non-normality is usually characterised by negative skewness and excess kurtosis. Brooks and Kat [2002], for example, find that hedge funds indices are on average negatively skewed and suffer from excess kurtosis. Negative skewness indicates an increased probability of an extreme loss while excess kurtosis indicates a high probability of larger gains or losses than in the case of a normally distributed data set. The events of late 2007 and early 2008 showed how risky it is to be exposed to an investment strategy with negative skewness. Funds which were marketed as low risk and well diversified such as equity market neutral and equity long/short had some of the largest losses during the credit crisis.

We utilize the TASS database as our source of hedge fund returns. In total there are forty eight DSB funds listed in the database. Of these forty eight, thirty three are dead at the end of December 2008.

However, there are quite a few funds with multiple share classes listed in the database. We remove all duplicate funds and are left with a final sample of thirty five funds. Of these thirty five DSB funds, twenty four are dead at the end of 2008. Looking at exhibit 1, which reports descriptive statistics for the sample it is clear that these norms of high kurtosis and negative skewness are not the case for DSB hedge funds.

INSERT EXHIBIT 1 HERE

Exhibit 1 shows that in the case of DSB hedge funds there are relatively low levels of both skewness and kurtosis and that the asymmetry which they exhibit is on average positive not negative. What does this mean for investors? Interestingly, the information presented above indicates that DSB hedge funds offer excellent diversification benefit when mixed with other asset classes such as stocks, bonds, and most other hedge funds strategies, which generally exhibit negative skewness and kurtosis. DSB hedge funds may provide a hedge to the downside risk inherent in not only traditional portfolio assets but also other hedge funds due to the fact that they appear to suffer from negative skewness and high kurtosis while DSB hedge funds exhibit positive skewness on average and low levels of kurtosis.

Autocorrelation

Autocorrelation is another statistical characteristic which hedge fund returns series tend to exhibit (see Brooks and Kat [2002], Getmansky et al [2004] and Bollen and Pool [2008] for further discussion). Autocorrelation in hedge fund returns is often due to hedge funds investments in illiquid or difficult to price assets. The existence of autocorrelation in a returns series means that the true risk associated with the hedge fund strategy will be underestimated with a corresponding overstatement of performance. So what is the situation as regards autocorrelation and DSB hedge funds? Again, it appears that DSB hedge funds are on average free from this characteristic of hedge funds.

INSERT EXHIBIT 2 HERE

The findings of no autocorrelation in DSB hedge funds seem sensible given their short selling mandate. A short selling strategy is one where the investor borrows a security, sells it at the current price hoping to profit in the future by buying the security at a later date, hopefully at a cheaper price , and returning it to whoever they borrowed the security from. It would therefore be unwise for a fund running a DSB trading strategy to short sell illiquid stocks which may be difficult both to borrow and/or cover.

Nonlinearity

The majority of hedge fund returns series have been found to be nonlinearly related to market returns (see Fung and Hsieh [1997, 2004], Mitchell and Pulvino [2001] and Agarwal and Naik [2004] for further discussion.) This means the returns of many hedge funds typically exhibit a nonlinear relationship with the risk factors that are the source of their returns. A relationship which is nonlinear can be difficult to model. Traditional linear factor models such as CAPM are inadequate at modelling this relationship. Therefore a large body of research, both academic and industry driven, has emerged surrounding nonlinear hedge fund performance measurement. Fung and Hsieh's [2004] seven factor asset-based style factor model (hereafter ABS factor model) is a well defined model which has become one of the leading benchmark performance measures in the hedge fund industry. Fung and Hsieh [2004] find that this specification it to be capable of explaining up to 80% of the monthly return variation for a diversified hedge fund portfolio. This is compared to less than 25% using regression factors based on traditional asset classes.

A factor based model - Fung and Hsieh ABS factor model

The Fung and Hsieh [2004] ABS factor model specifies three trend following factors for bond (BdOpt), currency (FXOpt) and commodities (ComOpt), two equity orientated risk factors; an equity market factor (S&P) and a size spread factor(SCLC) and two bond orientated risk factors; a bond market factor (10yr) and a credit spread factor (CredSpr). Using these risk factors we initially estimate the following regression:

$$R_t^i = \alpha_i + \sum_{i=1}^{N} \beta_k^i F_{kt} + e_t^i \tag{1}$$

Where R_t^i is the return on hedge fund i during month t, α_i is the intercept for hedge fund over the regression period, β_k^i is the average factor loading of hedge fund *i* on the *k*-th factor during the regression period, F_{kt} is the excess return on the *k*-th factor during month t, (*k* = 1,..., K) where the factor could be any of the seven ABS factors and $e_t^i$is an error term.[1]

Due to their construction, these ABS style factors capture much of the option like features of hedge funds while preserving the general lack of correlation with standard asset benchmarks. They thereby replicate the risk return profile of the hedge funds much better than a traditional linear benchmark model.

A parsimonious Fung and Hsieh ABS factor model

Given that Fung and Hsieh's [2004] model is constructed to estimate the performance of a broad based hedge fund portfolio it includes a number of independent variables which might not be related to DSB returns. To identify the most appropriate factors we carry out a stepwise regression procedure to identify the ABS factors applicable to our DSB hedge fund data set. Having carried out the stepwise regression on our DSB hedge fund series we find the risk factors which the DSB hedge fund has significant risk exposure to are the two equity orientated risk factors; S&P and SCLC.

[1] Data for the trend following factors is downloaded from David A. Hsieh's database and the remaining factors are constructed using data from DataStream.

INSERT EXHIBIT 3 HERE

The results reported the first panel in exhibit 3 are for the equally weighted DSB (hereafter EWDSB) hedge fund portfolio, formed from the thirty five funds in our data set, benchmarked against S&P and SCLC. The result of negative betas on both the equity market risk factors is as expected given the nature of the strategy.[2] DSB hedge funds have an average S&P 500 beta of -0.9146 and an average small cap spread of -0.5288. Both of these findings are reasonable as a negative exposure to the market is consistent with their short selling mandate and negative exposure to small cap stocks is also quite rational due to the higher potential for company failure (and therefore price decline) of small cap stocks.

Although the parsimonious Fung and Hsieh [2004] model explains a large portion of the performance of the strategy (adjusted R^2 of 74.40%), neither of the factors exhibit the option like features of hedge fund returns so we may not be capturing "alternative beta" with this model. Next, to investigate this possibility, we construct a theoretically appealing option based factor which should more closely replicate the nonlinear risk return profile of the DSB hedge fund series.

Development of put option risk factor

As mentioned previously hedge fund returns have been found to be nonlinearly related to traditional asset returns. Fung and Hsieh [2001] find that the returns for a specific trading strategy (commodity trading advisors - CTA's) tend to exhibit option like features. These returns tend to be large and positive during the best and worst performing months of asset markets. Mitchell and Pulvino [2001] also find evidence of nonlinearity in hedge fund returns for a different strategy – risk arbitrage. The results of this study indicate that risk arbitrage returns are uncorrelated with market returns in flat and appreciating markets. However, in months where the market is severely depreciating, risk arbitrage and equity market returns are positively correlated. Mitchell and Pulvino [2001] find that risk arbitrage returns are akin to writing a put option on the market.

In a similar manner we can consider the payoff to the DSB strategy to be a long put option. The DSB strategy recognises small losses on an ongoing basis with infrequent large profits. If a risk arbitrage strategy's risk profile can be proxied by taking a short position in an equity index put option then it seems reasonable that the risk associated with a DSB strategy could be proxied by a long put option position.

We construct the payoff of this put option risk factor in the spirit of Agarwal and Naik [2004] but we construct a portfolio mimicking the payoff to a long put option, by trading in the underlying rather than buying and selling the actual options. This is done for two reasons. First, trading the underlying

[2] Results at the individual fund level are similar and available from the authors on request.

stock is a much more cost effective manner of replicating the DSB hedge funds trading strategy than trading options directly. Second, options trade price data is difficult to obtain. We replicate the option payoff using a Black-Scholes pricing model to determine the delta of an at-the-money (ATM) put option with two months to expiry.

The delta of a European put is:

$$\Delta = e - qt[N(d_1 - 1)] \tag{2}$$

where

$$d_1 = \frac{\ln(\frac{S_0}{K}) + \left(r - q - \frac{\sigma^2}{2}\right)T}{\sigma\sqrt{T}} \tag{3}$$

and Δ is the delta of the option, *q* is the dividend yield on the underlying asset, *T* is the time to expiry of the asset, S_0 is the asset's share price on any given day, *K* is the fixed strike price of the option. *r* is the return on the risk free asset the market yield (three-month constant maturity U.S. Treasury securities) and σ is the volatility of the option (annualized standard deviation for the previous trading year).[3]

The mechanics of the replication strategy are as follows: on the first day of trading in January we calculate the delta of an ATM put option expiring in February (two-months to expiry). Using the total return (including dividends) on the S&P 500 as the underlying, we take a position which would produce the same factor return as trading the put option directly. The delta of the ATM put option changes on a daily basis as the inputs (time to maturity, stock price, risk free rate, volatility and dividend yield) of the Black Scholes pricing model vary. We therefore buy or sell the underlying stock on a daily basis relative to the changing delta of the option and compound the daily return into a monthly return. At the end of each month the process begins again. For example for February we would calculate the delta of an ATM put option with a March expiry and rebalance our stock position to mimic this option. This produces a time series of monthly returns which we then use to proxy the risk profile of the DSB hedge fund strategy.

The descriptive statistics for the put option risk factor (PutOpt) are reported in exhibit 4.

INSERT EXHIBIT 4 HERE

The put option variable has an average return of -0.0055. In stable and upward trending markets DSB hedge funds would be expected to recognise small losses. Given that over the period January 1994 –

[3] Data for constructing the put option factor is from DataStream.

December 2008 (the duration of our study) prices in the markets were on average on an upward trajectory a small negative average return for our risk factor seems appropriate. The put option risk factor exhibits low levels of positive skewness at 1.22 and has excess kurtosis of 5.26. We find no evidence of autocorrelation in the put option return series. Due to the put option risk factor's construction it shares many characteristics of the DSB hedge fund series, positive skewness, low levels of excess kurtosis, and no autocorrelation. As such it appears to be both theoretically and statistically an appropriate benchmark for DSB hedge fund returns. We can see from exhibit 5 that the put option mimics the return profile of the DSB hedge fund strategy quite closely.

INSERT EXHIBIT 5 HERE

The results from estimating our put option risk factor model are reported in the second panel of exhibit 3. We can see that both the put option risk factor coefficient and the alpha figure are statistically significant at the 1% level. As expected the DSB hedge funds have an average put option beta which is positive. With this model, the alpha figure is a statistically significant 1% per month. This model improves on the linear model as it successfully incorporates the nonlinear risk return profile which DSB hedge funds exhibit as a result of their use of unconventional investment technique (i.e. short selling). The alpha of 1% per month seems an extremely impressive level of return to attribute to manager's skill but we would caution the reader that the explanatory power of this model is lower than the linear factor model. Ignoring the exposure to traditional risk factors (traditional beta) may lead to misspecification. To avoid this we construct a combined factor model which will decompose the returns of our DSB strategy into traditional beta, alternative beta and alpha.

A combined traditional and alternative beta factor model

The combined model consists of our specifically constructed put option risk factor, PutOpt, along with the Fung and Hsieh [2004] ABS factors which were found to be significant explanatory variables (S&P and SCLC). The traditional risk factors such as S&P and SCLC are quiet adept at explaining the returns of the funds that result from the assets they invest in, but these factors do nothing to explain the returns due to the dynamic manner in which the fund manager invests (use of short selling techniques in the case of DSB hedge funds). Whereas with the PutOpt risk factor, it explains the returns of the fund which are due to the dynamic nature of the DSB investment strategy but it does not fully capture the returns attributable to the underlying asset. By constructing a model which includes both types of risk factors we have a model which is both theoretically appealing and has a high level of explanatory power.

We can see from the third panel of exhibit 3 that the combined factor model has the greatest explanatory power of the three models we have examined thus far, at 76.30%. We can also see from exhibit 3 that all our explanatory variables (PutOpt, S&P and SCLC) and also the alpha figure are statistically significant. Not only are the coefficients statistically significant but they also have the anticipated sign, as our EWDSB hedge fund portfolio is negatively related to both our equity risk factor and positively related to our put option risk factor. As with our previous model the alpha figure in our combined model is again statistically significant, this time at a level of forty three basis points per month. This equates to manager skill of approximately 5% per annum. This level of alpha is reasonable and in line with findings from other studies (see Jaeger and Wagner [2005] and Kat and Miffre [2008] for examples).

Alpha – The result of favourable trading conditions?

Our sample period (Jan 1994 – December 2008) encompasses one of a long period of sustained price increases, accompanied by several shorter periods of price declines. Any fund with a negative exposure to equity factors over this time period would be facing a constant battle trying to produce positive returns in unfavourable trading conditions. Therefore if a DSB hedge fund produces positive returns it seems reasonable to assume that these would be as a result of DSB hedge fund managers exhibiting skill in implementing their short selling strategy. A concrete illustration of this point can be seen by examining the performance of the DSB strategy omitting the very favourable credit crisis period of 2007 and 2008. January 2007 is chosen as the turning point to allow for two full years of data relating to the "Credit Crisis" time series. The findings of the sub-period analysis are displayed in exhibit 6.

INSERT EXHIBIT 6 HERE

As we can see from this sub-period analysis DSB hedge funds managers are adept at producing alpha in periods of less favourable market conditions. This makes practical sense as when market conditions are unfavourable the fund managers must implement their trading strategy extremely skilfully in order to survive. We can also see from exhibit 6 that in the period where market conditions were favourable (i.e. in 2007 and 2008) the only significant explanatory variable was S&P500.

These findings that DSB hedge fund managers are skilful in implementing DSB hedge fund trading strategy in periods of unfavourable trading conditions, further supports the argument that DSB hedge funds are a useful diversification tool. Not only do DSB hedge funds demonstrate the ability to produce positive excess returns in periods of market down turns but due to their skill at implementing a short selling trading strategy they also manage risk efficiently in periods when market conditions are less favourable.

Allowing for time variation in risk exposure

Much recent research has demonstrated the importance of allowing for time variation in risk factor exposure when modelling the returns of hedge funds (See for example Bollen and Whaley [2009]). Conversations with DSB hedge fund managers support these findings. Typically as opportunity sets evolve managers modify positions, gradually increasing short exposure in anticipation of markets declining and reducing short exposure when markets are expected to increase.

To model this relationship we specify a Logistic Smooth Transition Regression (LSTR) model (Teräsvirta and Anderson [1992]). The LSTR model is a form of threshold model which allows for the existence of varying risk regimes. When the threshold variable is above a certain level the behaviour of the dependent variable is given by one linear specification, whereas when the threshold variable is below a certain level the behaviour is given by an alternative linear specification. Unlike other threshold models, the LSTR model does not jump from one regime to another, incorporating instead a smooth transition.

Estimation of STR models consists of three stages (Granger and Teräsvirta [1993]):

(a) Specification of a linear model.

The initial step requires the specification of the linear model.

$$y_t = \alpha + \beta_1 S\&P_t + \beta_2 SCLC_t + \varepsilon_t \tag{4}$$

Where y_t is the excess return on the EWDSB hedge fund portfolio, $S\&P_t$ is the excess return of the S&P500 and $SCLC_t$ is the Small Cap Spread.

(b) Testing linearity and choosing the transition variable

The second step involves testing linearity against STR models using the linear model specified in (a) as the null. To carry out this test the following auxiliary regression is estimated:

$$u_t = \beta_0{}' x_t + \beta_1{}' x_t z_t + \beta_2{}' x_t z_t^2 + \beta_3{}' x_t z_t^3 \tag{5}$$

Where the values of u_t are the residuals of the linear model specified in the first step and z_t is the transition variable. With no *ex ante* expectation for the transition variable, we tested both the S&P500 and the Small Cap Spread to see which would be the most appropriate transition variable, z_t. The null hypothesis of linearity is $H_0 : \beta 1 = \beta 2 = \beta 3 = 0$.

(c) Choosing between LSTR and ESTR

If linearity is rejected next we must test for the most appropriate form of transition function (either logistic or exponential).[4] The selection between LSTR and ESTR models is based on the following series of nested F tests.

$$H3: \beta3 = 0 \tag{6}$$

$$H2: \beta2 = 0 | \beta3 = 0 \tag{7}$$

$$H1: \beta1 = 0 | \beta2 = \beta3 = 0 \tag{8}$$

Accepting (6) and rejecting (7) implies selecting an ESTR model. Accepting both (6) and (7) and rejecting (8) leads to an LSTR model as well as a rejection of (6).

INSERT EXHIBIT 7 HERE

The results of these hypothesis tests are presented in exhibit 7. The tests indicate that both the one month lag of the S&P500 and the Small Cap spread are suitable transition variables.[5] As the P-value is lower we choose the Small Cap Spread. With the rejection of (6) the nested hypothesis tests point towards the choice of an LSTR specification.

INSERT EXHIBIT 8 HERE

Exhibit 8 illustrates the estimated transition function for the model. The left hand panel plots the transition function against time and the right hand panel plots the transition function against the transition variable, *SCLC*. When the size spread is less than zero, approaching -2%, the transition function is equal to zero and DSB returns are given by

$$y_t = \alpha_1 + \beta_1^{SP} S\&P_t + \beta_1^{SCLC} SCLC_t + e_t \tag{9}$$

whereas when the size spread is greater than zero approaching +2%, the transition function is equal to 1 and DSB returns are given by

$$y_t = (\alpha_1 + \alpha_2) + (\beta_1^{SP} + \beta_2^{SP}) S\&P_t + (\beta_1^{SCLC} + \beta_2^{SCLC}) SCLC_t + e_t \tag{10}$$

Between ±2% the transition function lies between 0 and 1 and DSB returns are explained partially by (9) and (10). We can see in Panel A that the movement between the regimes is relatively evenly spread throughout the sample.

INSERT EXHIBIT 9 HERE

[4] Details of the difference between the LSTR and ESTR models are provided in the appendix.

[5] We conducted this test for each candidate for the transition variable drawing at lags from 1 to 8. For both variables lag 1 was the most significant.

The estimated coefficients are reported in exhibit 9. The first column present the total risk in each regime: α_1, β_1^{SP} and β_1^{SCLC}, when the one month lags of the size spread is less than -2%; and $(\alpha_1 + \alpha_2)$, $\left(\beta_1^{SP} + \beta_2^{SP}\right)$ and $\left(\beta_1^{SCLC} + \beta_2^{SCLC}\right)$, when it is greater than +2%. The second column presents the change in risk from moving from one regime to another, α_2, β_2^{SP} and β_2^{SCLC}. The third column displays corresponding T-Stats while the adjusted R^2 is reported in column four.

The results indicate that hedge fund managers have greatest short exposure when the one month lag of small cap spread is less than -2%. When the strategy is in this regime, alpha is significantly positive (+44 basis points per month). When the one month lag of the small cap spread is greater than this level, managers begin reducing short exposure until it reaches a minimum, when the small cap spread is greater than + 2%, at which point alpha is close to zero (-13 basis points per month).

The results from estimating the nonlinear LSTR model support earlier findings of hedge fund manager skill. Following a month of positive returns on the small cap spread, managers reduce short exposure. In this regime alpha is zero. When the small cap spread is negative, in the prior month, managers actively increase short positions and in this regime they earn positive annualized alpha of 5.4%.

Conclusion

Having examined the performance of DSB hedge funds in detail we report a number of interesting findings. As expected DSB hedge funds are a major source of diversification for investors. This is due mainly to the fact that they exhibit negative exposure to standard equity factors. Academics often advocate the diversification qualities associated with the hedge fund industry and their lack of correlation with standard asset classes (see for examples Fung and Hsieh [1997], [2001], Mitchell and Pulvino [2001] and Agarwal and Naik [2004]). However it has also been noted that in periods of market instability or market downturns hedge funds and the performance of other asset classes such as mutual funds become positively correlated. This is not the case for DSB hedge funds. Therefore they offer diversification benefits when incorporated into investors' overall portfolio of assets. Another interesting observation related to DSB hedge funds is that they exhibit a number of unusual (for hedge funds) statistical characteristics. We find no autocorrelation and positive skewness on average in our DSB hedge funds return series. The lack of autocorrelation simplifies the analysis of performance as we do need to unsmooth returns (Getmansky et al [2004]) whereas the positive skewness has important implications for investors as it can improve the overall statistical properties of portfolios.

However, by far the most interesting finding relating to DSB hedge fund strategies is their ability to produce alpha. Conventional wisdom suggests that DSB hedge fund managers are skilful investors. Looking at their risk return profile (limited upside return and theoretically unlimited downside risk) advocates of DSB hedge funds have argued that to run such a strategy the manager must have considerable skill. We find that a fully specified model which includes risk factors designed to capture traditional and alternative risk results leads to a finding of statistically significant alpha. Our finding of alpha is robust to less than favourable trading condition. This means that DSB hedge funds are an efficient mechanism for investors to manage downside equity market risk.

Prior literature stresses the importance of taking into account the option-like feature inherent in hedge funds when analysing their returns. We find that in the case of DSB hedge funds nonlinearity can be addressed by measuring the performance of the strategy using a long position in an ATM put option as a risk factor. We observed that the short selling strategy can be well replicated by our put option model, and that this model can serves as a benchmarking tool to measure the performance of the fund managers.

In our final analysis, we allow for time variation in DSB risk exposure using a LSTR model specification. The results indicate that DSB managers do vary risk exposure in response to changes in market conditions and the risk exposure and alpha of managers is highest when the small cap spread is less than minus 2%. As the small cap spread moves above this level risk exposure and alpha decreases.

DSB hedge funds are unique investment vehicles, ones with a risk/return profile, statistical characteristics and alpha producing qualities very specific to them. However if correctly incorporated into investors' portfolio of assets the unique nature of DSB hedge funds, their ability to produce alpha and their unique statistical characteristics could be exploited to improve the returns of investors' overall portfolios.

Appendix: ESTR and LSTR Specifications

Consider the following nonlinear model.

$$y_t = \alpha' x_t + \beta' x_t f(z_t) + e_t$$

Where $\alpha' = (\alpha_0, \ldots, \alpha_t), \beta' = (\beta_0, \ldots, \beta_t),\ x_t$ is a matrix of risk factors and the variable z_t is the transition variable. If $f(z_t)$ is a smooth continuous function the risk factor coefficients will change smoothly along with values of z_t. The two particularly useful forms of the STR model that allow for a varying degree of transition are the LSTR (Logistic-STR) and ESTR (Exponential-STR) models.

Choosing $f(z_t) = [1 + \exp\left(-\gamma(z_t - c)\right)]^{-1}$ yields the logistic STR (LSTR) model where γ is the smoothness parameter (i.e. the slope of the transition function) and c is the threshold. In the limit as γ approaches zero or infinity, the LSTAR model becomes a linear model since the value of $f(z_t)$ is constant. For intermediate values of γ, the degree of decay depends upon the value of z_t. As z_t approaches -∞, θ approaches 0 and the behaviour of y_t is given by $y_t = \alpha' x_t + e_t$. As z_t approaches +∞, θ approaches 1 and the behaviour of y_t is given by $y_t = (\alpha' + \beta')x_t + e_t$

Choosing $f(z_t) = 1 - \exp(-\gamma(z_t - c)^2)$ yields the exponential STAR (ESTAR) model. For the ESTAR model, as γ approaches infinity or zero the model becomes a linear model as $f(z_t)$ becomes constant. Otherwise the model displays nonlinear behaviour. It is important to note that the coefficients for the ESTAR model are symmetric around $z_t = c$. As z_t approaches c, $f(z_t)$approaches 0 and the behaviour of y_t is given by $y_t = \alpha' x_t + e_t$. As z_t moves further from c, θ approaches 1 and the behaviour of y_t is given by $y_t = (\alpha' + \beta')x_t + e_t$.

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Exhibit 1

Descriptive Statistics of DSB Hedge Fund Series (1994-2008)

	Fund 1 – 18						Fund 19 - 35				
Fund	μ	σ	SR	Skew	Kurt	Fund	μ	σ	SR	Skew	Kurt
1	0.0057*	0.03	0.25	0.12	-0.30	19	0.0088**	0.04	0.56	-0.02	0.49
2	0.0016	0.03	-0.18	0.84	2.28	20	-0.0097	0.15	-0.30	0.35	5.69
3	0.0020	0.07	-0.06	0.26	1.12	21	0.0061	0.10	0.10	-0.07	7.11
4	0.0290*	0.08	1.19	0.86	0.48	22	-0.0048	0.09	-0.31	0.58	0.76
5	0.0057	0.04	0.24	0.53	-0.80	23	0.0063	0.12	0.09	-0.11	9.58
6	0.0031	0.04	-0.01	0.62	0.51	24	0.0075***	0.02	0.63	0.67	1.26
7	0.0075	0.05	0.32	0.65	-0.35	25	0.0013	0.02	-0.29	-1.00	0.88
8	0.0126	0.04	0.75	0.49	1.21	26	0.0148	0.17	0.24	0.27	-0.38
9	0.0056**	0.02	0.49	-0.87	0.70	27	-0.0071	0.06	-0.59	0.12	1.27
10	0.0218*	0.05	1.34	0.49	-0.27	28	0.0041	0.07	0.05	-0.18	1.84
11	0.0485***	0.08	2.02	0.92	0.10	29	-0.0020	0.09	-0.21	0.42	0.19
12	0.0082	0.05	0.34	-0.24	0.89	30	-0.0005	0.04	-0.34	0.76	2.66
13	0.0149	0.04	1.12	-0.39	-0.54	31	0.0039	0.06	0.04	-0.02	1.68
14	-0.0060	0.08	-0.41	1.25	3.58	32	-0.0173**	0.06	-1.25	-0.08	-0.71
15	0.0020	0.04	-0.11	0.84	2.64	33	0.0076	0.04	0.39	1.22	2.05
16	-0.0022	0.13	-0.15	0.28	0.31	34	0.0092**	0.02	0.89	0.15	1.41
17	0.0067	0.07	0.18	0.62	1.05	35	0.0044	0.03	0.15	0.14	-0.41
18	0.0041	0.07	0.04	0.61	1.02	**Average**	**0.0058**	**0.06**	**0.21**	**0.32**	**1.40**

This table reports the descriptive statistics of the thirty five hedge funds included in the sample. For each fund μ is the mean monthly return, σ is the standard deviation of the returns, SR is the Sharpe ratio of the fund, Skew is the skewness of the funds return distribution and Kurt is the kurtosis of the funds return distribution. ***,** and * indicate significance at the 1%, 5% and 10% level respectively

Exhibit 2

Average Autocorrelation of Individual DSB Hedge Fund Series (1994-2008)

	Fund 1 - 18		Fund 19 - 35
Fund	LB pvalue	Fund	LB pvalue
1	0.046**	19	0.431
2	0.387	20	0.524
3	0.657	21	0.057*
4	0.754	22	0.514
5	0.723	23	0.037**
6	0.835	24	0.210
7	0.885	25	0.498
8	0.714	26	0.276
9	0.076*	27	0.952
10	0.022**	28	0.179
11	0.046**	29	0.094*
12	0.056*	30	0.049**
13	0.800	31	0.545
14	0.749	32	0.226
15	0.718	33	0.599
16	0.524	34	0.106
17	0.028**	35	0.472
18	0.702	**Average**	0.414

This table reports the p-values of the Ljung-Box test for first order autocorrelation up to a lag of twelve. The LB P-values are at an $\alpha = 0.05$ level of significance. ***,** and * indicate significance at the 1%, 5% and 10% level respectively.

Exhibit 3

Results of Factor Modelling for DSB Hedge Funds Strategy (1994 -2008)

Model Specification	Asset Class Factors	Coefficient	T-Stat	Adj R2
Fung and Hsieh Factors	S&P 500	-0.9146***	-20.51	74.40%
	Small Cap Spread	-0.5288***	-9.62	
	Alpha	**0.0012**	0.62	
Put Option Factor	Put Opt	1.7912***	14.51	53.90%
	Alpha	**0.0100*** **	3.79	
Combined Factor Model	Put Opt	0.6628***	3.93	76.30%
	S&P 500	-0.6414***	-7.85	
	Small Cap Spread	-0.5348***	-10.12	
	Alpha	**0.0043** **	2.13	

This table reports results from estimating three linear factor model specifications for the equally weighted DSB hedge fund portfolio from January 1994 to December 2008. ***,** and * indicate significance at the 1%, 5% and 10% level respectively.

Exhibit 4

Descriptive Statistics of Put Option Risk Factor (1994-2008)

Variable	μ	σ	Skew	Kurt	LB pval
Put Option	0.0208	0.0208	1.22	5.26	0.4103

This table reports summary statistics for the put option risk factor. For the put option risk factor μ is the mean monthly return, σ is the standard deviation of the returns, Skew is the skewness of the risk factor's return distribution and Kurt is the kurtosis of risk factor's return distribution. ***,** and * indicate significance at the 1%, 5% and 10% level respectively

Exhibit 5

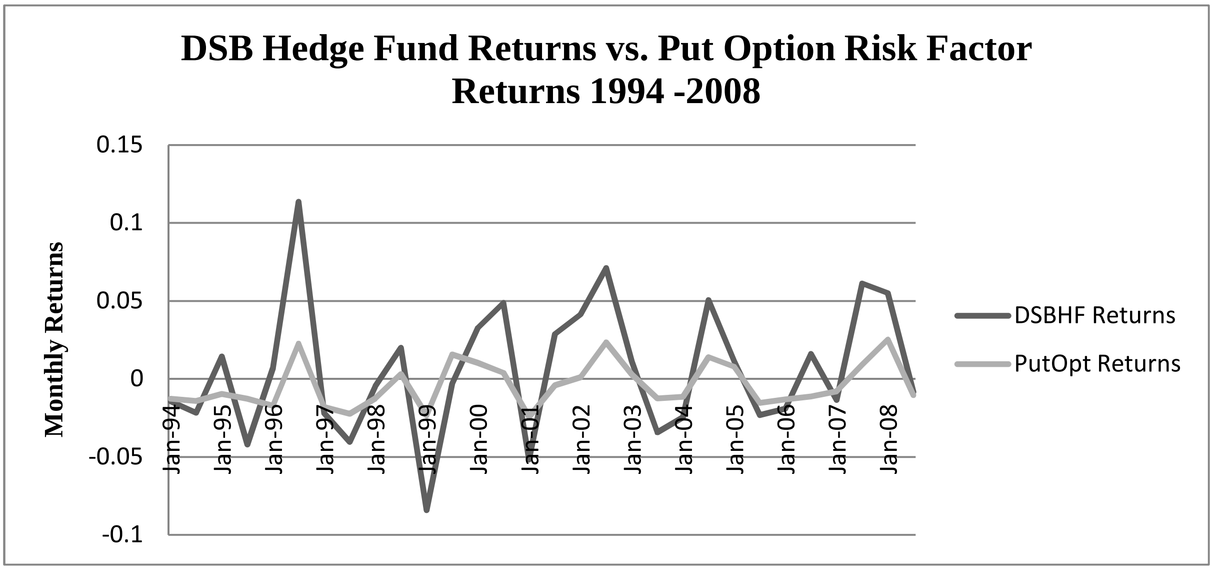

DSB Hedge Fund Returns vs. Put Option Risk Factor Returns 1994 -2008
Monthly Returns
0.15
0.1
0.05
0
-0.05
-0.1
Jan-94
Jan-95
Jan-96
Jan-97
Jan-98
Jan-99
Jan-00
Jan-01
Jan-02
Jan-03
Jan-04
Jan-05
Jan-06
Jan-07
Jan-08
DSBHF Returns
PutOpt Returns

Exhibit 6

Pre and post credit crisis results

Model Specification	Asset Class Factors	Coefficient	T-Stat	Adj R^2
Time period: Pre Credit Crisis Combined Factors	Put Opt	0.5645***	3.03	78.60%
	S&P 500	-0.7841***	-8.14	
	Small Cap Spread	-0.5865***	-11.02	
	Alpha	**0.0048****	2.33	
Time period: Post Credit Crisis Combined Factors	Put Opt	0.1847	0.56	77.80%
	S&P 500	-0.5572***	-4.10	
	Small Cap Spread	-0.1708	-0.96	
	Alpha	**0.0037**	0.75	

This table reports results from estimating the combined factor model for the equally weighted DSB hedge fund portfolio from January 1994 to December 2006 and January 2007 to December 2008. ***,** and * indicate significance at the 1%, 5% and 10% level respectively.

Exhibit 7

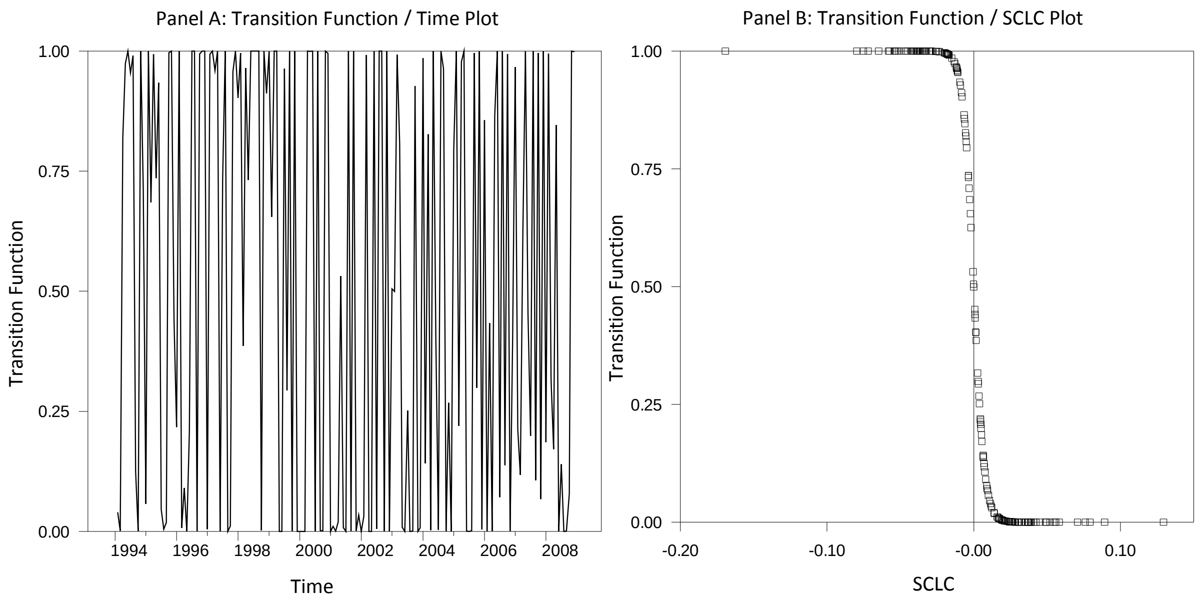
Hypothesis tests to choose STR Model and transition function

Delay	H_0	H_1	H_2	H_3
Panel A: S&P500				
1	0.0037	0.0006	0.8541	0.1126
Panel B: Small Cap Spread				
1	0.0000	0.0034	0.0001	0.0674

This table reports P-Values for the STR hypothesis tests. H_0 is a test for non-linearity. H_1, H_2 and H_3 are tests for choosing between the LSTR and ESTR specifications.

Exhibit 8

Transition function for the smooth transition regression model



The left hand panel plots the transition function $f(z_t)$ against time. Right hand panel plots $f(z_t)$ against the transition variable z_t for the DSB series.

Exhibit 9

Results from estimating STR model for DSB equal weighted series

Model Specification	Asset Class Factors	Coefficient	ΔCoeff	T-Stat	Adj R2
	Smoothing Coefficient	280.05*		1.84	75.93%
Regime 1					
Small Cap Spread < 0	S&P 500	-0.9965***		-18.65	
	Small Cap Spread	-0.7704***		-11.89	
	Alpha	**0.0044****		2.22	
Regime 2					
Small Cap Spread > 0	S&P 500	-0.8525	0.1440**	2.07	
	Small Cap Spread	-0.3603	0.4101***	4.62	
	Alpha	**-0.0013**	**-0.0057***	-1.88	

This table reports results from estimating the LSTR model for the equally weighted DSB hedge fund portfolio from January 1994 to December 2008. ***,** and * indicate significance at the 1%, 5% and 10% level respectively.