

**Dedicated Short Bias Hedge Funds:  
Diversification and Alpha during Financial Crises**

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# **Dedicated Short Bias Hedge Funds: Diversification and Alpha during Financial Crises**

## **Abstract**

During the recent financial crisis 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 DSB hedge fund performance over an extended sample period, from January 1994 to December 2008. Performance and risk evaluation is carried out on an equally weighted DSB hedge fund portfolio using three different factor model specifications and both linear and nonlinear estimation techniques. We conclude that DSB hedge funds are a significant source of diversification for equity market 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 crisis periods, which are particularly favorable for the DSB strategy.

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 subprime crisis, 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) reveled 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 capitalize on the market conditions of 2007 and 2008. Some critics may argue that DSB hedge funds strong performance during the financial 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. However following an in-depth investigation of the performance of these hedge funds we find that not only do DSB funds provide excellent equity market 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 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 allowing for crisis and no-crisis periods we find alpha to be statistically significant during both the less favorable no-crisis period and the 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? 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 (favorable trading conditions) which will act as a hedge against losses suffered by other assets in investors’ portfolios over the same time period. Secondly if these claims of “alpha” during periods of unfavorable trading conditions are substantiated then investors gain, as, despite the fact trading conditions are unfavorable, the

manager's skill at implementing a DSB trading strategy will make it an efficient hedge against future falls in asset prices.

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. The majority of hedge fund returns series have also 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 modeling this relationship. Therefore a large body of research, both academic and industry driven, has emerged surrounding nonlinear hedge fund performance measurement.

These features make hedge fund performance difficult to measure and/or benchmark. Not only are the return 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 analyze the performance of any hedge fund strategy in isolation to gain a true understanding of performance. We therefore examine the performance of DSB hedge funds in isolation to determine the statistical characteristics associated with this specific strategy, and control for these when developing performance measures for DSB hedge funds. The layout of the rest of the paper is as follows; Section 2 reviews the Data and identifies DSB statistical characteristics. In Section 3 we examine the performance of the DSB funds against three distinct linear models and over two time periods, before estimating a nonlinear specification. We illustrate the diversification benefits of DSB funds in Section 4. Finally, we conclude with a discussion of our main findings in Section 5.

## **2. Data**

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.<sup>1</sup>

In Exhibit 1 we report summary return and assets under management (AUM) statistics for the sample of thirty five funds and an equally weighted portfolio.<sup>2</sup> The annualized mean return of eight of the funds is significantly positive with only one significant negative mean return. An equally weighted portfolio of the full sample of funds has a positive mean annualized return of 4% and a Sharpe ratio of 0.21.

#### INSERT EXHIBIT 1 HERE

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 characterized by negative skewness and excess kurtosis. 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, this indicates that DSB hedge funds, while primarily a tool for hedging the downside risk inherent in traditional equity portfolios assets, may also be a useful diversification tool in a broader portfolio of other assets, including hedge fund strategies which typically suffer from negative skewness and high kurtosis while DSB hedge funds exhibit positive skewness on average and low levels of kurtosis.

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 fund 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 can be easily 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.

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<sup>1</sup> The attrition rate is not primarily due to poor performance. Between 1994 and 2000, a period of very positive equity market returns only four funds (Fund 12, 13, 14 and 16) leave the sample. Of these four only two exhibit negative mean returns. During the 2001 and 2002 bear market, an additional six funds (Fund 15, 17, 18, 20, 25 and 26) liquidate. Of these funds five have positive mean returns averaging 3.7% per annum. Then during the period of very positive equity market returns, from 2003 to the end of 2007 another nine funds (Fund 19, 22, 23, 24, 27, 29, 30, 31 and 32) liquidated. Of the nine funds, five had negative returns with Fund 32 performing particularly badly, returning on average -21 percent per annum. Finally during the recent financial crisis another five funds (Fund 21, 28, 33, 34 and 35) liquidated returning on average +7.5 percent per annum to their investors.

<sup>2</sup> We choose to form an equally weighted portfolio to ensure a reasonably sized sample. The majority of funds do not report a continuous time series of AUM data to TASS. Results, available from the authors on request, using a value weighted portfolio, formed on available AUM data, and the CSFB Tremont Value Weighted DSB Index are similar.

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. In addition DSB funds tend to focus short selling on equities, rather than other less liquid securities favored by other hedge fund strategies.

Before discussing the AUM data it is important to highlight that at least one observation is missing for twenty of the funds in the sample and funds 3, 34 and 35 do not report any data for assets under management. Nonetheless, the mean AUM data is useful as it gives an indication of the relatively small size of DSB funds. Mean AUM varies from less than \$1m (fund 20) up to \$102m, for fund 29 which peaked at \$220m in February 2008. Across the sample the mean AUM is a modest \$31m and the total reported AUM of all live funds at the end of December 2008 was \$461m. Illustrating the relative small size of the DSB strategy, Barclay Hedge estimates indicate that the hedge fund industry had total AUM of \$1 trillion at the end of December 2008.<sup>3</sup>

### **3. The performance of DSB hedge funds**

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 is able to explain up to 80% of the monthly return variation for a diversified hedge fund portfolio. This compares to less than 25% using regression factors based on traditional asset classes. In this section of the paper we assess DSB hedge fund performance, initially with the Fung and Hsieh [2004] model before investigating performance relative to an additional put option factor and a combined risk factor model. We provide further evidence on performance in crisis and no-crisis periods (Billio, Getmansky and Pelizzon [2011]) and finally allow for time varying risk exposure.

#### **3.1 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 (*PTFSBD*), currency (*PTFSFX*) and commodities (*PTFSCOM*), two equity orientated risk factors; an equity market factor (*S&P*) and a size spread factor (*SC-LC*) and two bond orientated risk factors; a bond market factor (*BDI0RET*) and a credit spread factor (*BAAMTSY*). Using these risk factors we initially estimate the following regression:

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<sup>3</sup> Source: <http://www.barclayhedge.com/>

$$R_t^i = \alpha_i + \sum_{k=1}^N \beta_k^i F_{kt} + e_t^i \quad (1)$$

Where  $R_t^i$  is the excess return on hedge fund  $i$  during month  $t$ ,  $\alpha_i$  is the intercept for hedge fund  $i$  over the regression period,  $\beta_k^i$  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  $t$ , ( $k = 1, \dots, K$ ) where the factor could be any of the seven ABS factors and  $e_t^i$  is an error term.<sup>4</sup>

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.

Exhibit 2 reports the results from estimating two specifications of the Fung and Hsieh [2004] model. First we estimate the model for the full sample period and second we estimate the model with crisis / no-crisis dummy variables. The first panel of Exhibit 2 reports the results for the full sample period. Only the *S&P* and *SC-LC* coefficients are significant (-0.97 and -0.56 respectively) and the estimated alpha from this model is +0.34 percent per month. None of the bond market or option based factor coefficients are significant.

#### INSERT EXHIBIT 2 HERE

We follow Billio, Getmansky and Pelizzon [2011] and define crisis periods as Asian (June 1997 - January 1998), Russian and LTCM (August 1998 - October 1998), Brazilian (January 1999 - February 1999), Internet Crash (March 2000 - May 2000), Argentinean (October 2000 - December 2000), September 11, 2001, drying up of merger activities, increase in defaults, and WorldCom accounting problems (June 2002 - October 2002), the 2007 subprime mortgage crisis (August 2007 - January 2008), and the 2008 Global financial crisis (September 2008 - November 2008). We then estimate two betas (crisis and no-crisis) for each Fung and Hsieh [2004] variable and two alphas (crisis and no-crisis). The results are presented in the second panel of Exhibit 2. The estimated alpha from this specification is 1.09 percent per month in the no-crisis periods and 0.43 percent per month during crisis periods.<sup>5</sup> Recall that the opportunities for the DSB manager are greater during the crisis periods. In the no-crisis period the alpha may be larger but returns to the strategy are in fact negative. The skill of the DSB manager is in minimizing losses during these less favorable no-crisis periods. Only the *S&P* and *SC-LC* coefficients are significant in both periods with both coefficients increasing

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<sup>4</sup> Data for the trend following factors is downloaded from David A. Hsieh's database and the remaining factors are constructed using data from DataStream.

<sup>5</sup> If instead we estimate the model with one alpha for both crisis and no-crisis periods, alpha is 0.0052 which lies between the crisis and no-crisis alphas reported in Exhibit 2, but is greater than the alpha of 0.0034 reported for the model without crisis/no-crisis dummy variables.

in absolute terms during the crisis periods. Of the option based factors, only the coefficient on the *PTFSBD* factor is significant (at the 5 percent level), and only in the no-crisis period.

Although the Fung and Hsieh [2004] model explains a large portion of the performance of the strategy (adjusted  $R^2$  of 81.30%), none of the option based factors are significant from zero in the crisis period (and only *PTFSBD* is significant in the no-crisis period), so we may not be capturing “alternative beta” with this model. To investigate this possibility, next we construct a theoretically appealing option based factor which should more closely replicate the nonlinear risk return profile of the DSB hedge fund series.

### **3.2 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 an equity index put option.

In a similar manner we can consider the payoff to the DSB strategy to be a long put option. The DSB strategy recognizes 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 equity index put option position.

We construct the payoff of this tradable 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 buying and selling the underlying rather than buying and selling options.<sup>6</sup> This is done for two reasons. First, trading the underlying stocks 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 the 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:

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<sup>6</sup> To correctly analyze excess performance (alpha) it is important that all risk factors are tradable. An investor could replicate our *PutOpt* factor using the underlying stocks in the S&P500 or an exchange traded fund such as the SPDR S&P500 ETF.



$$\Delta = e - qt[N(d_1 - 1)] \quad (2)$$

where

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

and  $\Delta$  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  $\sigma$  is the volatility of the option (annualized standard deviation for the previous trading year).<sup>7</sup>

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 short position which would produce the same exposure 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 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 3.

INSERT EXHIBIT 3 HERE

The put option variable has a mean annualized return of -0.06. In stable and upward trending markets DSB hedge funds would be expected to recognize small losses. Given that over the period January 1994 – December 2008 (the duration of our study) prices in the markets were on average on an upward trajectory a 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. The results in Exhibit 4 show that the correlation between the put option and the Fung and Hsieh (2004) option based risk factors is low.<sup>8</sup>

<sup>7</sup> Data for constructing the put option factor is from DataStream.

<sup>8</sup> The low correlation can be explained by the differences in construction of the factors. Fung and Hsieh (2004) option based factors are constructed using lookback straddles, to capture the returns of trend following hedge

Clearly, the Put Opt factor should add explanatory power to the option like factors. The correlation with the linear *S&P* factor is, unsurprisingly, negative, with a coefficient of -0.85.<sup>9</sup>

INSERT EXHIBIT 4 HERE

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. In Exhibit 5 results show 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 first panel of Exhibit 6. 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.

INSERT EXHIBIT 6 HERE

### 3.3 Combined factor model

The combined model consists of our specifically constructed put option risk factor, *PutOpt*, along with the Fung and Hsieh [2004] factors. The traditional risk factors, which were significant in Exhibit 2 (*S&P* and *SC-LC*) are quite 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

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funds (which profit from both very negative and very positive underlying returns), whereas the *PutOpt* factor is designed to capture profits only when the underlying equity market is negative. As a result the lookback straddle is constructed using a combined long position in both a put and a call option, whereas *PutOpt* is constructed to mimic the returns of a put option in isolation.

<sup>9</sup> As correlation amongst explanatory variables can give rise to spurious univariate significance levels we report results for just the *PutOpt* factor before estimating the combined model. It is also important to note that the estimated intercepts are unaffected by multicollinearity.

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.

In the second panel of Exhibit 6 results show that the combined factor model has the greatest explanatory power of the three linear models we have examined thus far, at 79.40%. We can also see from Exhibit 6 that all our equity related explanatory variables (*PutOpt*, *S&P* and *SC-LC*) and also the alpha figure are statistically significant.<sup>10</sup> 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 factors 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).

### **3.4 Crisis and no-crisis performance**

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 unfavorable 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 within crisis and no-crisis periods. Again we use the Billio, Getmansky and Pelizzon [2011] crisis definitions. The findings of the sub-period analysis are displayed in Exhibit 7.

INSERT EXHIBIT 7 HERE

As is evident from the sub-period analysis DSB hedge fund managers are adept at producing alpha in periods of less favorable market conditions (1.10 percent per month, significant at the 10% level). While alpha may be positive in no-crisis periods, returns are in fact negative.<sup>11</sup> This makes practical sense as when market conditions are unfavorable the fund managers must implement their trading

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<sup>10</sup> The alpha of 0.0043 is coincidentally identical to the crisis alpha reported in Exhibit 2.

<sup>11</sup> During the no-crisis period the annualized mean returns to the equal weighted portfolio of DSB hedge funds is -2.79 percent compared to +6.77 percent in the crisis period. Though the strategy generates alpha during the no-crisis period the raw returns are negative. This has two possible effects which may lead to the high attrition rate observed earlier in the paper. The investors in the fund may grow impatient with the poor performance of the fund, as measured by raw returns, or the investment manager may not generate sufficient fee income from the performance fee to justify continuing the fund.

strategy extremely skillfully in order to survive. We can also see from Exhibit 7 that in the period where market conditions were favorable DSB hedge funds generated alpha of 0.52 percent per month.

These findings that DSB hedge fund managers are skilful in implementing DSB hedge fund trading strategy in periods of unfavorable trading conditions, further supports the argument that DSB hedge funds are a useful tool for diversifying equity market risk. 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 favorable.

### **3.5 Allowing for time variation in risk exposure**

Much recent research has demonstrated the importance of allowing for time variation in risk factor exposure when modeling 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 behavior of the dependent variable is given by one linear specification, whereas when the threshold variable is below a certain level the behavior 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.

$$y_t = \alpha + \beta_1 S\&P_t + \beta_2 SC\&LC_t + \varepsilon_t \quad (4)$$

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  $SC\&LC_t$  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:

$$u_t = \beta_0' x_t + \beta_1' x_t z_t + \beta_2' x_t z_t^2 + \beta_3' x_t z_t^3 \quad (5)$$

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).<sup>12</sup> The selection between LSTR and ESTR models is based on the following series of nested F tests.

$$H3: \beta_3 = 0 \quad (6)$$

$$H2: \beta_2 = 0 | \beta_3 = 0 \quad (7)$$

$$H1: \beta_1 = 0 | \beta_2 = \beta_3 = 0 \quad (8)$$

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 8 HERE

The results of these hypothesis tests are presented in Exhibit 8. The tests indicate that both the one month lag of the S&P500 and the Small Cap spread are suitable transition variables.<sup>13</sup> To be consistent with the rest of the paper, which focuses on diversification and S&P500 related crises, we condition on the S&P500.<sup>14</sup> The nested hypothesis test point towards the choice of an LSTR specification.

INSERT EXHIBIT 9 HERE

Exhibit 9 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,  $S\&P$ . When the excess returns on the  $S\&P$  are greater than -4%, the transition function is equal to zero and DSB returns are given by

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

<sup>12</sup> Details of the difference between the LSTR and ESTR models are provided in the appendix.

<sup>13</sup> 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.

<sup>14</sup> The results conditioning on the small cap spread are very similar to the S&P500 and are not reported to save space, but are available from the authors on request.

whereas when  $S\&P$  is approaching -6%, the transition function is equal to 1 and DSB returns are given by

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

Between -4% and -6% the transition function lies between 0 and 1 and DSB returns are explained partially by (9) and (10). Results in Panel A show that the movement between the regimes is relatively evenly spread throughout the sample, with the exception of the 2003 to 2007 period when equity market returns were very positive.

INSERT EXHIBIT 10 HERE

The estimated coefficients are reported in Exhibit 10. The first column present the total risk in each regime:  $\alpha_1$ ,  $\beta_1^{SP}$  and  $\beta_1^{SCLC}$ , when the one month lags of  $S\&P$  is greater than -4%; and  $(\alpha_1 + \alpha_2)$ ,  $(\beta_1^{SP} + \beta_2^{SP})$  and  $(\beta_1^{SCLC} + \beta_2^{SCLC})$ , when it is less than -6%. The second column presents the change in risk from moving from one regime to another,  $\alpha_2$ ,  $\beta_2^{SP}$  and  $\beta_2^{SCLC}$ . 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  $S\&P$  is less than -6%. When the strategy is in this regime, alpha is positive (+31 basis points per month). When the one month lag of  $S\&P$  is greater than this level, managers begin reducing short exposure until it reaches a minimum, when  $S\&P$  is greater than -4%, at which point alpha is not significant from zero.

The results from estimating the nonlinear LSTR model support earlier findings of hedge fund manager skill. Following a month of returns on  $S\&P$  greater than -4%, managers reduce short exposure. In this regime alpha is zero. When the  $S\&P$  returns are less than -6%, in the prior month, managers actively increase short positions and in this regime they earn positive annualized alpha of 3.8%.

#### 4. Diversification benefits of DSB hedge funds

To illustrate the diversification benefits of the DSB strategy we report in Exhibit 11 the correlation between the CSFB Tremont Value Weighted DSB hedge fund index returns and other value weighted hedge fund index strategy returns over the Full Sample Period, crisis Periods, and no-crisis Periods.<sup>15</sup>

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<sup>15</sup> We are grateful to the anonymous referee for suggesting we investigate the diversification benefits of adding the DSB strategy to portfolios of hedge funds.

<sup>16</sup> For all sample periods DSB is negatively correlated with the Aggregate index of hedge fund performance and all of the sub-strategy indices in Exhibit 11.

INSERT EXHIBIT 11 HERE

Billio, Getmansky and Pelizzon [2011] note the increase in correlation amongst hedge funds during financial crisis. Looking at the correlations in crisis and no-crisis periods this is not the case for the DSB hedge fund strategy. With the exception of Fixed Income Arbitrage, DSB becomes more *negatively* correlated with other strategies and the diversification benefits of the DSB strategy *increase* during financial crisis. This is unique to the DSB strategy.

To further illustrate the diversification benefits of adding DSB exposure to investments in hedge funds we create a simple portfolio with an  $x\%$  ( $x = 0, 10, 20$ ) allocation to the CSFB Tremont DSB Index and  $1 - x\%$  allocation to a portfolio with equal weighted investments in the Convertible Arbitrage, Equity Market Neutral, Event Driven, fixed Income Arbitrage, Global Macro and Long Short Equity Indices.

Panel B of Exhibit 11 displays the descriptive statistics for each of the portfolios. As the allocation to DSB increases there is a corresponding decrease in standard deviation with a consequent increase in Sharpe ratios. From a mean/variance perspective the negative correlation between DSB and other strategies adds diversification benefits to investments in hedge funds.

To investigate the effect of increasing allocations to DSB on S&P500 exposure we estimate a single factor model for each of the DSB/hedge fund portfolios with dummy variables for crisis and no-crisis periods.

INSERT EXHIBIT 12 HERE

The results of these tests, reported in Exhibit 12, are striking. As the allocation to DSB increases, from zero to twenty percent, the S&P500 exposure decreases in both crisis and no-crisis periods. At the same time this decrease in S&P500 exposure is accompanied by an increase in single factor alpha from 0.0022 to 0.0043. These simple tests using CSFB Tremont index data illustrate the economically significant diversification benefits of adding the strategy to a portfolio of hedge funds.

## **5. Conclusion**

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<sup>16</sup> To ensure these results are not due to our choice of index we also examine the relationship between our equally weighted portfolio and the HFRI equally weighted hedge fund strategy indices. These results are available from the authors on request.

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 equity market risk diversification for investors. This is due mainly to the fact that they exhibit negative exposure to standard equity factors and are negatively correlated with other hedge fund styles, becoming more negatively correlated during financial crisis. 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. Uniquely this is not the case for DSB hedge funds. Therefore they also maintain diversification characteristics 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 not 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 leads to a finding of statistically significant alpha. Our finding of alpha is robust to less than favorable trading condition. We find evidence of significant alpha in no-crisis periods, though in these periods DSB returns are negative. 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 analyzing 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 serve as a benchmarking tool to measure the performance of the fund managers. When we assess performance with this model the DSB hedge funds continue to exhibit alpha. In our final performance 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 excess return on the S&P500 is less than minus 6%. As the S&P500 excess return moves above this



level risk exposure and alpha decrease. Again these results provide added evidence of the alpha generation of DSB hedge fund managers.

The implication of this research is that investors in hedge funds should consider allocating a portion of their portfolio to the DSB strategy. DSB hedge funds are unique investment vehicles, ones with risk/return profile, statistical characteristics and alpha producing qualities very specific to them. In our final analysis we take a simple approach to constructing portfolios of hedge funds, incorporating DSB, to illustrate their diversification properties. This evidence indicates that the negative correlation, which is unique to DSB funds, adds economically and statistically significant diversification benefits in a portfolio setting. As DSB exposure increases, standard deviation falls as does S&P500 exposure. At the same time Sharpe ratios and crisis alphas increase. If correctly incorporated into investors' portfolio of assets the unique nature of DSB hedge funds, their ability to produce alpha and their diversification benefits can be exploited to improve the performance of investors' overall portfolios. We leave it to future research to identify the optimal allocation to the strategy.

## Appendix: ESTR and LSTR Specifications

Consider the following nonlinear model.

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

Where  $\alpha' = (\alpha_0, \dots, \alpha_t)$ ,  $\beta' = (\beta_0, \dots, \beta_t)$ ,  $x_t$  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  $f(z_t) = [1 + \exp(-\gamma(z_t - c))]^{-1}$  yields the logistic STR (LSTR) model where  $\gamma$  is the smoothness parameter (i.e. the slope of the transition function) and  $c$  is the threshold. In the limit as  $\gamma$  approaches zero or infinity, the LSTAR model becomes a linear model since the value of  $f(z_t)$  is constant. For intermediate values of  $\gamma$ , the degree of decay depends upon the value of  $z_t$ . As  $z_t$  approaches  $-\infty$ ,  $\theta$  approaches 0 and the behaviour of  $y_t$  is given by  $y_t = \alpha' x_t + e_t$ . As  $z_t$  approaches  $+\infty$ ,  $\theta$  approaches 1 and the behavior 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  $\gamma$  approaches infinity or zero the model becomes a linear model as  $f(z_t)$  becomes constant. Otherwise the model displays nonlinear behavior. 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  $c$ ,  $\theta$  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**

Fund	$\mu$	$\sigma$	SR	Skew	Kurt	LB P-Value	$\mu_{AUM}$	$\sigma_{AUM}$
1	0.07*	0.12	0.25	0.12	-0.30	0.046**	16.01	12.64
2	0.02	0.10	-0.18	0.84	2.28	0.387	60.57	24.44
3	0.02	0.24	-0.06	0.26	1.12	0.657	-	-
4	0.35*	0.26	1.19	0.86	0.48	0.754	12.72	8.48
5	0.07	0.13	0.24	0.53	-0.80	0.723	27.48	17.69
6	0.04	0.13	-0.01	0.62	0.51	0.835	14.40	9.04
7	0.09	0.16	0.32	0.65	-0.35	0.885	41.43	15.94
8	0.15	0.15	0.75	0.49	1.21	0.714	11.29	4.66
9	0.07**	0.06	0.49	-0.87	0.70	0.076*	68.76	18.73
10	0.26*	0.17	1.34	0.49	-0.27	0.022**	38.51	18.09
11	0.58***	0.27	2.02	0.92	0.10	0.046**	61.08	42.76
12	0.10	0.18	0.34	-0.24	0.89	0.056*	3.80	1.27
13	0.18	0.12	1.12	-0.39	-0.54	0.800	2.45	4.40
14	-0.07	0.27	-0.41	1.25	3.58	0.749	2.43	3.66
15	0.02	0.13	-0.11	0.84	2.64	0.718	74.27	32.61
16	-0.03	0.43	-0.15	0.28	0.31	0.524	20.15	8.09
17	0.08	0.24	0.18	0.62	1.05	0.028**	78.97	14.72
18	0.05	0.25	0.04	0.61	1.02	0.702	1.99	3.16
19	0.11**	0.12	0.56	-0.02	0.49	0.431	21.71	15.91
20	-0.12	0.52	-0.30	0.35	5.69	0.524	0.40	0.29
21	0.07	0.35	0.10	-0.07	7.11	0.057*	20.44	22.68
22	-0.06	0.31	-0.31	0.58	0.76	0.514	33.02	32.70
23	0.08	0.40	0.09	-0.11	9.58	0.037**	9.31	4.01
24	0.09***	0.08	0.63	0.67	1.26	0.210	14.04	20.28
25	0.02	0.08	-0.29	-1.00	0.88	0.498	18.38	5.93
26	0.18	0.58	0.24	0.27	-0.38	0.276	3.56	2.95
27	-0.08	0.21	-0.59	0.12	1.27	0.952	28.69	10.43
28	0.05	0.23	0.05	-0.18	1.84	0.179	3.33	1.68
29	-0.02	0.30	-0.21	0.42	0.19	0.094*	102.26	52.16
30	-0.01	0.13	-0.34	0.76	2.66	0.049**	9.70	12.17
31	0.05	0.21	0.04	-0.02	1.68	0.545	1.57	0.79
32	-0.21**	0.20	-1.25	-0.08	-0.71	0.226	37.96	19.54
33	0.09	0.14	0.39	1.22	2.05	0.599	99.06	54.41
34	0.11**	0.08	0.89	0.15	1.41	0.106	-	-
35	0.05	0.10	0.15	0.14	-0.41	0.472	-	-
<b>Equal</b>	<b>0.04</b>	<b>0.18</b>	<b>0.21</b>	<b>0.32</b>	<b>1.40</b>	<b>0.414</b>	-	-

This table reports the descriptive statistics of the thirty five hedge funds included in the sample. For each fund  $\mu$  is the annualized mean monthly return,  $\sigma$  is the annualized 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. LB P-Value is the p-values of the Ljung-Box test for first order autocorrelation up to a lag of twelve.  $\mu_{AUM}$  is the mean assets under management reported by each fund and  $\sigma_{AUM}$  is the standard deviation of assets under management. Equal is an equally weighted portfolio of DSB hedge funds. \*\*\*,\*\* and \* indicate significance at the 1%, 5% and 10% level respectively

**Exhibit 2**  
**Fung and Hsieh Full Sample and Crisis Dummy Results**

Model Specification	Asset Class Factors	Coefficient	T-Stat	Adj R2
Full Sample	Alpha	0.0034**	1.94	79.3%
	S&P	-0.9747***	-22.69	
	SC-LC	-0.5583***	-11.32	
	BAAMTSY	-0.0157	-0.66	
	BD10RET	-0.0083	-0.27	
	PTFSFX	-0.0029	-0.31	
	PTFSCOM	-0.0039	-0.29	
	PTFSBD	-0.0079	-0.65	
Time Period: No-Crisis	Alpha	0.0109*	1.89	81.3%
	S&P	-0.8351***	-9.00	
	SC-LC	-0.4793***	-4.07	
	BAAMTSY	-0.0831	-1.38	
	BD10RET	-0.0813	-0.92	
	PTFSFX	0.0090	0.37	
	PTFSCOM	-0.0127	-0.35	
	PTFSBD	-0.0768**	-1.94	
Time Period: Crisis	Alpha	0.0043**	2.44	81.3%
	S&P	-1.0722***	-22.35	
	SC-LC	-0.5935***	-11.10	
	BAAMTSY	0.0124	0.50	
	BD10RET	0.0012	0.04	
	PTFSFX	-0.0005	-0.05	
	PTFSCOM	-0.0006	-0.05	
	PTFSBD	0.0027	0.22	

This table reports results from estimating the Fung and Hsieh (2004) linear factor model specification for the equally weighted DSB hedge fund portfolio from January 1994 to December 2008 and also with dummy variables for the crisis and no-crisis periods (Billio et al, [2011]). \*\*\*, \*\* and \* indicate significance at the 1%, 5% and 10% level respectively.

**Exhibit 3**  
**Descriptive Statistics of Put Option Risk Factor**

Variable	$\mu$	$\sigma$	Skew	Kurt	LB pval
PutOpt	-0.06	0.072	1.22	5.26	0.4103

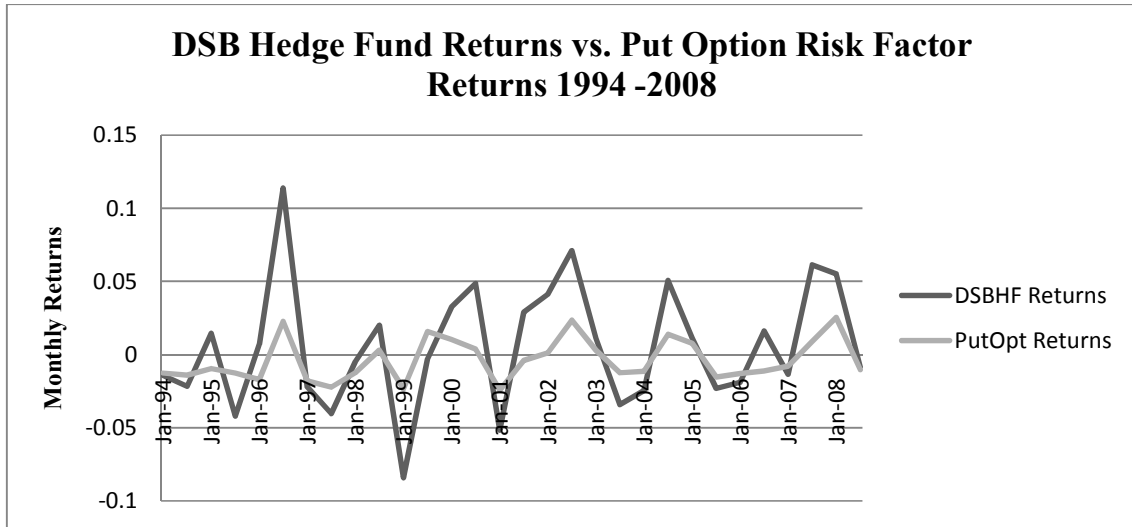
This table reports summary statistics for the put option risk factor. For the put option risk factor  $\mu$  is the annualized mean monthly return,  $\sigma$  is the annualized standard deviation of the returns, Skew is the skewness of the risk factor's return distribution and Kurt is the kurtosis of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

**Exhibit 4**  
**Factor Correlation Matrix**

	PTFSFX	PTFSCOM	S&P	SC-LC	BD10RET	BAAMTSY	PutOpt
PTFSBD	0.19	0.18	-0.16	-0.06	-0.20	0.25	0.18
PTFSFX	*	0.36	-0.23	0.00	-0.14	0.25	0.19
PTFSCOM	*	*	-0.15	-0.02	-0.09	0.17	0.17
S&P	*	*	*	0.02	0.20	-0.43	-0.85
SC-LC	*	*	*	*	0.12	-0.18	0.00
BD10RET	*	*	*	*	*	-0.86	-0.15
BAAMTSY	*	*	*	*	*	*	0.29

This table reports linear correlation coefficients for the Fung and Hsieh (2004) seven ABS factors and PutOpt, the put option factor.

Exhibit 5





**Exhibit 6**  
**Put Option and Combined Factor Model Results**

Model Specification	Asset Class Factors	Coefficient	T-Stat	Adj R2
Put Option Factor	Alpha	0.0100***	3.79	53.90%
	PutOpt	1.7912***	14.51	
Combined Factor Model	Alpha	0.0043**	2.13	79.40%
	PutOpt	0.2628***	2.20	
	S&P	-0.6414***	-7.85	
	SC-LC	-0.5348***	-10.12	
	BAAMTSY	-0.0097	-0.40	
	BD10RET	-0.0064	-0.21	
	PTFSFX	-0.0033	-0.35	
	PTFSCOM	-0.0052	-0.39	
PTFSBD	-0.0093	-0.77		

This table reports results from estimating two 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 7**  
**Crisis and No-Crisis Period Combined Model Results**

Model Specification	Asset Class Factors	Coefficient	T-Stat	Adj R <sup>2</sup>
				83.15%
Time period: No-Crisis	Alpha	0.0110*	1.69	
	PutOpt	0.0171	0.05	
	S&P	-0.8282***	-4.68	
	SC-LC	-0.4803***	-3.30	
	BAAMTSY	-0.0828	-1.34	
	BD10RET	-0.0813	-0.91	
	PTFSFX	0.0089	0.36	
	PTFSCOM	-0.0129	-0.35	
	PTFSBD	-0.0770*	-1.90	
	Time period: Crisis	Alpha	0.0052***	2.75
PutOpt		0.3318**	2.32	
S&P		-0.9196***	-7.46	
SC-LC		-0.5827***	-10.81	
BAAMTSY		0.0173	0.69	
BD10RET		0.0054	0.17	
PTFSFX		-0.0010	-0.10	
PTFSCOM		-0.0018	-0.14	
PTFSBD		0.0005	0.05	

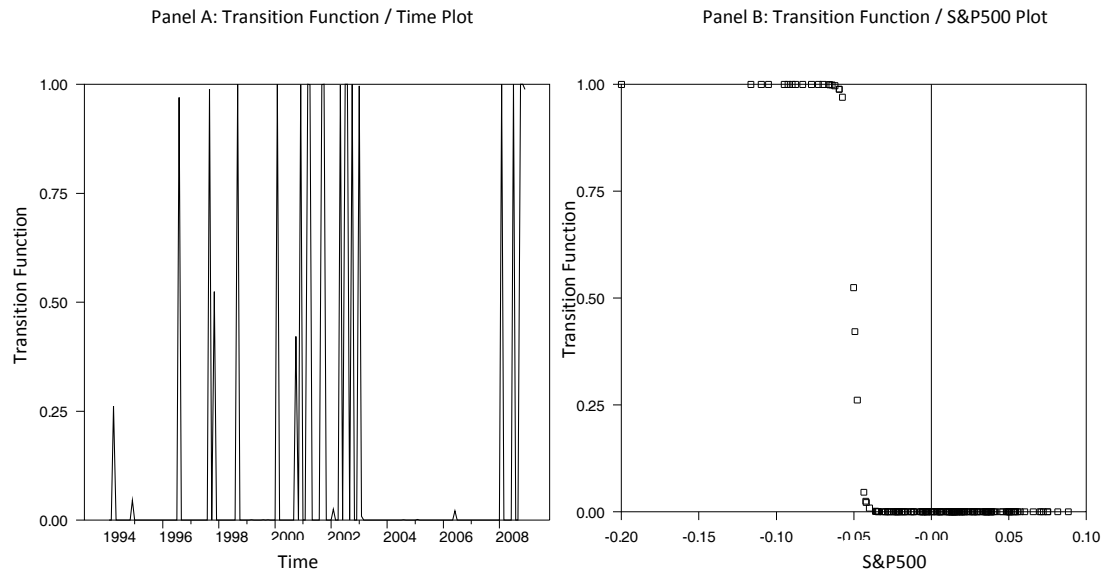
This table reports results from estimating the combined factor model for the equally weighted DSB hedge fund portfolio from January 1994 to December 2008 with dummy variables for the crisis and no-crisis periods (Billio et al, [2011]). \*\*\*, \*\* and \* indicate significance at the 1%, 5% and 10% level respectively.

**Exhibit 8**  
**Hypothesis Tests to Choose STR Model and Transition Function**

Delay	H <sub>0</sub>	H <sub>1</sub>	H <sub>2</sub>	H <sub>3</sub>
Panel A: S&P				
1	0.0037	0.0006	0.8541	0.1126
Panel B: SC-LC				
1	0.0000	0.0034	0.0001	0.0674

This table reports P-Values for the STR hypothesis tests. H<sub>0</sub> is a test for non-linearity. H<sub>1</sub>, H<sub>2</sub> and H<sub>3</sub> are tests for choosing between the LSTR and ESTR specifications.

## Exhibit 9 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 10**  
**Results from Estimating STR Model for DSB Equal Weighted Series**

Model Specification	Asset Class Factors	Coefficient	$\Delta$ Coeff	T-Stat	Adj R2
Regime 1 S&P > -0.04	Smoothing Coefficient	473.46***		3.45	77.07%
	Alpha	-0.0070		-1.22	
	S&P	-0.6095***		-6.57	
	SC-LC	-0.5117***		-4.35	
Regime 2 S&P < -0.06	Alpha	0.0031	0.0101*	1.67	
	S&P	-1.0392	-0.4297***	-4.08	
	SC-LC	-0.5828	-0.0712	-0.35	

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.

**Exhibit 11**  
**Relationship between Dedicated Short Bias and other Hedge Fund Styles**

*Panel A: Correlations*

	Aggregate	Convertible Arbitrage	Equity Market Neutral	Event Driven	Fixed Income Arbitrage	Global Macro	Long Short Equity
Full Sample	-0.46	-0.46	-0.12	-0.57	-0.17	-0.12	-0.68
No-Crisis Period	-0.37	-0.19	-0.09	-0.43	-0.21	-0.03	-0.50
Crisis Period	-0.47	-0.47	-0.30	-0.60	-0.09	-0.16	-0.72

*Panel B: Descriptive Statistics for Portfolio Allocations to DSB*

DSB Allocation	$\mu$	$\sigma$	SR	Skew	Kurt
0%	0.08	0.06	0.99	-2.16	6.69
10%	0.07	0.05	1.07	-2.60	9.29
20%	0.06	0.04	1.00	-2.34	7.34

Panel A reports correlation coefficients for the CSFB Tremont Dedicated Short Bias Value Weighted Hedge Fund Index, Aggregate hedge fund index and a range of value weighted sub-strategy indices for the Full Sample and No-Crisis and Crisis Periods (Billio et al [2011]). Panel B provides descriptive statistics for a portfolio formed by allocating  $x\%$  to the DSB index and  $1 - x\%$  to a portfolio formed from an equal weighted allocation to the Convertible Arbitrage, Equity Market Neutral, Event Driven, Fixed Income Arbitrage, Global Macro and Long Short Equity indices.

**Exhibit 12****Crisis and No-Crisis S&P500 Beta and Alpha of Hedge Fund Portfolios with DSB Allocation**

Model Specification	Asset Class Factors	Coefficient	T-Stat	Adj R <sup>2</sup>
<i>Panel A: 0% Allocation to DSB</i>				
Time period: No-Crisis	Alpha	0.0068***	5.74	44%
	S&P	0.1721***	5.37	
Time period: Crisis	Alpha	0.0022	0.93	
	S&P	0.2719***	7.29	
<i>Panel B: 10% Allocation to DSB</i>				
Time period: No-Crisis	Alpha	0.0067***	6.30	33%
	S&P	0.0552*	1.91	
Time period: Crisis	Alpha	0.0029	1.35	
	S&P	0.1927***	5.72	
<i>Panel C: 20% Allocation to DSB</i>				
Time period: No-Crisis	Alpha	0.0067***	6.38	23%
	S&P	-0.0617**	-2.17	
Time period: Crisis	Alpha	0.0036*	1.71	
	S&P	0.1136***	3.44	

This table reports results from estimating a single factor (S&P500 excess return) model for portfolios formed with a 0% (Panel A), 10% (Panel B) and 20% (Panel C) allocation to the DSB hedge fund index. The balance of the portfolio is divided equally between the Convertible Arbitrage, Equity Market Neutral, Event Driven, Fixed Income Arbitrage, Global Macro and Long Short Equity indices. Results are from January 1994 to December 2008. The model includes dummy variables for the crisis and no-crisis periods (Billio et al, [2011]). \*\*\*, \*\* and \* indicate significance at the 1%, 5% and 10% level respectively.