Factors that Affect the Performance of Distressed Securities Hedge Funds

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Abstract: We present a four factor model to replicate distressed securities hedge fund returns. The model considers the returns of short put options, a short straddle on bonds, the spread between high yield and Treasury bonds, and stocks with small market capitalization. Based on this model, we conduct a multivariate analysis of how fund characteristics affect risk-adjusted performance. A high-water mark and performance-based compensation are positively related to risk-adjusted performance, which is in line with much of the hedge fund literature. In contrast to other work, however, we find that lock-up is negatively related to performance and that fund age is unrelated to performance. Our work provides a better understanding of the nature and critical factors for the success of distressed securities hedge funds.

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1. Introduction

The aim of this paper is to shed light on the risk and return characteristics of distressed securities hedge funds. These funds typically invest in companies that are experiencing financial or operational difficulties. Neither investors nor regulators know where these funds invest, the extent of leverage they use, or which factors are important for their risk and return. For both investment and regulatory decisions, however, this type of information is highly relevant.

While distressed securities hedge funds are analyzed in general studies of the hedge fund industry (e.g., Capocci and Hübner, 2004; Coën and Hübner, 2009; Meligkotsidou et al., 2009), we follow Fung and Hsieh (2004; 2011) and Agarwal et al. (2011) and argue that strategy-specific models are required to explain the systematic risks of individual hedge fund strategies. In this work, we use a recently introduced factor model for distressed securities hedge funds (see Bontschev and Eling, 2010). Based on this model, we conduct a multivariate analysis to evaluate how fund characteristics affect risk-adjusted performance and fund survival. Furthermore, we use the alphas derived from the factor model to analyze performance persistence in the performance of distressed securities hedge funds.

We find that the existence of a high-water mark and performance-based compensation positively affect risk-adjusted performance. Past fund returns, the standard deviation of these returns, and the high-water mark provision are important determinants of fund survival. We find short-term persistence (mostly driven by losers) and only limited evidence for long-term persistence. These findings as to fund characteristics, persistence and survival are in line with the general hedge fund literature (such as Capocci and Hübner, 2004; Coën and Hübner, 2009; Meligkotsidou et al., 2009; Liang and Park, 2010).[1] Our analysis thus complements existing

[1] Our findings deviate from other studies in that we find lock-up to be negatively related to performance and fund age unrelated to performance and survival, which might be explained by the special characteristic of distressed security hedge funds. These findings underline the above argument that strategy-specific models are needed to explain the systematic risks of individual hedge fund strategies.

literature with a strategy-specific look at the nature of distressed securities hedge funds, which has not yet been provided in literature.[2]

The remainder of the paper is organized as follows. In Section 2, we review the related literature. In Section 3, we describe the data used in the empirical part. Section 4 presents the model developed by Bontschev and Eling (2010). In Section 5, a cross-sectional analysis of distressed securities hedge fund returns is conducted. Section 6 presents the results of the persistence and the survival analysis. Section 7 concludes.

2. Related Literature

2.1 Hedge Fund Performance

Two strands of literature are relevant for this work: first, the work on factor models, which can be traced back to Fung and Hsieh (1997) and, second, the strand of literature linking fund characteristics such as age, fund size, high-water marks, leverage, lock-up, notice period, redemption period, etc. to risk-adjusted performance. Typically, the second strand builds on the first, as factor models are used to derive alphas, which are then explained by the aforementioned fund characteristics. We also follow this approach in our work.

The literature on factor models is based on the fact that although the returns of traditional investment funds can be explained by the linear models of Sharpe (1992), Fama and French (1993, 1996), or Carhart (1997), these models do not sufficiently capture the characteristics of hedge fund returns. The dynamic investment behavior of hedge funds, their use of derivatives, and the fee structure result in returns that exhibit non-linear patterns over time (see Fung and Hsieh, 1997, 1999). Fung and Hsieh (1997, 2001, 2002b), Agarwal and Naik (2004), and

[2] We thus complement both the existing literature that conducts very general and broad analyses of all hedge fund strategies (such as Capocci and Hübner, 2004; Coën and Hübner, 2009; Meligkotsidou et al., 2009) and the literature that conducts a detailed analysis of selected hedge fund strategies (Mitchell and Pulvino (2001) consider merger arbitrage, Fung and Hsieh (2001) trend following, Duarte et al. (2007) fixed income, Eling and Faust (2010) emerging markets, and Agarwal et al. (2011) convertible arbitrage hedge funds). To our knowledge this is thus the first paper that focuses on distressed securities hedge funds.

Baghai-Wadji and Klocker (2007) show that factor models used to explain the return-generation process must take these peculiarities of hedge funds into account.

In principle, the dynamic investment behavior of hedge funds can be accommodated in two ways: with factor models that use time-varying beta factors (e.g., Bollen and Whaley, 2009; see also Billio et al., 2010) or by explaining the systematic risk through static multi-factor models, which use buy-and-hold factors as well as non-linear factors. Because non-linearities are already embedded in such factors, there is no need for a particular structure of a multi-factor model. Fung and Hsieh (2002b) use the term "asset-based style" (ABS) to describe these factors because they cover both the asset classes and the trading strategies that underlie a hedge fund strategy. These factors include, e.g., return differences between asset classes or the returns of option strategies. Agarwal and Naik (2004) use index returns of traditional asset classes and returns of option portfolios to explain the systematic risks of stock-market-oriented hedge funds (for a methodological discussion of style analysis, see also ter Horst et al., 2004).

For a number of hedge fund strategies there are models that take asset-based style factors into account when estimating market- and strategy-specific risk. For example, Mitchell and Pulvino (2001) show a systematic, non-linear relation between merger-arbitrage hedge fund returns and those of the S&P 500 Index. The returns of merger-arbitrage hedge funds can be replicated through a long position in risk-free bonds and short positions in index put options. Fung and Hsieh (2001) develop a multi-factor model for trend-following hedge funds in which the returns of option portfolios are used as regressors. This allows to capture the non-linearities relevant for this strategy group. Estimating the systematic risk of broadly diversified hedge fund portfolios in the form of funds-of-funds can also be aided by ABS factors and index returns of traditional asset classes, as demonstrated by the seven-factor model of Fung and Hsieh (2004). Recent studies by Duarte et al. (2007) and Agarwal et al. (2011) propose

ABS factor models to explain the risk and return profile of fixed income arbitrage hedge funds and convertible arbitrage funds.

Following Fung and Hsieh (2002a), Bontschev and Eling (2010) present an ABS factor model for the strategy group distressed securities hedge funds. They conduct an analysis of dynamic investment behavior by means of a static multi-factor model using non-linear factors. In this model, the returns of distressed securities hedge funds are explained by four risk factors: (1) a short put position on a stock index, (2) a short straddle on a bond index, (3) a spread factor that reflects the difference in returns of a high-yield bond index over 10-year U.S. Treasury bonds, and (4) an index for stocks with a small market capitalization. We use this model in our empirical analysis.

2.2 Fund Characteristics and Risk-Adjusted Performance

The second strand of literature relevant for this work deals with how fund characteristics relate to hedge fund performance. Many authors use multivariate analysis to provide information as to the direction and extent to which fund characteristics such as fee structure, lock-up and notice periods or assets under management (AUM) influence the risk-adjusted performance. Estimation of alpha is typically based on a given factor model structure. From the perspective of potential investors, insights about the relations between qualitative criteria and hedge fund performance could be relevant for investment decisions and contract design. In the literature, the following variables are often found to be relevant:

Fee structure—Parameters representing the fee structure include the fixed management fee and the performance-linked incentive fee. Because loss sharing is not foreseen in contracts, the fee structure resembles a long call option profile that the managers holds on the managed portfolio. Ackerman et al. (1999), Koh et al. (2003), and Edwards and Caglayan (2001) show that hedge funds, which collect higher incentive fees have better performance, but Brown et al. (1999) find no evidence for this proposition. Agarwal and Kale (2007) also arrive at the conclusion that neither the management fee and risk-adjusted performance nor the incentive fee and risk-adjusted performance have statistically significant, positive relations. Payment of the incentive fee is generally linked to the principle of a high-water mark. The profit sharing of the fund management corresponds to a call option on the managed portfolio. Through the high-water mark, the call option is out of the money, which induce incentives for management to achieve above-average performance. Studies by Agarwal and Kale (2007) or Agarwal et al. (2009) confirm the positive relation between high-water mark and risk-adjusted performance.

Lock-up and restriction period—Lock-up and restriction period (i.e. the sum of the notice and redemption periods; see Agarwal et al. (2009)) are set at the initiation of a hedge fund. As stated in Agarwal et al. (2009), the longer these mandatory periods are, the greater is the flexibility for the fund's management to effectively implement its strategy. However, shorter lock-up periods might force fund managers to perform better than their peers due to the threat of an abrupt capital withdrawal after bad performance. Empirically, however, Liang (1999), Aragon (2007), and Agarwal et al. (2009) find a statistically significant, positive relation between the length of lock-up/restriction period and the risk-adjusted hedge fund return.

Leverage—Leverage arises, for example, through the use of derivatives and debt financing or through short selling. In a perfect market without market frictions, leverage should not affect risk-adjusted performance, since it represents nothing more than moving along the capital market line. Only when market frictions such as insolvency costs and taxes are present, leverage might affect performance. Empirically, Liang (1999) documents that hedge funds using leverage only slightly outperform their peers in terms of returns, while having a higher standard deviation of returns. Schneeweis et al. (2005) find only small differences in risk-adjusted performance depending on leverage. The use of leverage is necessary for many hedge funds strategies, which attempt to exploit small price differences, such as arbitrage strategies. Compared to other hedge fund strategies, the use of leverage is less common for distressed securities hedge funds (Schneeweis et al., 2005; see also Chen, 2011, who shows that the event-driven category is among the strategies with the lowest use of derivatives). We thus expect no significant relationship between leverage and risk-adjusted performance in our case.

Fund size—Liang (1999) shows that the size of the AUM has a significantly positive effect on performance. The underlying rationale might be that larger funds realize economies of scale. Agarwal and Kale (2007) and Edwards and Caglayan (2001) arrive at a similar conclusion. The relation between AUM and performance should not, however, be linear. From a certain level of AUM onward, further increases should lead to an opposite effect on the risk-adjusted performance, as very large funds are less flexible in reacting to market changes and adjustments in strategy.

Age—Longevity might indicate a fund manager's quality, thus having a positive effect on performance. There could be a negative relation between age and risk if one assumes that younger fund managers have a bigger risk appetite. Their goal is to achieve high relative performance and higher fund inflows in order to build up a reputation within the industry. Funds that have been in existence for some time and have built up a solid AUM basis might show less willingness to take risk. This might also be motivated by the reemployment risk of fund management (see Brown et al., 2001). The costs for a manager—in the case of his/her dismissal—are even higher the older the fund and the more experienced the manager is. Agarwal and Kale (2007) find a statistically significant, negative relation between fund age and risk-adjusted performance, but Koh et al. (2003) do not observe any statistically significant effects between performance and age. At the hedge fund manager level, Boyson (2010) analyzes managers' herding behavior over their careers and finds that "…more senior managers who deviate from the herd have a significantly higher probability of failure and do not experience higher fund inflows than their less-senior counterparts". Furthermore, more experienced managers underperform less-experienced managers. Due to data limitations, we cannot analyze individual fund managers in this work, but include the age of the fund to incorporate such effects.

The discussion so far focused on risk-adjusted performance, but next to the question which factors are important for explaining performance, we are also interested in what factors influence distressed securities hedge funds survival. Many authors have analyzed the survival behavior of hedge funds in recent years (see, amongst others, Liang, 2000; Brown et al., 2001; Baquero et al., 2005, Malkiel and Saha, 2005; Liang and Park, 2010). These studies differ with respect to the proposed methodology for modelling the liquidation process and with respect to the included variables. While Liang (2000), Baquero et al. (2005), and Malkiel and Saha (2005) use probit analysis, Brown et al (2001) and Liang and Park (2010) use both Cox (1972) proportional hazard models and discrete-time binary choice models (logit and probit models). As we will discuss below we use a parametric logit model to analyze the effects of fund-specific characteristics on fund survival, but also implement various other approaches for the sake of robustness.

3. Data

The data set considered in this paper consists of monthly returns of distressed securities hedge funds from January 1995 until December 2007. In contrast to Bontschev and Eling (2010), we use a long time horizon for model development (alternatively, the data might be split in two periods, one for model development and one for an out-of-sample analysis.) Our results thus can be used to validate the empirical results of Bontschev and Eling (2010) for a longer time horizon as well as for a different and larger data set.[3] In this context, the time period from January 1995 to December 2007 is advantageous for three reasons. First, inspection of this period allows construction of a sample that is not much exposed to the common data

[3] Bontschev and Eling (2010) consider only January 1998 to January 2002 in developing their model and then provide out-of-sample analysis using data from February 2002 until January 2006. They use a combination of the TASS and CISDM data for their analysis, i.e., 63 funds from TASS and 30 funds from CISDM.

biases in the analysis of hedge funds returns.[4] Second, the period of examination spans the Russia crisis in August 1998 and the collapse of Long Term Capital Management, the bursting of the New Economy bubble in March 2000, and the attacks of September 11, 2001, i.e., three important market events for hedge funds. Third, the horizon of analysis is composed in relatively equal phases of rising and falling stock and bond markets.[5]

The sample consists of 139 hedge funds compiled from the Center for International Securities and Derivatives Markets (CISDM) data set. In CISDM's classification scheme, distressed securities are explicitly defined as a category, making it easy to select the relevant hedge funds. CISDM is based on Managed Account Reports (MAR), which have tracked the performance of managed futures since 1979 and of hedge funds since 1994. CISDM thus has one of the most comprehensive, and one of the oldest, databases on hedge funds; at present, it contains approximately 4,500 active and more than 9,000 inactive funds.

Because of the voluntary nature of reporting, hedge fund databases never reflect the total hedge fund universe. Furthermore, constructing a database always involves a number of biases. The goal of sample construction is to eliminate these biases as much as possible. For example, to eliminate instant history bias, the returns of the first 12 months were omitted.[6] Multi-period sampling bias can be presumed to be quite small due to the method of sample construction. We require a minimum of 24 monthly return observations.[7] Selection bias ap-

4 For example, liquidated funds have been captured in hedge fund databases only since 1994. For this reason, older data should not be used for the analysis of hedge funds. See Fung and Hsieh (2000) and Liang (2000).

5 Several studies are confined to the analysis of one market phase. However, Capocci et al. (2005) show that market phase influences performance analyses, which is why it is important to consider both rising and falling market phases.

6 Instant history bias occurs when returns in the incubation period of the hedge fund are considered in empirical analyses. Doing so can overestimate hedge fund returns. For TASS, Brown et al. (2001) show that the incubation period can be as long as 15 months for hedge funds. The authors calculate an instant history bias of 3.6% p.a. Fung and Hsieh (2000) find an instant history bias of 1.4% p.a. in the TASS sample, again with an incubation period of 15 months. Edwards and Caglayan (2001) find for the CISDM sample an annual instant history bias of 1.17%. Ackermann et al. (1999) calculate on the basis of the CISDM data and conclude that instant history bias is insignificant.

7 According to Ackermann et al. (1999), return data should be available for at least 24 months in order to eliminate multi-period sampling bias. Fung and Hsieh (2000) extend this to 36 months and show that multi-period sampling bias is negligibly small.

pears to be negligible, particularly since the direction of the bias is ambiguous.[8] The only bias of particular importance is the survivorship bias.[9] This bias cannot be eliminated, but it can be quantified. There are two commonly used definitions of survivorship bias: the difference in fund returns between the surviving funds and the dissolved funds (see Ackermann et al., 1999) or the difference between the returns of the surviving funds and all funds (see Liang, 2000). We follow Liang (2000) and find a survivorship bias of only 0.0011% per month, which is relatively low compared to other values found in literature. Various authors estimate the potential magnitude of the survivorship bias. Ackermann et al. (1999) calculate an overestimation of returns due to survivorship bias of 0.16% annually for the CISDM database, while Edwards and Caglayan (2001) find this figure to be 1.85% p.a. for the same database. Liang (2000) calculates a deviation of 2.24% p.a. for the TASS data set. Our finding thus confirms that the magnitude of survivorship bias in the CISDM data set is relatively small compared to other hedge fund databases.

Table 1 shows descriptive statistics of the monthly distressed securities hedge fund returns (net of fees) from January 1995 to December 2007. Next to the mean values calculated for each individual hedge fund (average), Table 1 shows an equally weighted hedge fund portfolio and three benchmark indices: the S&P 500, the Russel 2000 and the MSCI World. To calculate the average, all returns are considered on a single fund basis. For the equally weighted portfolio, all fund returns are cumulated into a naïvely diversified portfolio.

8 Selection bias arises due to the voluntary nature of reporting. Hedge fund managers are not required to release information about returns, leading to a bias of returns since, in general, only good funds provide information. This bias is limited, however, as hedge funds stop reporting after achieving a particular fund volume so as to stop attracting further capital. Fung and Hsieh (2000) thus describe selection bias not to be substantial.

9 Survivorship bias arises when only those funds are observed that are still in existence. Because it is especially unsuccessful funds, for example, those with poor performance, that are closed and leave the database, the data set offers a view of reality that is too positive.

Table 1: Return distribution—distressed securities hedge funds and benchmark indices

	Min./Max. in %	Mean in %	Median in %	SD in %	Skew-ness	Excess kurtosis	Jarque/Bera	AC (1)	Ljung/Box
Distressed hedge funds (average)	-7.99/10.02	1.04	1.00	2.88	-0.07	3.93	-	-	-
Equally weighted portfolio	-9.95/6.39	1.11	1.18	1.70	-1.74	11.16	131.56***	0.40	23.78**
S&P 500 Index	-14.58/9.67	0.83	1.21	4.09	-0.63	0.92	38.42***	0.00	0.00
Russel 2000	-19.49/16.42	0.86	1.56	5.36	-0.49	1.12	29.43***	0.06	0.65
MSCI World	-13.32/9.06	0.84	1.23	3.85	-0.69	1.00	38.33***	0.04	0.29

Significance levels are: *=10% level, **=5% level, and ***=1% level.

Compared to the benchmark indices, hedge funds achieve, on average, relatively high returns with a relatively low standard deviation (SD). To test the normal distribution hypothesis, the Jarque and Bera (1987) test statistic was computed. This is rejected for each of the observed cases, even for the benchmark indices, while autocorrelation of degree one (AC (1)) is present to a statistically significant extent only in the naïvely diversified hedge fund portfolio (see Ljung and Box, 1978).[10] If we observe the correlation among the returns of the distressed securities hedge funds, there are high values depending on the time horizon. These high correlations indicate the presence of common factors.[11]

4. Factor Model and Risk-Adjusted Performance

Bontschev and Eling (2010) show that the risk and return characteristics of distressed securities hedge funds can be explained by a linear combination of four factors: (1) a short put position on a stock index—the OTM Put factor as derived by Agarwal and Naik (2004); (2) a short straddle position on a bond index—the PTFSBD factor as derived by Fung and Hsieh (2001); (3) the returns of a spread factor that reflects the difference in returns of a high-yield index over 10-year U.S. Treasury bonds; and (4) stocks with a small market capitalization—

[10] To correct autocorrelation of degree one, a method presented in Kat and Lu (2002) can be applied. This method involves weighting the autocorrelation coefficients of degree one, and thus constructing a "new", non-autocorrelated time series out of the "old" (autocorrelated) time series. We use this method in robustness tests.

[11] In Bontschev and Eling 2010 we conducted a principal component analysis proceeded by a Bartlett test for sphericity, which tests whether the correlations also appear in relation to the whole population and whether they are suited for principal component analysis. We find that first two principal components explain up to 70% of the variance-covariance structure depending on the analyzed time period.

the Fama and French (1993) SMB factor.[12] This asset-based style factor model shows strong explanatory power for the return of this hedge fund strategy over time and can, for example, be used to detect deviations from a fund's declared investment style.

Based on the factor model and estimated alphas, we conduct a multivariate analysis that provides information about the direction and extent to which fund characteristics influence risk-adjusted performance. We thus follow Bontschev and Eling (2010) and model the returns of distressed securities hedge funds by using the four factors mentioned above. Model (1) in Table 2 shows the coefficients estimates for the ABS model. To address illiquidity risk we analyzed different model structures. To proxy for market liquidity, we employ the Pástor and Stambaugh (2003) aggregate monthly innovation in liquidity measure and the spread of Moody's Baa over Moody's Aaa. We analyzed whether those factors are significant and whether they add significant explanatory power.

As expected, there is significant exposure to all risk factors. The sign of the SMB factor shows a positive exposure to companies with a small market capitalization. The negative sign of the OTMPut factor shows that returns of distressed securities hedge funds resemble a short position in index put options. The positive sign of the SpreadLHYCaa factor indicates long positions in high-yield bonds with short positions in U.S. Treasuries. The adjusted R^2 for the full model is 55.67%. The associated RESET (Regression error specification test; see Ramsey 1969) statistic confirms the selected functional form. The values for the variance inflation factor lie between 1.048 and 1.184 and thus are far from the area of critical multicollinearity. The standard errors presented in italics in Table 2 are Newey and West (1987) estimated to a lag of six. The model results confirm the results presented by Bontschev and Eling (2010) for a longer time period and using an alternative data set.

Table 2: Results — four factor model

[12] See Agarwal and Naik (2004). The OTM put option data was provided by Vikas Agarwal. The PTFSBD factor derived by Fung and Hsieh (2001) was provided by David Hsieh. See

	(1)	(2)	(3)	(4)
Alpha	0.009*** *0.002*	0.0004 *0.008*	0.010*** *0.002*	0.002 *0.008*
SMB	0.157*** *0.032*	0.1557*** *0.0318*	0.157*** *0.032*	0.156*** *0.032*
OTMPut	-0.008*** *0.002*	-0.0084*** *0.0015*	-0.008*** *0.002*	-0.008*** *0.002*
SpreadLHYCaa	0.081*** *0.028*	0.0865*** *0.0302*	0.087*** *0.029*	0.092*** *0.030*
PTFSBD	-0.025*** *0.013*	-0.0261*** *0.0128*	-0.025** *0.013*	-0.026*** *0.013*
SpreadBaaAaa		0.1349 *0.1107*		0.125 *0.115*
Pástor /Stambaugh (2003) liquidity factor			-0.031 *0.026*	-0.028 *0.027*
Adj. R^2	0.5567	0.5584	0.5576	0.5587

(1) ABS model structure; **(2)** ABS model structure + Spread Moody's Baa/Aaa; **(3)** ABS model structure + Pástor /Stambaugh (2003) liquidity factor; **(4)** ABS model structure + Spread Moody's Baa/Aaa + Pástor /Stambaugh (2003) liquidity factor. The significance levels are: *=10% level, **=5% level, and ***=1% level.

A model comparison illustrates the advantages of the proposed structure compared to the models commonly used in performance measurement analyis and shows the necessity of incorporating factors that capture the non-linearities of this particular hedge fund strategy.[13] Liquidity aspects were particularly addressed (see Models (2) to (4) in Table 2). The spread of Moody's Baa over Moody's Aaa (SpreadBaaAaa) and the liquidity measure of Pástor and Stambaugh (2003) were added to the ABS model structure.[14] The adjusted R^2 of the full model remains unchanged when considering these factors; the effect of the factors themselves is statistically insignificant. The stability of the ABS model structure was analyzed using the standard CUSUM test of Brown et al. (1975) and the OLS-CUSUM test proposed by Ploberger and Krämer (1992). No breakpoints can be identified.

http://faculty.fuqua.duke.edu/~dah7/HFRFData.htm.

13 The adjusted R^2 for the CAPM, or for the three-factor model of Fama and French (1993, 1996), and the four-factor model of Carhart (1997) are substantially lower (~30%) compared to the proposed model. The HML and momentum factors remain statistically insignificant. The seven-factor model of Fung and Hsieh (2004) also has a significantly lower adjusted R^2.

14 See Agarwal et al. (2009, 2010) and Fung and Hsieh (2011). The spread of Moody's Baa/Aaa was used in an earlier version of Agarwal et al. (2010) to capture liquidity in the bond market.

5. Fund Characteristics and Risk-Adjusted Performance

A multivariate analysis should now provide information as to the direction of and extent to which fund characteristics such as fee structure, lock-up and notice periods, fund volume etc. influence risk-adjusted performance. Alpha values are determined based on the introduced ABS model structure. From the perspective of potential investors, insights about the connections between qualitative criteria and hedge fund performance could be relevant for investment decisions and contract design. The following variables are considered in the regression:

Fee structure—We use three parameters for the fee structure: the management fee, the performance-linked incentive fee, and the high-water mark, which is included as a binary indicator variable.

Lock-up and restriction period—Lock-up and restriction period (sum of the notice and redemption periods) are included.

Leverage—Leverage is captured by a binary indicator variable.

Fund size—Fund size is measured by the natural logarithm of assets under management.

Age—We control for the age of the fund and include the natural logarithm of age as regressor variable.

Flow—Flow is the money flows of fund i in year $t-1$.

The regression equation is:

$$Alpha_{i,t} = \beta_0 + \beta_1 AUM_{i,t-1} + \beta_2 Age_{i,t-1} + \beta_3 Flow_{i,t-1}$$

$$+\beta_4 MFee_i + \beta_5 IFee_i + \beta_6 HW_i + \beta_7 LU_i + \beta_8 RP_i + \beta_9 Lev_i + \varepsilon_{i,t}\,,\ t = 1,2,...,T\,;\, i = 1,2,...,N.$$

$Alpha_{i,t}$ is the risk-adjusted performance of each distressed securities hedge fund i in the interval t.[15] $AUM_{i,t-1}$ is the fund volume and $Age_{i,t-1}$ the corresponding age of distressed securities

[15] The risk-adjusted performance for fund i is determined on the basis of the developed ABS model structure and based on a time horizon of 18 months. For the sake of robustness we calculated alpha values based on 12-month rolling window regressions. The results confirm the findings presented in this section.

hedge fund i at time t-1. Flow is the money flows of fund i in year $t-1$.[16] The fund-specific management and incentive fees are expressed by $MFee_i$ and $IFee_i$. HW_i and Lev_i are dummy variables for fund i, which are one if a high-water mark or leverage exists, and zero otherwise. LU_i is the lock-up period; RP_i is the restriction period, which is defined as the sum of the notice and repayment periods. $\varepsilon_{i,t}$ is the error term.

Table 3 provides summary information on the input variables used in the cross-sectional analysis. Panel A presents mean and standard deviation for the variables. Panel B provides summary information for the time-invariant variables.

[16] Following previous studies (e.g., Agarwal et al., 2009, Agarwal and Kale, 2007) we calculate flow as follows: $Flow_{i,t} = \frac{AUM_{i,t} - AUM_{i,t-1}(1+Returns_{i,t})}{AUM_{i,t-1}}$, where $AUM_{i,t}$ and $AUM_{i,t-1}$ are the assets under management of fund i at the end of year t and $t-1$ and $Returns_{i,t}$ is the return for fund i during year t.

Table 3: Summary statistics — input variables cross-sectional analysis

Time varying variables						
Year	Alpha		Assets under management		Flow	
	Mean	SD	Mean ($M)	SD ($M)	Mean	SD
1996	0.0135	0.0050	58.1	97.3	0.8667	1.0962
1997	0.0156	0.0017	64.6	109.2	0.6105	2.6133
1998	0.0135	0.0029	89.6	144.5	0.6845	1.2996
1999	0.0243	0.0046	114.3	186.8	1.0672	1.7248
2000	0.0269	0.0088	95.1	158.5	0.5332	0.8675
2001	0.0085	0.0015	102.5	177.1	-0.0833	0.4361
2002	0.0061	0.0011	134.2	246.2	0.4360	1.0458
2003	0.0098	0.0026	159.4	322.9	0.4120	1.0219
2004	0.0170	0.0031	179.3	373.4	1.0333	1.9686
2005	0.0167	0.0039	242.5	515.7	0.5271	1.3735
2006	0.0184	0.0046	343.6	746.2	0.7664	1.4295
2007	0.0226	0.0025	309.2	627.2	1.0231	3.2395

Time-invariant variables		
	Mean	SD
Age (years)	7.15	3.98
Management fee (%)	1.40	0.42
Incentive fee (%)	19.17	3.29
Lock-up period (month)	12.96	8.48
Funds with high-water mark (%)	79.01	-
Funds with leverage (%)	18.66	-
Restriction period (month)	7.09	4.37

The table shows, for the years 1996 to 2007, the mean and standard deviation (SD) of alpha, assets under management, and the flow variable. The mean and standard deviation for the time-invariant variables are presented also. The calculation of lock-up period is based on those funds, which provide information to use a lock-up period.

As seen in Table 3, we find, on average, positive alpha values.[17] Alpha increases from 1998 to 2000 and then decreases at the end of the ".com-bubble" in 2001. The high standard deviation of alpha could indicate differences in manager skills, with some hedge fund managers receiving high alpha values also in 2001. The question of whether certain distress securities hedge fund managers can consistently outperform their peers will be discussed in the analysis of

[17] Based on the results of the rolling window regression analysis, Table 3 shows average monthly alpha. For the cross sectional analysis average yearly alpha values were calculated; to mitigate outliers we require at least six monthly alpha observations for a fund.

performance persistence (see Section 6). Regarding fund size, it is striking that the assets under management of distressed securities hedge fund significantly increased until the end of 2006. This confirms the growing importance of distressed securities hedge funds in financial markets. Moreover, the growing fund volume suggests good performance, since good performance increases fund size and attracts new investors. This finding is confirmed by the flow variable, which is positive in all years, with one exception (the year 2000). The high standard deviation of the flow variable shows that fund flow is very dispersed among hedge fund managers, with some managers receiving high inflows and others not. The low standard deviation for the fee variables (management fee and incentive fee) shows that there is a market standard for the fee structure. Typically, the management fee is around 1% or 1.5%, the incentive fee around 20%. About 80% of all distressed securities hedge funds have a high-water mark; however, leverage is used by only 20% of the hedge fund managers in our sample, which provides evidence that distressed securities is not among the highly leveraged hedge fund strategies (see Schneeweis et al., 2005).

Table 4 shows the results of the cross-sectional regressions. The column FM (1973) displays Fama and MacBeth (1973) standard errors. Based on results provided by Petersen (2009), we address the problem of estimating standard errors in panel data sets. In addition to White standard errors, clustered standard errors were calculated. CL(Y) indicates the results of a clustering by time periods/years, CL(F) stands for a clustering by fund, and CL(F,Y) indicates that clustering was done for both dimensions.

Table 4: Results — cross-sectional analysis of risk-adjusted performance

		Pooled OLS				
	FM (1973)		White (1980)	CL (F)	CL (Y)	CL (F,Y)
Log (AUM)$_{t-1}$	0.03244** (0.01250)	0.03561*** (0.0096)	0.03561*** (0.0086)	0.03561*** (0.009)	0.03561*** (0.0134)	0.03561*** (0.0135)
Log (Age)$_{t-1}$	-0.01060 (0.03498)	-0.01132 (0.0214)	-0.01132 (0.0237)	-0.01132 (0.0284)	-0.01132 (0.0234)	-0.01132 (0.0277)
Flow$_{t-1}$	-0.02292* (0.01531)	-0.00227 (0.0068)	-0.00227 (0.0083)	-0.00227 (0.0085)	-0.00227 (0.0083)	-0.00227 (0.0082)
MFee	-0.09639* (0.05740)	-0.09187*** (0.0275)	-0.09187*** (0.0314)	-0.09187* (0.0533)	-0.09187** (0.0393)	-0.09187 (0.058)
IFee	0.02348** (0.01074)	0.02263* (0.0119)	0.02263*** (0.0078)	0.02263** (0.0108)	0.02263*** (0.0062)	0.02263** (0.0095)
HW	0.05212*** (0.01836)	0.038 (0.0282)	0.038 (0.0261)	0.038* (0.0195)	0.038 (0.0445)	0.038 (0.0407)
LU	-0.00462*** (0.00123)	-0.00321*** (0.0011)	-0.00321*** (0.0011)	-0.00321** (0.0013)	-0.00321** (0.0013)	-0.00321** (0.0015)
Lev	0.01334 (0.01469)	0.00863 (0.0268)	0.00863 (0.0275)	0.00863 (0.0108)	0.00863 (0.0267)	0.00863 (0.006)
RP	0.00002 (0.00358)	0.00142 (0.0027)	0.00142 (0.0026)	0.00142 (0.0033)	0.00142 (0.0041)	0.00142 (0.0045)
Constant	-0.74168** (0.33463)	-0.79421** (0.3257)	-0.79421*** (0.2464)	-0.79421*** (0.2729)	-0.79421** (0.3156)	-0.79421** (0.3329)
Adj.R^2	0.1069	0.0907	0.0907	0.0907	0.0907	0.0907

In addition to White (1980) standard errors, clustered standard errors were calculated. CL(Y) indicates clustering by time periods/years, CL(F) stands for a clustering by fund, and CL(F,Y) indicates clustering by fund and time. The pooled OLS regressions contain time dummies (year). The column FM(1973) displays the Fama and MacBeth calculations. For fund volume and age, the natural logarithm was used—Log (AUM)$_{t-1}$ and Log (Age)$_{t-1}$. MFee and IFee are the management and incentive fee, respectively. HW and Lev are indicators for high-water mark and leverage. LU and RP stand for lock-up and restriction period. The dependent variable is the risk-adjusted performance. The significance levels are: *=10% level, **=5% level, and ***=1% level.

The coefficients of the Fama and MacBeth estimates (FM (1973)) are average time values of the corresponding cross-section regressions. The results of these estimations show that the existence of a high-water mark (HW) and performance-based compensation (IFee) have a significant, positive influence on risk-adjusted performance. Distressed securities hedge funds which have a high-water mark achieve a 5.21% higher risk-adjusted performance. There is a negative statistically significant relation between the fixed management fee (MFee) and risk-adjusted performance. In general, the results regarding the fee structure are in line with those of Ackermann et al. (1999), Liang (1999), Edwards and Caglayan (2001), and Agarwal and

Kale (2007), all of whom find that incentive-based compensation increases fund performance. Moreover, in the Fama-MacBeth framework, we find a negative relation between the lock-up period and risk-adjusted performance. As discussed earlier, there are two effects regarding the lock-up/restriction period variable. One could assume that longer lock-up and restriction period might positively affect fund performance due to the greater flexibility they afford in implementing investment strategies. However, shorter lock-up periods might induce fund managers to perform better than their peers due to the threat of an abrupt capital withdrawal following bad performance. We find a negative relation between lock-up and fund performance, thus supporting the second effect. As expected, leverage has no influence on risk-adjusted performance. Fund volume has a positive, statistically significant relation to risk-adjusted performance, which is an indication of economies of scale. This finding is in line with Liang (1999) and Agarwal and Kale (2007) and shows that funds with high alphas attract new investors and thus accumulate more assets. Finally, there is no statistically significant relation between fund age and risk-adjusted performance. While many authors find age to be significant, our results are in line with those presented by Koh et al. (2003) who does not observe significant effects between performance and age.

To validate the robustness of the results, Fama and MacBeth (1973) regressions were complemented by pooled OLS estimations with White (1980) and clustered standard errors. The estimations of the standard errors that result from a clustering by fund and/or year differ from and, for the most part, are greater than the White standard errors. We cluster by two dimensions, as this method produces less biased standard errors. The column CL (F,Y) shows the results for clustering by two dimensions. Only three variables remain statistically significant. The incentive fee has a positive and significant influence on risk-adjusted performance. Distressed securities hedge funds using performance-based remuneration have a risk-adjusted performance that is 2.26% higher than those without. High-water mark, leverage, and restriction period have no statistically significant influence on performance, while the lock-up period negatively affects to the risk-adjusted performance. This underlines our hypothesis that shorter lock-up and restriction period enable investors to withdraw capital, creating incentives for an individual distressed securities hedge fund managers to perform better than the peer group. AUM are positively related to risk-adjusted performance, thus providing evidence of economies of scale. Age has no statistically significant influence on the risk-adjusted performance of distressed securities hedge funds. In contrast to the Fama and MacBeth (1973) framework, the flow variable remains negative, but statistically insignificant. [18]

6. Performance Persistence and Fund Survival

Based on the individual alpha estimates for each of the 139 distressed securities hedge funds and the methodology provided by Agarwal and Naik (2000) and Brown and Goetzmann (1995), we use non-parametric tests to evaluate the level and the direction of performance persistence. Non-parametric approaches include the contingency-table-based cross-product ratio test and the chi-square test. Contingency-table-based methods involve the construction of tables of winners and losers. Winners are those distressed securities hedge funds whose alpha is higher than the median alpha over the chosen period; losers are those funds whose alpha is lower than the median alpha of the particular hedge fund strategy. Funds that are winners (WW) and losers (LL) in both periods are "persistent."[19] WL (LW) indicates winner (loser) in the first period and loser (winner) in the period thereafter. The cross-product ratio (CPR) test (Agarwal and Naik, 2000) is the ratio of the funds with performance persistence to funds that did not persist:

[18] Further robustness tests were conducted to analyze the findings presented in this section. For example, results for an alpha estimation period of 12 months confirm most of the results presented in this section.

[19] Baquero et al. (2005), Boyson and Cooper (2008) and Brown et al. (1999) point out that an analysis of hedge fund performance persistence should be based on risk- or style-adjusted returns.

$CPR = (WW \cdot LL)/(WL \cdot LW)$.

Under the null hypothesis—no performance persistence—each of the four categories represents 25%, in which case the CPR is one. Statistical significance of the CPR can be tested by using the standard error of the natural logarithm of CPR $\alpha_{\ln(CPR)}$:[20]

$$\alpha_{\ln(CPR)} = \sqrt{1/WW + 1/WL + 1/LW + 1/LL}\,.$$

The test statistic for the chi-square test is given by:

$$\chi^2 = (WW - D1)^2/D1 + (WL - D2)^2/D2 + (LW - D3)^2/D3 + (LL - D4)^2/D4\,,$$

with $D1 = (WW + WL) \cdot (WW + LW) / N$, $D2 = (WW + WL) \cdot (WL + LL) / N$, $D3 = (LW + LL) \cdot (WW + LW) / N$, and $D4$ with $D4 = (LW + LL) \cdot (WL + LL) / N$. N is the number of funds. Corresponding to the chi-square distribution with one degree of freedom, a value of the test statistic with greater than 3.84 (6.64) indicates significant persistence at the 5% (1%) confidence level.

Table 5 shows that in a two-period framework, the level of statistically significant persistence varies with the time horizon. In accordance with Agarwal and Naik (2000), Boyson and Cooper (2008), Malkiel and Saha (2005), Eling (2009), and Edwards and Caglayan (2001), we find evidence for short-term persistence on a monthly, quarterly, half-yearly, and even yearly level. However, performance persistence for distressed securities hedge funds is driven mostly by losers. We find limited evidence for long-term persistence. Both CPR and the chi-square test are significant at a yearly level, but the degree of significance is much lower compared to the monthly, quarterly, and half-yearly figures. Moreover, both tests lose their significance when considering a time horizon of two years.[21] We thus conclude that in line with

[20] Corresponding to the standard normal distribution, a value greater than 1.96 (2.58) indicates significant persistence at the 5% (1%) confidence level.

[21] We also conducted the performance persistence analysis for sub-periods of our data set. These tests show that the results of the persistence analysis depend on the time horizon. For example, when only the time period 1998 to 2001 is considered for the persistence analysis (this is the time horizon considered in Bontschev and Eling, 2010), we only find persistence up to six months. The evidence for long-term performance persistence documented on a yearly level in Table 5 thus must be viewed with some caution because it depends on the time horizon.

much of the hedge fund literature, there is evidence for short-term performance persistence, but only limited or no evidence for long-term persistence.

Table 5: Results — performance persistence

	WW	WL	LW	LL	CPR	χ^2-statistics
A. Monthly	3432	563	546	4042	45.13***	4703.57***
B. Quarterly	966	300	288	1155	12.914***	861.11***
C. Half-yearly	400	185	171	488	6.17***	224.65***
D. Yearly	139	100	98	178	2.53**	26.46**
E. Biennial	38	38	38	63	1.66	2.71

Finally, we investigate which factors influence survival of distressed securities hedge funds. As discussed, prior studies differ with regard to the modelling of the liquidation process and with respect to the included variables (some authors use discrete-time binary choice models such as probit analysis, while others rely on Cox (1972) proportional hazard model). We use a parametric logit model to analyze the effects of fund-specific characteristics on fund survival.[22] Knowing that the logit model requires strong parametric as well as distributional assumptions, we complement our analysis by applying the semi-parametric Klein and Spady (1993) approach. The results remain largely unchanged. To proper assign a fund to each of the two categories "survived" or "liquidated" we apply the procedure proposed by Liang and Park (2010). Thus, liquidation means that a fund states to be no longer active; stopped reporting. Furthermore, we assign a fund to this category if AUM decreased over the last twelve month and if it has a negative average return over the previous twelve month.

With regard to the explanatory variables, we follow Liang and Park (2010) and include the monthly average return during the previous twelve month (Ret) and AUM during previous twelve month (AUM) in the analyses. Furthermore, we use standard deviation of the respective fund returns (SD_Ret) and AUM (SD_AUM). Fund age is measured in month (Age). We

[22] We also implemented a probit model. As expected, results remain unchanged. As mentioned by Baba and Goko (2009) regression models with dichotomous dependant variables have the disadvantage, in that they

also included the three dichotomous variables high-water mark (HW), lock-up (LU) and leverage (Lev). The logit model is thus given by the following equation:[23]

$$\begin{aligned}\Pr(LIV = 1) = \Lambda(&\beta_0 + \beta_1 Ret + \beta_2 SD\_Ret + \beta_3 AUM + \beta_4 SD\_AUM \\ &+ \beta_5 Age + \beta_6 HW + \beta_7 LU + \beta_8 Lev)\end{aligned}$$

The dependant variable is the probability of hedge fund survival. Table 6 illustrates the results. As documented by previous literature (e.g., Liang, 2000; Brown et al., 2001; Baquero et al., 2005; Malkiel and Saha, 2005; Liang and Park, 2010), we find that fund returns, risk, and high-water mark play an important role in the explanation of fund survival. Fund return has a statistically significant positive influence on fund survival. We observe a negative relation between risk, measured as standard deviation, and fund survival. According to prior studies (e.g., Liang and Park, 2010), hedge funds that state to have a high-water mark provision have a significantly higher survival probability than its peers which is confirmed for our sample of distressed securities hedge funds. As stated by Liang and Park (2010), the high-water mark requires hedge fund managers to recover past losses, thus it serves as a quality signal. In our sample, the marginal effect for the high-water mark variable indicates a 39.3% higher survival probability for distressed securities hedge funds with high-water mark provisions.

cannot handle the problem of right censoring. On the other hand the Cox proportional hazard model is subject to a restrictive assumption of the proportionality of hazard ratios with respect to duration time.

23 We also analyzed the inclusion of other fund specific variables such as incentive or management fee. These variables remain insignificant. Based on a Likelihood-ratio test we excluded them from the model, thus presenting the final (nested) model.

Table 6: Results — survival analysis logit model

	Logit Model	
	Coeff.	Marginal effect ($f(\vec{x}_i\beta)\cdot\hat{\beta}_j$)
Ret	2.484*	0.211*
SD_Ret	-1.079**	-0.092**
AUM	0.003	0.001
SD_AUM	-0.016	-0.001
Age	-0.002	-0.001
HW	4.621***	0.393***
LU	-1.622	-0.138
Lev	-1.467	-0.125
Constant	-0.439	-0.037
Log-Likelihood	-13.090	
AIC	44.181	

The table shows the results from a Maximum-Likelihood estimation of the logit regression. The dependant variable is fund survival (LIV=1). Ret, AUM stand for the monthly average return, AUM during the previous twelve month. SD_Ret and SD_AUM indicate the respective standard deviations. Age is fund age measured in month. HW, LU, and Lev are indicators for high-water mark, lock-up and leverage. Standard errors are calculated using Huber-White sandwich estimator. The significance levels are: *=10% level, **=5% level, and ***=1% level.

7. Conclusions

In this study, we use an asset-based style model and analyze factors that affect the performance of distressed securities hedge funds. The returns of distressed securities hedge funds exhibit non-linear patterns caused, in particular, by dynamic trading strategies. The return profile of distressed securities hedge funds resembles a short put position on a stock index and a short straddle position on a bond index. The proposed asset-based style model explains 55% of the return structure, a value comparable to values documented for other hedge fund strategies (see, e.g., Eling and Faust, 2010).

The chosen risk factors are all based on traded securities and their derivatives so that modeling the performance characteristics over longer time periods and transparency is possible. This offers insight into the risk profile of this particular hedge fund strategy. For supervisory authorities, such information can increase the general understanding of the characteristics of this hedge fund category and facilitate monitoring.[24] For investors, it is important to be fully aware of risk factors so as to appraise the risk-adjusted performance of individual distressed securities hedge funds and ensure optimal allocation of assets. At the individual fund level, it can furthermore be assessed whether a fund manager has deviated from the declared investment style over time.

The results of the Fama and MacBeth (1973) cross-sectional regressions are in line with previous literature. To validate the robustness of the Fama and MacBeth (1973) results, we followed Petersen (2009) and conducted pooled OLS estimations with White (1980) and clustered standard errors. We demonstrated how clustering by fund and time influences levels of significance of respective coefficients. In this respect, we decided on clustering by funds and time. Controlling for size, flow, and age, we find a positive and statistically significant relation between incentive fee and risk-adjusted performance of distressed funds. In contrast to current literature, we find a negative relation between the length of the lock-up period and risk-adjusted performance of distressed funds.

The analysis of persistence provides evidence of short-term performance persistence that is mostly driven by the losers. Only limited evidence is found for long-term persistence. This finding is in line with much of the persistence literature (see Agarwal and Naik, 2000; Eling, 2009). The results of the logit model confirm that past fund returns, risk and the existence of a high-water mark as a quality signal are important factors for hedge fund survival, findings which are again in line with much of the general hedge fund literature (e.g., Liang and Park, 2010). Overall, our results improve understanding of the return sources of distressed securities hedge funds and the drivers of their risk-adjusted performance.

[24] Monitoring can take place, for example, inasmuch as the exposures of relevant market participants to these risk factors are observed. Assuming that for different strategy groups an increase in betas of risk factors can be observed, this could indicate convergent bets of different market participants, see Fung and Hsieh (2004).

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