Market Conditions and Hedge Fund Survival

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As the hedge fund industry has grown, there has been increased concern that, during sharp market moves, hedge fund failures could exacerbate the deterioration in financial conditions and deepen a crisis. However, there has not been much formal analysis regarding the impact of financial market conditions on hedge fund survival. To help fill this gap, this paper examines the relationship between financial market conditions and the likelihood of hedge fund failure after controlling for performance and other characteristics. The analysis is conducted using data on individual funds and industry aggregates. We find that market returns and volatility influence fund failures, although the impact depends on the funds' investment strategies. The results of the analysis are then used to predict hedge fund failures based on actual market returns and on stress scenarios. We find that the hedge fund industry is generally robust to different shocks.

The hedge fund industry has expanded rapidly over the past decade. The growth in this industry has provided benefits to the financial system by contributing to increased liquidity in financial markets and possibly by boosting the pace of financial innovation (Bernanke 2007, Financial Stability Forum 2007). However, with the expansion of the industry has also come increased concern about whether troubles in the hedge fund industry could have negative impacts on financial market stability (G-7 Finance Ministers and Central Bank Governors 2007). Hedge funds could affect financial markets either by providing the impetus for a shock or by augmenting the effect of a shock originating elsewhere. Part of this concern results from the fairly extensive use of leverage by hedge funds as well as the imprint made by the spectacular collapse of Long Term Capital Management (Izzo 2006, Financial Stability Forum 2000). Concern about the impact of hedge funds also arises because hedge fund investment strategies are generally opaque so that market participants do not know whether large price movements or shifts in sentiment might result in the failure of one or more hedge funds (Bernanke 2007).

In this paper, we analyze whether various financial market conditions are associated with an increased likelihood of individual fund failures or with an increase in the aggregate number of failures.[1] This exercise allows us to gain a better understanding of the factors that contribute to hedge fund failures. These results provide some perspective on how the industry might perform under different financial market stresses.

There has been some previous work examining the factors that affect hedge fund failures (Baba and Goko 2006; Chan, Getmansky, Haas, and Lo 2005; Baquero, Horst, and Verbeek 2005; Getmansky 2005; Getmansky, Lo, and Mei 2004, Liang 2000). This previous research has focused almost exclusively on the connection between failure and hedge fund characteristics and performance.[2] For instance, Baba and Goko (2006) employ hazard models to look at whether factors such as returns, investment flows, fee structures, and lock-up periods affect hedge fund survival. They find that strong returns and positive investment inflows in the recent past are related to a lower likelihood of failure. They also find evidence that incentive schemes and restrictions on

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[1] The hedge fund database we use does not precisely identify which funds are failed. The method we use for deciding to treat a fund as a failure is discussed in detail below.

[2] An interesting exception is (Khandani and Lo 2007), who look at hedge fund performance during the market turbulence of August 2007. That paper provides some in-depth analysis of how the turbulence of that specific episode affected the performance of some hedge funds. By contrast, this paper looks at the relationship between market conditions and hedge fund failures over a much longer period.

investor withdrawals matter, with the use of high-water marks and longer notice and payout periods reducing failure. Liang (2000) and Chan, Getmansky, Haas, and Lo (2005) find similar results using probit and logit analysis respectively. Getmansky (2005) provides a more detailed analysis of the impact on survival of investment flows to the fund and to other funds pursuing similar investment strategies. Getmansky, Lo, Mei (2004) find higher attrition rates at funds with a lower measure of illiquidity. While this research has connected fund characteristics to failures, it has generally not explored the impact of conditions in financial markets on hedge fund failures. As market commentary about the systemic risk posed by hedge funds often points to concerns about how the industry will perform during stressful times in financial markets (see for example the discussion in Garbaravicius and Dierick (2005, pp. 43-49)), this paper takes a step toward filling an important gap in the literature.

In this paper, we analyze a variety of market factors to determine whether they are associated with hedge fund failures. Using data from 1994, when the database we use began collecting data on hedge fund failures, to 2006, we regress hedge fund failures on a variety of market returns, spreads, and realized volatility measures as well as hedge fund characteristics. The analysis is conducted using individual fund level data, which allows us to control for a number of fund level factors and characteristics found to be important in previous research, and using aggregate industry data, which smooths over idiosyncrasies associated with individual funds. The analysis is conducted using the entire sample period and, to account for changes in industry practices regarding the use of incentives and for strategic adjustments in hedge funds' investment strategies in response to changing conditions, using rolling windows.

The use of rolling windows also allows us to make out-of-sample forecasts and explore whether these models are able to provide a reasonable estimate of the number of funds that liquidated in the past under the market conditions that actually prevailed at the time. Using our regression results, we explore how different market shocks might have been expected to affect the hedge fund industry. The shocks used are a repeat of the market movements that occurred in August 1998, a four standard deviation decline in equity markets, and a four standard deviation decline in the dollar. Estimating the impact of the different shocks over time provides some indication of whether the hedge fund industry appears to be sensitive to different shocks and how the sensitivity varies over time.

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The results based on analysis of individual hedge funds identify several hedge fund characteristics and performance measures that appear be associated with increased likelihood of failure. These findings generally follow previous work. For instance, funds earning higher returns have a lower likelihood of failure, as do funds that employ high-water marks. Investor behavior is also associated with survival; funds estimated to have relatively low investment inflows are more likely to liquidate than funds receiving relatively strong inflows.

Market returns and conditions also matter, even after controlling for hedge fund performance. A positive U.S. stock market return generally decreases the likelihood of failure, unless the fund has a short-bias strategy. Higher volatility in financial markets also matters, although the size and direction appears to vary over time. Higher spreads in the swap market also boost the likelihood of failure, particularly among funds reporting that they use leverage. The analysis using industry aggregates is limited to a smaller number of explanatory factors; nevertheless the results are generally, though not always, similar to those of the analysis that uses individual funds.

When looking at predictions of fund liquidations in response to actual market movements, the analysis using industry aggregates does fairly well in predicting liquidations one month ahead. Periods in which liquidations are elevated are generally picked up in the analysis, and the overall level of predicted failures is close to the actual level. By contrast, predictions of the number of fund liquidations using individual funds tend to be quite volatile and are not necessarily in line with actual liquidations.[3] Thus, when examining the likely impact of different stress scenarios, we use the results from the industry level analysis. Overall, the industry appears quite robust to large shocks; although, there are periods in which sensitivity to different shocks has been relatively elevated.

Our analysis suggests that market conditions do indeed affect the likelihood that a hedge fund fails and provides some guidance regarding situations where one might expect hedge fund failures to be elevated. When considering these results, it is important to note that while we establish statistical associations between market factors and survival, we do not identify the channel through which these variables have an impact. In the analysis, we control explicitly for factors such as the recent rate of return at the hedge funds and estimated investment flows, so finding that

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[3] Further, the success of the analysis using individual funds in identifying which funds are the most likely to fail is limited at best.

market returns and volatility matter suggests that conditions in financial markets matter for reasons beyond their simple impact on the hedge funds' bottom lines. Some potential alternatives include the possibility that market returns and volatility affect the ability of the hedge fund to obtain credit or the possibility that market conditions affect hedge fund managers' beliefs about future returns and therefore the incentives to liquidate.

The paper is organized as follows. Section 1 presents the hedge fund and market data. The analysis of the factors that have been associated with individual hedge fund liquidations is presented in Section 2. Analysis using industry aggregates in discussed in Section 3. Predictions of hedge fund failures, both using actual market data and market movements associated with some stress tests are reported in Section 4. Section 5 concludes.

Section 1. Discussion of the data

The hedge fund data used in this paper are from the Lipper/TASS hedge fund database (TASS database). This section reviews the information provided in the database and discusses issues related to the determination of which funds are considered to have failed. This section also presents the market data used in the analysis.

Section 1.1. Hedge fund data

The TASS database provides information on both active funds and funds that have stopped reporting for a variety of reasons. Funds that have stopped reporting are stored in a "graveyard." The information in the database includes self-reported monthly return, net asset value (NAV), and estimated asset histories as well as information on broad investment strategies, fee structures, and other characteristics. Funds also indicate the currency in which they value their portfolio; this analysis is restricted to funds that value their portfolios in U.S. dollars. Funds of hedge funds are also excluded from the analysis. The database currently contains about 2200 currently reporting hedge funds and about 2500 funds that have stopped reporting that meet these criteria.[4]

While the quality of the TASS database is generally good, some biases are certainly present, many of which have been identified in the literature. In particular, many large funds and funds closed to new investment do not report to the database, which is important to keep in mind when considering the implications of this analysis. Other biases identified in the literature include self-

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[4] Note that a significant number of funds that have stopped reporting are not considered failures.

selection bias, in which funds may only seek to start reporting to the database once they have had performed well (Baquero, Horst, and Verbeek 2005), and back-fill bias, where funds that have been around for a while provide longer histories of returns to the database (Fung and Hsieh 2000). While these latter biases clearly affect calculations of industry returns and risk-return trade-offs, they should not affect the results presented here.

Section 1.1.1. Hedge fund failures

TASS began retaining information on funds that left the database starting in 1994, which provides the starting point for the analysis. (We end our sample period in December 2006.) TASS indicates which one of seven different reasons best explains why the fund exited the database; these reasons include: liquidation, no longer reporting, unable to contact, closed to new investment, merged with another entity, dormant, and unknown. Some of the funds that stopped reporting exited at the height of their historical NAV, possibly because they closed to new investment and saw no advantage to continuing to report their information. Thus, not all funds that exited the database should be considered failures. TASS also provides general notes on each hedge fund which sometimes include further detail on why the hedge fund is no longer in the database. Based on these notes and conversations with the staff at TASS, we classify a fund as failing based on both the provided reason for exit as well as the information contained in the notes. In particular, funds are considered to have failed if the reason given for exiting the database is that the fund liquidated, was unable to be contacted, was dormant, or the reason was unknown (or missing), unless certain keywords appear in the general notes.[5] Funds exiting because they were no longer reporting, closed to new investment, or merged with another entity are not considered to have failed unless certain keywords appear in the notes. The list of keywords appears in Appendix 1.[6] Based on these criteria, we consider about 1,300 funds to have failed. Figure 1 plots the number of hedge funds exiting the database each month grouped into funds considered failures and funds who stopped reporting for another reason. The figure shows some propensity for funds to fail at year-end, so we include a December dummy in our regressions.

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[5] Funds categorized as unable to be contacted are not considered failures after 2004. TASS staff indicated that there was a procedural shift that occurred at this point.

[6] The procedure used here is quite similar to the one used by Getmansky (2005). By comparison, Chan, Getmansky, Haas, and Lo (2005) treat all funds in the graveyard database as failures and Baba and Goko (2006) consider only funds that liquidated to have failed.

All funds report a net asset value (NAV) each month, which reflects the value of the equity in the fund. If the fund were to go bankrupt, this value should reach zero. While NAVs approach zero in a fair portion of funds identified as failures, in other cases it does not. The last reported NAV of failing funds has a median value of about 900.[7] Thus, many of the failures likely reflect liquidations under pressure from investors or creditors or liquidations as the manager of the fund decided that the fund had not performed, or was not likely to perform, as he or she might have hoped.

The TASS database indicates the last date for which the fund provides return data (which is the last day of the month). We take this date as the day the fund failed. Using this date as the failure date implies that the decision to close the fund is based on the market conditions for that month and the fund performance reported for that month. Thus, we assume that market movements during the month (or months) after the last date the fund provides data do not have much impact on failures. As the precise date of failure is not known, excluding information that may or may not have affected hedge fund survival seems reasonable.

Subsection 1.1.2. Hedge fund attributes

In the database, hedge funds provide information about their investment strategy. TASS groups the funds into one of 10 broad investment-style categories, and indicator variables for the most popular categories, such as long/short equity, managed futures, or emerging market, are used in the analysis.[8] We also include variables denoting whether the fund indicated that it had a global focus and whether the fund reported being generally short or long the market. Funds report whether they use leverage as part of their strategy and we include this indication in the analysis. We apply all these strategy indicators to the funds' entire histories even though they are only reported for the most recent period. By comparing TASS data of different vintages, for example the investment strategies reported in March 2006 (the earliest vintage we obtained) to those reported in March 2007, we find only a handful of changes in reported strategies amongst several thousand different funds, suggesting that our use of the currently reported strategy in all time periods is not far off.

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[7] Even though this value is decidedly positive, it may still be below the funds initial NAV indicating that investors did lose money overall. In examining the performance of hedge funds identified as failures during the months prior to failure, we find that the median such fund had cumulative negative returns during the six months preceding exit and had a final NAV roughly equal to their initial NAV.

[8] In our analysis, we consider funds to use a particular strategy if there is an affirmative response in the TASS database and consider the fund not to have adopted a particular strategy otherwise. Thus, in cases where the response from the hedge funds are missing we consider the fund to have not adopted a particular strategy.

It is not clear that one should expect that these investment strategies necessarily make failure more or less likely by themselves; however, they likely influence whether different market factors matter. For instance, the effect of a fall in the stock market on the likelihood that a fund fails may be quite different for a fund with a short bias than for a fund with a long bias.

Funds also report information related to their fee structures and withdrawal rules in the database and this information is used in the analysis. We include variables indicating whether the manager's compensation is affected by a high-water mark or whether the manager has personal capital invested in the fund. Other variables, such as whether the fund has a lock-up period or a longer than average redemption period (more than 30 days), are related to the ability of investors to withdraw their money from the hedge funds.[9] The rules related to manager and investor incentives and restrictions might well be expected to influence the probability of failure. Having a manager with personal capital invested in the fund might reduce risk taking by the fund and thus reduce the likelihood of failure. The impact of high-water marks is not clear, they may encourage the hedge fund manager to take more risk to achieve certain gains, or, as suggested by Panageas and Westerfield (2006), they might discourage risk taking to reduce the possibility of losses.[10] By slowing investor withdrawals following poor market conditions or bad returns, longer redemption periods or the use of lock-up periods seem likely to be associated with lower probability of failure.

Summary statistics of the characteristics of funds active as of December 2006 and funds considered to have failed appear in Table 1. In addition to the variables discussed previously, a few other demographic variables used in the analysis, such as average age of the fund, appear in the table. Funds with a long/short equity strategy are the most numerous, both for active and failed funds. A managed futures strategy appears much more common among failed funds than among active funds. A little more than 20 percent of active funds report having a short-bias investment strategy, while around 30 percent of failed funds reported having a short-bias strategy. The share of funds that reported pursuing a global investment strategy is close to 35 percent for active funds and slightly higher for failing funds. About 60 percent of active funds report using leverage while 70 percent of failed funds reported doing so. Using a high-water mark was much less common among

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[9] Although in the analysis using rolling windows, there is only sufficient heterogeneity in some characteristics, such as the length of the redemption period, use of a lock-up period, and use of a high-water mark, to estimate effects starting with the rolling window ending in April 2000.

[10] Panageas and Westerfield (2006) argue that in a repeated game, which presumably reflects behavior of a hedge fund manager that intends to oversee the fund for a notable period, high-water marks reduce risk taking.

failed funds than active funds, though this may reflect an increased use of these performance criteria over time. Perhaps surprisingly, a greater share of failed funds had managers with personal capital in the fund than is the case with currently active funds. A redemption period longer than 30 days, the average length reported in the database, is more common at active funds than among failed funds.

Hedge fund rates of return have been found to impact the likelihood of failure in previous work. In this analysis, we include contemporaneous returns, returns lagged one month, and cumulative returns for the period two to six months prior to the current observations. We also calculate the volatility of each hedge fund's returns using rolling 24-month backward-looking windows.

Following a procedure outlined by TASS, changes in estimated assets can be decomposed into components due to investment flows and returns. Essentially, changes in assets due to returns are calculated and subtracted from the assets under management. The residual difference between current and previously reported assets under management is due to net investment flows. (For further details see Lipper (2006).) The flows used in the analysis cumulate inflows during the six months preceding the current month. As these flows are imprecise, we group them into quintiles and use dummy variables to indicate which bucket the hedge fund's investment inflows fall into.

Finally, we create a measure of the illiquidity of each hedge fund's portfolio based on the idea that funds with more illiquid portfolios will have more serially correlated returns. (See Chan, Getmansky, Haas, and Lo (2005) for a further discussion of this idea.) To calculate this measure, we regress each hedge fund's current return on the returns during the preceding three months; these regressions are calculated using 24-month backward-looking rolling windows. The sum of the coefficients on the lagged returns is our measure of illiquidity.

Section 1.2. Market data

A variety of information from financial markets is also used in the analysis, often in conjunction with various hedge fund strategy information. We include returns on the S&P 500, an emerging-market equity index, the Merrill Lynch government and corporate bond index, the dollar,

and oil.[11] In addition to returns, for some of these markets we use measures of realized volatility, measured by the standard deviation of daily returns in the market during the month. We also include the realized volatility of one-month LIBOR rates. As the impact of the market factors may depend on the hedge fund's style of investment, interactions between the market factors and variables indicating that the hedge funds pursued a particular strategy are included in the analysis.

Other financial market indicators are also used. In particular, we include the spread on the 10-year swap over comparable maturity Treasuries. As with the market returns and realized volatilities, we interact this measure with different strategies.[12] Additionally, we include the monthly default rate on corporate bonds.

Summary statistics of the different market measures appear in Table 2. Correlations of returns in different financial markets and of the volatilities in these markets are reported in Table 3. While some of the correlations are significantly different than zero, they are generally small. The only correlation above 0.25 is between returns on the S&P 500 and the emerging market stock index; while this correlation is notable, we do not find any evidence of multicollinearity.[13]

It is not necessarily clear how one might expect these variables to be related to hedge fund failures. Depending on whether hedge funds are long or short the market, on average, the market returns could have a positive, negative, or no effect on failures. Although they note that the conventional wisdom is that hedge funds prefer more volatile markets, as volatility may generate more trading opportunities, Garbaravicius and Dierick (2005) find that hedge fund returns are higher when stock markets are less volatile. They suggest that a potential reason for this finding is that leveraged funds may be prompted by their prime brokers to liquidate losing positions to meet margin calls in more volatile markets. It may also be the case that market participants, especially lenders, may be less willing to extend credit to hedge funds during more uncertain times, so that periods of higher volatility would be associated with higher failure rates.

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[11] We also tried including a non-US industrial-economy equity index, the Merrill Lynch high yield corporate bond index, an emerging-market bond index, and the Goldman-Sachs commodity index. These market factors did not appear to be notably related to hedge fund failures.

[12] We also experimented with implied volatilities. These measures were highly correlated with the realized volatility measures we used; the realized volatility measures appear to fit the data a bit better, so we used them rather than the implied volatility measures.

[13] We also examined whether different hedge fund characteristics where highly correlated. While some of these correlations were significantly different than zero, none were particularly large. One notable correlations was that funds with longer than 30-day lock-up periods also tended to have longer than average redemption periods. Even this correlation was below 0.3.

Section 2. Determinants of hedge fund failure using individual funds

The analysis of the factors that influence the failures of individual funds is conducted using logistic analysis of pooled hedge fund data. Indicators of failure are regressed on hedge fund characteristics, including recent performance, investment inflows, and investment strategy; market returns, with investment strategy interactions; market volatilities, again with investment strategy interactions; and other factors, such as swap spreads. Each hedge fund appears in each month that it is alive with updated market measures and interaction terms.[14] Funds that exit the data set without failing simply have no data following their last report.[15] As we include measures based on past hedge fund returns, such as return volatility, hedge funds are not included in the analysis until they have two years of data. We conduct the estimation using the entire sample period from January 1994 to December 2006 and, because the influence of the different factors likely changes over time, using rolling 54-month windows.[16]

Results for the entire sample period appear in Table 4. The mean and median coefficients for the different windows, the standard deviation of coefficients across windows, together with the share of times the variable is significant at the 10 percent level, appear in Table 5. In general, our results regarding variables specific to the individual funds are in-line with the results of previous research. Funds with better returns were less likely to fail; a one percentage point increase in the rate of return, roughly one-third of a standard deviation in any particular month, decreases the probability of failure by 4 percent. Similarly, funds that were experiencing low investment flows, either outflows or relatively small inflows, tend to be more likely to fail than those that were experiencing relatively strong investment inflows. These findings generally match those of Baba and Goko (2006) and Chan, Getmansky, Haas, and Lo (2005).[17] Our measure of illiquidity is associated with a higher likelihood of failure. Funds with more volatile returns are less likely to

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[14] Following Bertrand, Duflo, and Mullainathan (2004), we adjust the standard errors for the fact there are multiple observations for each hedge fund by clustering at the individual hedge fund level.

[15] Allison (1995) notes that, under mild assumptions, this procedure is equivalent to using duration analysis with time-varying covariates. See also Kalbfleisch and Prentice (2002) for a further discussion of discrete failure time models.

[16] Below, the 54-month windows will allow us to see how well the model predicts the failures associated with the large market movements in September 1998. Analysis using longer windows does not notably change the results.

[17] We also experimented with variables related to fund size, including the log of assets under management and dummies for different levels of assets under management. In line with previous work, we find that larger funds are less likely to fail than smaller funds. We do not include size in the specification for two reasons. First, assets under management are not available for about 10 percent of the sample, so using linear functions of assets under management involves a notable reduction in the sample size. Second, using size dummies produces forecasts in which no fund outside the two smallest groups fails and generally reduces the accuracy of our forecasts. We did not find that there were significant changes in the effect of other factors depending on whether or not the measures of size were included.

fail, with a one percentage point increase in the standard deviation of returns, a bit less than half a standard deviation, reducing the probability of failure by 6 percent. By themselves, investment strategies do not appear to have had much impact on failure, although, based on the results of some rolling-window regressions, there has been some tendency for funds with a short-bias investment strategy to have a higher probability of failure. In the overall sample, funds reporting that they used leverage were 48 percent less likely to fail than funds not reporting that they used leverage; in the rolling windows, however, the mean and median coefficient suggests that use of leverage increased the probability of failure (we look at this issue a bit further below). We also find some evidence that high-water marks and the use of lock-up periods are associated with reduced failure.[18] These findings match the tenor of Baba and Goko (2006), who also find that the use of a high-water mark decreased the likelihood of failure. Older hedge funds were found to be generally less likely to fail than other funds.[19]

Market returns also influence hedge fund survival. Positive returns in U.S. equity and bond markets are associated with lower failures; the coefficient on the S&P 500 indicates that an additional one-percentage point increase in the index, one-fourth of a standard deviation, would reduce the likelihood of failure by 5 percent.[20] As might be expected, rising U.S. stock markets are even more beneficial for funds with long bias strategies and not as good for funds with a short bias. Gains in emerging markets appear to increase the likelihood of hedge fund failure as does an appreciating dollar. Interaction terms involving these latter market returns were generally insignificantly different than zero.

We also find that market volatilities appear to play a role in the likelihood of failure. Using the entire sample, we find that higher volatility of the S&P 500 reduced the likelihood of failure. This reduction in the likelihood of failure was greater for funds with a longer than average redemption period and smaller for funds that tended to have more volatile returns. The results are slightly different when rolling windows are used. Here volatility in the S&P 500 boosts failure

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[18] The recent report by the Financial Stability Forum (2007) notes that use of lock-up periods has increased. The findings here, echoing those of the report, suggest that this trend may reduce the risk of hedge fund failure.
[19] Our liquidity measure and the standard deviation of hedge fund returns each require that the funds have at least two years of data. Thus, when computing age, we use the number of months the fund has been around beyond two years.
[20] Agarwal and Naik (2004) find that even though market factors can explain a considerable portion of the returns of various hedge fund investment-style indexes, the explanatory power of these same factors for the returns of individual hedge funds using that investment style varies widely. Similarly, while the findings here indicate that particular market returns and conditions affect the probability of failure of hedge funds on average, the effect of these market conditions on the probability of failure of particular funds likely differs considerably.

rates, but less so for funds with more volatile returns; similar to the whole period analysis, funds with a longer-than average redemption period were less likely to fail during periods of heightened volatility. Volatility in one-month LIBOR rates appear to have little impact on the probability of failure. Oil price volatility was significant in about one-fourth of the rolling windows, but was not significant in the whole period analysis. Curiously, increases in the volatility of emerging market stocks led to lower hedge fund survival, unless the fund had an emerging market strategy. Higher swap spreads appear to increase the likelihood of failure in funds reporting that they used leverage, but were generally not detrimental to other funds. We also find that a rise in corporate bond defaults is associated with an increase in the probability of hedge fund failure.

It is useful to examine how the effects of different market measures and fund characteristics have changed over time, and various coefficients from the rolling-window regressions are plotted in Figure 2. Figure 2a shows the coefficients for returns on the S&P 500 and on the dollar. The coefficient for the return on the S&P 500 has generally been negative, although periodically it has been close to zero or slightly positive. By contrast, the coefficient for the return on the dollar has moved down sharply, with an appreciating dollar increasing hedge fund failure probabilities early in the observation period, but having little impact recently. Coefficients related to realized volatilities are shown in Figure 2b. Higher volatility on the S&P 500 increased failures in the late 1990s, but has recently been associated with a slightly lower probability of failure. By contrast, higher hedge fund return volatility in conjunction with higher stock market volatility has been associated with a higher likelihood of failure recently, while previously the coefficient was negative.[21] The relationship of volatility of the foreign exchange index to hedge fund failures has also evolved over time and appears to have had a negligible effect on failure probabilities recently. As shown in Figure 2c, swap spreads have generally had little effect on hedge fund failures, although of late, wider spreads have been associated with a higher likelihood of failure. Early in the current decade, leverage was associated with an increased the probability of failure, although the effect has declined during the past several years. The evolution of the coefficients on whether the hedge fund has a long- or short-bias strategy is shown in Figure 2d. Having a short-bias strategy was associated with a higher probability of failure in 2005 and 2006. During most of the analysis period, having a long-bias strategy had little effect; however, the coefficient became notably

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[21] The chart does not indicate the overall effect of hedge fund return volatility as the coefficient on the standard deviation of returns is negative.

negative in 2005, suggesting that having a long-bias strategy increased the odds of survival, and then jumped into positive territory at the end of 2006.

Section 3. Determinants of hedge fund failure using industry aggregates

In addition to analyzing the factors that influence the failure of individual funds, we also explore whether market conditions and industry average characteristics provide information about the aggregate number of hedge fund failures each month. This analysis is conducted using count data analysis.[22] As before, we conduct the analysis using the entire sample period and using 54-month rolling windows to allow for changes in behavior and exposure to different markets over time. Because of the more limited number of observations, we use fewer explanatory variables. The market returns are as before. For hedge fund characteristics, we use the shares of the industry possessing particular characteristics, or, for information on performance, the median hedge fund return lagged one period.[23] Tests indicate some serial correlation so, following Cameron and Trivedi (1998), we include the lagged number of failing hedge funds as an explanatory variable.

The results for the whole sample period appear in Table 6 and the mean and median coefficients from the rolling window regressions, the standard deviation of the coefficients across sample periods, as well as the share of times the variable is significant at the 10 percent level, appear in Table 7. The coefficients indicate the proportionate change in the number of failures for a one-unit increase in the independent variable.

The results are broadly similar to those from the analysis using individual funds. The return on the S&P 500 has a negative coefficient, so that a positive return in the stock market is associated with fewer failures, and is significant in the overall sample, though only in about one-quarter of the rolling windows. The coefficient from the overall sample suggests that an additional one percentage

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[22] Count data analysis assumes that events, hedge fund failures in this analysis, are generated through a Poisson or similar process which can be influenced by various independent variables. The dependent variable in the analysis is then the number of events in a particular window and takes on whole number values. In the case of over or under-dispersion, where the mean number of events differs from the variance of the number of events, a negative binomial distribution can be used instead of the Poisson distribution. Determining the effect of the independent variables involves maximizing the log-likelihood function:

$$\ln L(\beta) = \sum_{i=1}^{n} \left(y_i X_i' \beta - \exp(X_i' \beta) - \ln(y_i!) \right)$$

where y is the dependent variable vector, X is the matrix of independent variables, β is the coefficient vector, and n is the number of observations. For further detail, see Cameron and Trivedi (1998).

[23] Using the contemporaneous median return yielded similar results. The use of lagged returns facilitates the forecasting and stress testing analysis.

point increase in the return on the S&P 500, again about one-fourth of a standard deviation, would decrease the number of failed funds by 2 percent; during the average month, eleven funds fail, so an additional one percentage point in the S&P 500 return would be expected to result in roughly 0.25 fewer failures. Positive returns on the government and corporate bond index generally reduced the expected number of failures while positive returns on emerging market stocks, based on the rolling-window regressions, showed some tendency to increase them. Realized volatility on the one-month LIBOR boosted failures notably in the whole sample period and one-third of the rolling windows; a one-unit increase in the volatility here, a bit more then one standard deviation, would be expected to result in one additional failure. Other measures of realized volatility had little effect.

Hedge fund characteristics also matter. A higher median hedge fund return in the previous month reduced hedge fund failures; based on the coefficients from the full sample, a one percentage point increase in the lagged median return, a three standard deviation move, would be expected to reduce failures by 7 percent (about 0.8 failures). More widespread use of leverage on the part of hedge funds is generally associated with increased failures with a one percentage point increase in the share of hedge funds reporting the use of leverage, about half the standard deviation of this variable, boosts failures by 20 percent (about 2.6 failures). A higher share of funds with a lock-up period is associated with fewer failures as is having a higher share of funds with a short-bias strategy.

Again it is useful to observe how some coefficients have evolved over different windows, especially since the rolling-window regression summary statistics suggest that some coefficients exhibit a fair bit of variation. Selected coefficients appear in Figure 3. Figure 3a illustrates coefficients on market returns. The coefficients on the S&P 500 are consistently negative, which indicates that positive market returns reduce failures. As in the analysis of individual funds, the coefficient on the foreign exchange index starts positive but declines and becomes negative in recent years. The coefficient on emerging market returns is always positive. Figure 3b shows the time series of the coefficients on the realized volatilities. The coefficient on the realized S&P 500 volatility was slightly positive early in this decade, but has since been close to zero, or somewhat negative. Volatility on the dollar has generally been associated with more failures, although the size of the effect has varied considerably. Greater short-term interest rate volatility has consistently been associated with higher failure numbers. The coefficients on different hedge fund characteristics are

shown in the Figure 3c. The coefficients on leverage have been positive since mid-2002.[24] The coefficients on the share of funds with a short-bias strategy was negative until around 2003, but has since been slightly positive. The share of funds with a lock-up period has generally been associated with reduced failures, although the effects in 2005 and 2006 were quite small.

Section 4. Predicting hedge fund failures

Based on the results of the previous analysis, we predict hedge fund failures under different situations. We start by producing one-month ahead forecasts based on actual market returns, using both the individual hedge fund data and the industry aggregates. We then predict hedge fund failures under various stress scenarios.

Section 4.1. One-month ahead forecasts using individual fund data

Using the results of the analysis from the individual fund data, we predict the number of hedge fund failures one month after the end of each of the 54-month rolling windows. To calculate the expected number of failures, we use the distribution of model-based failure probabilities for funds that failed within the sample window; we take the 90th percentile of this distribution as a cut-off point in predicting failures.[25] Based on the estimated coefficients, actual hedge fund characteristics, and market movements one-month after the end of the sample window, we calculate predicted failure probabilities. Funds with predicted failure probabilities exceeding the 90th percentile cut-off are considered to have failed.

The predicted number of failures for different months, together with the actual number of failures is plotted in Figure 4.[26] In general, this procedure produces some large misses and measures of the prediction fit are fairly poor (Theil's U = 1.78).[27] For the first few years, the predicted number of failures is quite volatile and often considerably exceeds the actual number of

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[24] This pattern is notably different from the one observed in the analysis of individual funds. A further investigation of this issue is a topic for further research.

[25] Alternative cut-off points did not affect the forecast performance notably.

[26] The actual number of failures in this panel differs slightly from those in Figure 1. The difference occurs because only failing funds with two years of data prior to failure are included. Funds are required to have two years of data because we are only able to generate predictions regarding failure for funds with at least two years of data due to the use of the measures of illiquidity of the funds' portfolios and the standard deviation of returns.

[27] Theil's U is a statistic that provides a measures of the fit of the prediction. This measure scales the root mean squared error by the mean squared size of the variable being forecasted. Larger values of Theil's U indicate poorer performance. See Green (1997, pp. 370-373).

failures. From 2002 to 2005, the prediction process often results in zero failures, notably below actual failures.

Section 4.2. One-month ahead forecasts using industry aggregate data

We next calculate a one-month ahead forecast using the results from the analysis of industry aggregate failures. As with the individual data, we make our predictions for the month following each of the 54-month rolling sample windows using the coefficients from the analysis window as well as actual hedge fund characteristics and market movements. When using industry aggregates, we are able to directly generate a prediction about the number of failures.

The results of this exercise are shown in Figure 5. In general, the model predictions seem a reasonable match to the actual hedge fund failures (Theil's U = 0.48). A fair number of the ups and downs are captured and the average number of predicted failures is quite close to the average number of actual failures.

Section 4.3. Predictions using various stress scenarios

The largest actual movement of financial markets during the period analyzed in this paper occurred in August 1998. As the first stress test, we use the industry aggregate model to predict the hedge fund failures that would have resulted in each month if markets behaved exactly like they did during August 1998. The second stress test is a shock to the domestic equity markets. For each month in the sample, we predict the number of failures that might result if domestic equity markets plunged by four standard deviations and other markets moved based on correlations observed during the model estimation window. (We set realized volatilities for the S&P 500, the foreign exchange index, and oil equal to their largest values.) The third stress test is a shock to the value of the dollar. Similar to the second stress test, we assume that the dollar experiences a four standard deviation decline in value and other financial markets move based on correlations observed during the model estimation window. In all stress tests, actual industry characteristics are used.

The results appear in Figure 6. For comparison, the average number of failures per month from July 1998 to December 2006 is also shown. As one would expect, the vulnerability of the hedge fund industry to different shocks has varied over time. The sensitivity to a shock similar to August 1998 was strong until mid-2004. A plunge in the stock market is not expected to have a substantial impact. During late 2004, there was a spike in the predicted number of failures resulting

from a plunge in the value of the dollar. However, these shocks do not appear to generate substantial numbers of failures, with failures during peak sensitivity periods only a bit more than double the average number of actual failures observed.

Finding that shocks do not result in large numbers of failures might not be too surprising. There were several large shocks to financial markets that occurred during the period analyzed, but they did not result in particularly large numbers of failures. Only 11 funds in the TASS database failed in August 1998 despite a 16 percent decline in the S&P 500 index, a four standard deviation shock, and sharp movements in other asset prices. Less than 60 funds failed in the four months following September 11, 2001 despite significant movements in asset prices. If the hedge fund industry was not affected significantly by these realized shocks, it may be quite reasonable that stress scenarios would not generate large numbers of failures.

Section 5. Conclusion

Using data on individual hedge funds and on industry aggregates, this paper has investigated whether different market factors and individual hedge fund characteristics are associated with the failure of hedge funds. Similar to previous work, we find that poor returns and investment outflows are associated with increased likelihood of failure. Also similar to previous work, we find that restrictions on the ability of investors to withdraw funds and performance incentives for managers can reduce failure probabilities.

An important contribution of this paper is to provide information on how market conditions affect failure probabilities. We find that, even controlling for rates of return, hedge funds are more likely to fail in periods when U.S. stock markets are declining and the dollar is depreciating. Volatile markets are bad for some funds, while other funds appear to benefit from turbulent markets. In general, the factors that boosted failure probabilities at the individual fund level are found to increase failures when analyzing industry aggregates.

A second contribution of this paper is to provide predictions about how the hedge fund industry might fare in different situations. The stress scenarios we consider include a repeat of the sharp asset price movements of August 1998, a four standard deviation drop in the S&P 500 stock market index, and a four standard deviation fall in the value of the dollar. We find that, although there have been periods when sensitivity to some shocks has been elevated, the hedge fund industry is generally robust to these stress scenarios.

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Appendix A - Keywords used in determination of failure

Funds reported to have liquidated are considered to have failed unless one of the following phrases (or a similar phrase) appears in the notes:
- comments made by members of the Securities and Exchange Commission
- fund matured
- reached maturity
- became a feeder fund
- closed to new invest
- no longer being marketed
- removed at fund manager request
- no longer publishing performance figures
- no longer publish results
- no longer reporting

Funds placed in the graveyard prior to 2005 (see footnote 3) because TASS was unable to contact them are considered to have failed unless one of the following phrases (or a similar phrase) appears in the notes:
- closed to new investor
- subscriptions shall be accepted
- no longer reporting
- to new direct outside investment
- to collect updated information
- to receive updated information
- contact the manager with no response
- after several attempts to contact
- fax numbers changing

Funds placed in the graveyard for unknown reasons are considered to have failed unless one of the following phrases (or a similar phrase) appears in the notes:
- difficulties in sending the data
- decided to discontinue reporting
- fund has matured
- fund matured
- reconstructed
- closed to new investors

Funds where the reason for exit is missing are assumed to have failed unless one of the following phrases (or a similar phrase) appears in the notes:
- closed to new investor
- no longer reporting
- to collect updated information
- to new direct outside investment

Funds where the reason for being placed in the graveyard is listed as no longer reporting are assumed to have *survived* unless one of the following phrases (or a similar phrase) appears in the notes:
- liquidated
- fund closed
- closing down at
- awaiting liquidation
- liquidating in the near future
- process of liquidating
- last investor redeemed
- unable to contact
- shareholder redemptions
- poor fundraising environment

Table 1
Summary statistics for hedge funds characteristics

	Live funds	Funds considered failures (whole sample)	Significantly different at 10 percent level
Number of Funds	2205	1300	
Share using a long/short equity strategy	40.1%	36.2%	Yes
Share using a managed futures strategy	8.2%	17.5%	Yes
Share using a emerging market strategy	8.5%	7.7%	No
Share pursuing a global investment strategy	35.2%	38.2%	Yes
Share using a short-bias strategy	21.4%	29.0%	Yes
Share using a long-bias strategy	28.3%	24.4%	Yes
Share using leverage	61.8%	69.8%	Yes
Share in which manager has personal capital invested	33.4%	43.8%	Yes
Share in which the fund has a lock-up period	41.1%	17.6%	Yes
Share in which the fund uses a high water-mark	82.4%	40.8%	Yes
Share in which the redemption period is longer than 30 days	42.0%	18.5%	Yes
Age of fund (years)	5.3	4.1	Yes

Source: TASS database.

Table 2

Summary statistics of market measures over the sample period

	Mean	Standard Deviation	Minimum	Maximum
Return on the S&P 500 (percentage points)	0.81	3.96	-14.58	11.16
Return on emerging market equities (percentage points)	0.93	6.49	-29.29	16.45
Return on the dollar (percentage points)	-0.06	1.83	-4.47	6.35
Return on govt. and corp. bonds (percentage points)	0.60	1.23	-4.03	4.19
Return on oil (percentage points)	0.92	8.39	-22.19	36.59
Realized volatility on the S&P 500 (percentage points)	0.9	0.5	0.3	2.7
Realized volatility on the dollar (percentage points)	0.4	0.1	0.1	0.7
Realized volatility on one-month LIBOR (percentage points)	2.1	0.7	1.0	5.0
10-year swap spreads (basis points)	56.4	24.0	29.0	135.9

Source: Market data.

Table 3
Correlations of financial markets

Table 3A – Correlation of market returns

	The S&P 500	Emerging market equities	The dollar	Govt. and corp. bonds	Oil
The S&P 500		0.68***	-0.09	0.004	-0.03
Emerging market equities	0.68***		-0.15*	-0.12	0.13*
The dollar	-0.09	0-.15*		-.15*	-0.16*
Govt. and corp. bonds	0.004	-0.12	-0.15*		-0.004
Oil	-0.03	0.13*	-0.16*	-0.004	

Notes: The symbols (***), (**), and (*) indicate statistical significance at the 1, 5, and 10 percent level, respectively.
Source. Market data.

Table 3B – Correlation of market volatilities

	The S&P 500	The dollar	One-month LIBOR
The S&P 500		0.07	0.14*
The dollar	0.07		0.01
One-month LIBOR	0.14*	0.01	

Notes: The symbols (***), (**), and (*) indicate statistical significance at the 1, 5, and 10 percent level, respectively.
Source. Market data.

Table 4
Failure regression using individual funds – entire sample period

Variable	Coefficient	Significance	Standard Errors
Fund Characteristics			
Rate of return	-0.04	***	0.01
Rate of return (lagged one month)	-0.04	***	0.01
Rate of return (two-six months prior)	-0.03	***	0.00
Illiquidity measure	0.05	*	0.03
Std. dev. of hedge fund returns	-0.06	***	0.02
Missing flow data	0.50	***	0.14
Lowest inflow quintile	0.67	***	0.12
Second inflow quintile	-0.34	***	0.14
Fourth inflow quintile	-0.78	***	0.16
Highest inflow quintile	-1.11	***	0.22
Long-short equity strategy	0.25		0.23
Managed futures strategy	-0.13		0.16
Emerging market strategy	0.14		0.30
Has a global strategy	0.16		0.23
Has a short-bias strategy	0.22		0.31
Has a long-bias strategy	-0.27		0.32
Reports using leverage	-0.48	**	0.22
Manager invests personal capital	0.04		0.10
Fund has a lock-up period	-0.10		0.17
Fund has a high watermark	-0.10		0.13
Longer than average redemption period	0.20		0.30
Log (age over two years)	-0.28	***	0.04
Market Returns			
Return on the S&P 500	-0.05	***	0.01
Return on emerging market equities	0.04	***	0.01
Return on govt. and corp. bond index	-0.04	*	0.03
Return on oil	0.000		0.004
Return on foreign exchange	0.05	**	0.02
Return on the S&P 500 * long-short equity strategy	-0.01		0.02
Return on the S&P 500 * short-bias strategy	0.04	**	0.02
Return on the S&P 500 * long-bias strategy	-0.04	***	0.02
Return on emerging mkt. equities * emerging mkt. strategy	0.02		0.02
Return on foreign exchange * global strategy	-0.04		0.04

Table 4 (continued)

Variable	Coefficient	Significance	Standard Errors
Realized market volatilities			
Volatility of the S&P 500	-0.425	***	0.151
Volatility of the S&P 500 * long-short equity	-0.36	**	0.18
Volatility of the S&P 500 * hedge fund return volatility	0.034	**	0.017
Volatility of the S&P 500 * long redemption period	-0.68	***	0.24
One-month LIBOR	-0.16	**	0.08
One-month LIBOR * short-bias strategy	-0.16		0.14
One-month LIBOR * long-bias strategy	0.15		0.14
Oil price volatility	0.04		0.05
Volatility of the value of the dollar	0.45		0.34
Volatility of the value of the dollar * global strategy	-0.55		0.52
Volatility of emerging mkt. equities	0.03	***	0.01
Volatility of emerging mkt. equities * emerging mkt. strategy	-0.05	*	0.03
Other factors			
10-year swap spread	-0.004		0.003
10-year swap spread * long-bias strategy	0.003		0.004
10-year swap spread * short-bias strategy	0.001		0.004
10-year swap spread * leveraged	0.006	**	0.003
Default rate on corporate bonds	0.21	***	0.05
Intercept	-3.44	***	0.30
December dummy	0.74	***	0.10

Summary statistics:
Failures: 966
Observations: 91096
Separate Hedge Funds: 91096
Somer's D: 0.48
Log Likelihood: -4984.4
Notes: Estimated using logistic analysis. Coefficients, β, can be transformed by $100*(\exp(\beta) - 1)$ to indicate the percentage change in the probability of failure for each one-unit increase in the independent variable. The symbols (***), (**), and (*) indicate statistical significance at the 1, 5, and 10 percent level, respectively. Standard errors have been adjusted for clustering and are in italics. Data are market data or from the TASS database.

Table 5
Summary statistics for coefficients from regressions of individual funds

Variable	Mean coefficient across samples	Median coefficient across samples	Standard deviation of coefficients across samples	Percent of samples significant at the 10% level
Fund Characteristics				
Rate of return	-0.03	-0.03	0.01	82%
Rate of return (lagged one month)	-0.03	-0.03	0.01	71%
Rate of return (two-six months prior)	-0.02	-0.03	0.01	100%
Illiquidity measure	0.07	0.06	0.07	9%
Std. dev. of hedge fund returns	0.001	0.012	0.06	31%
Missing flow data	0.66	0.68	0.07	100%
Lowest inflow quintile	0.53	0.60	0.21	100%
Second inflow quintile	-0.35	-0.33	0.13	60%
Fourth inflow quintile	-0.71	-0.71	0.15	97%
Highest inflow quintile	-1.09	-1.03	0.20	90%
Long-short equity strategy	-0.15	-0.15	0.29	2%
Managed futures strategy	0.10	0.15	0.27	21%
Emerging market strategy	0.24	0.31	0.26	18%
Has a global strategy	-0.04	-0.04	0.28	0%
Has a short-bias strategy	0.26	0.43	1.02	42%
Has a long-bias strategy	0.26	0.11	0.51	10%
Reports using leverage	0.10	0.06	0.71	26%
Manager invests personal capital	-0.04	-0.04	0.06	0%
Fund has a lock-up period (#)	-0.26	-0.44	0.45	49%
Fund has a high watermark (#)	-0.99	-1.21	0.70	100%
Longer than average redemption period (#)	-0.36	-0.55	0.67	13%
Log (age over two years)	-0.26	-0.26	0.02	100%
Market Returns				
Return on the S&P 500	-0.04	-0.04	0.02	57%
Return on emerging market equities	0.02	0.02	0.02	48%
Return on govt. and corp. bond index	-0.03	-0.02	0.09	38%
Return on oil	0.002	-0.001	0.010	19%
Return on foreign exchange	0.05	0.05	0.07	33%
Return on the S&P 500 * long-short equity strategy	-0.005	0.002	0.021	0%
Return on the S&P 500 * short-bias strategy	0.05	0.04	0.04	51%
Return on the S&P 500 * long-bias strategy	-0.04	-0.05	0.04	51%
Return on emerging mkt. equities * emerging mkt. strategy	0.03	0.03	0.03	34%
Return on foreign exchange * global strategy	-0.04	-0.04	0.04	0%

Table 5 (continued)

Variable	Mean coefficient across samples	Median coefficient across samples	Standard deviation of coefficients across samples	Percent of samples significant at the 10% level
Realized market volatilities				
Volatility of the S&P 500	0.109	0.130	0.401	29%
Volatility of the S&P 500 * long-short equity	-0.003	0.002	0.018	0%
Volatility of the S&P 500 * hedge fund return volatility	-0.019	-0.022	0.046	26%
Volatility of the S&P 500 * long redemption period (#)	-0.218	-0.625	1.152	31%
One-month LIBOR	0.02	-0.01	0.17	4%
One-month LIBOR * short-bias strategy	-0.09	-0.08	0.15	5%
One-month LIBOR * long-bias strategy	0.11	0.08	0.17	7%
Oil price volatility	0.01	0.02	0.14	23%
Volatility of the value of the dollar	-0.34	-0.55	1.28	23%
Volatility of the value of the dollar * global strategy	-0.04	0.11	0.85	0%
Volatility of emerging mkt. equities	0.01	0.01	0.03	37%
Volatility of emerging mkt. equities * emerging mkt. strategy	-0.03	-0.04	0.03	15%
Other factors				
10-year swap spread	-0.004	-0.003	0.014	43%
10-year swap spread * long-bias strategy	-0.001	-0.001	0.008	4%
10-year swap spread * short-bias strategy	0.000	-0.006	0.017	45%
10-year swap spread * leveraged	0.003	0.005	0.011	19%
Default rate on corporate bonds	0.05	0.19	0.55	38%
Intercept	-3.82	-4.04	1.45	100%
December dummy	0.86	0.74	0.30	85%

Notes: Estimated using logistic analysis. Coefficients, β, can be transformed by 100*(exp(β) - 1) to indicate the percentage change in the probability of failure for each one-unit increase in the independent variable. Data are market data or from the TASS database. The symbol (#) indicates that the variable is included in analysis windows ending in April 2000 or after.

Table 6
Failure regression using industry aggregates
(Whole sample period)

Variable	Coefficient	Significance	Standard Errors
Intercept	-22.25	***	*5.16*
Log funds	2.40	***	*0.60*
Lagged failures	0.09		*0.06*
Return on the S&P 500	-0.02	**	*0.01*
Return on emerging market equities	0.01		*0.01*
Return on govt. and corp. bond index	-0.06	*	*0.03*
Return on the dollar	-0.01		*0.02*
Realized vol. on the S&P 500	0.03		*0.12*
Realized vol. on the dollar	-0.03		*0.35*
Realized vol. of 1-month LIBOR	0.09	*	*0.05*
10-year swap spread	0.004	*	*0.002*
December dummy	0.67	***	*0.10*
Lagged median return	-0.08	**	*0.04*
Share less than 2-years old	-0.01		*0.02*
Share with a lock-up period	-0.07	***	*0.02*
Share leveraged	0.21	***	*0.06*
Share with a short-bias strategy	-0.20	***	*0.05*

Summary statistics:
Number of observations: 155
Log likelihood: 1727.8
Notes: Estimated using count-data analysis. Coefficients indicate the proportionate change in the number of failures for each one-unit increase in the independent variable. Standard errors are in italics. The symbols (***), (**), and (*) indicate statistical significance at the 1, 5, and 10 percent level, respectively. Data are market data or from the TASS database.

Table 7

Summary statistics for coefficients from regressions using industry aggregates

Variable	Average coefficient across samples	Median coefficient across samples	Standard deviation of coefficients across samples	Percent of samples significant at the 10 percent level
Intercept	-56.49	-54.57	36.30	54%
Log funds	7.98	7.80	3.50	70%
Lagged failures	0.10	0.09	0.15	29%
Return on the S&P 500	-0.03	-0.03	0.01	27%
Return on emerging mkt. equities	0.02	0.02	0.01	32%
Return on govt. and corp. bond index	-0.03	-0.03	0.06	27%
Return on the dollar	0.01	0.01	0.04	19%
Realized vol. on the S&P 500	0.00	0.02	0.16	2%
Realized vol. on the dollar	0.51	0.47	0.55	15%
Realized vol. of 1 month LIBOR	0.06	0.09	0.13	30%
10-year swap spread	0.01	0.01	0.01	25%
December dummy	0.64	0.70	0.20	81%
Lagged median return	-0.04	-0.04	0.04	1%
Share less than 2-years old	-0.08	-0.08	0.07	25%
Share with a lock-up period	-0.21	-0.23	0.16	61%
Share leveraged	0.16	0.17	0.25	34%
Share with a short-bias strategy	-0.150	0.034	0.39	37%

Notes: Estimated using count-data analysis. Coefficients indicate the proportionate change in the number of failures for each one-unit increase in the independent variable. Data are market data or from the TASS database.

Figure 1
Number of funds exiting the TASS database each month
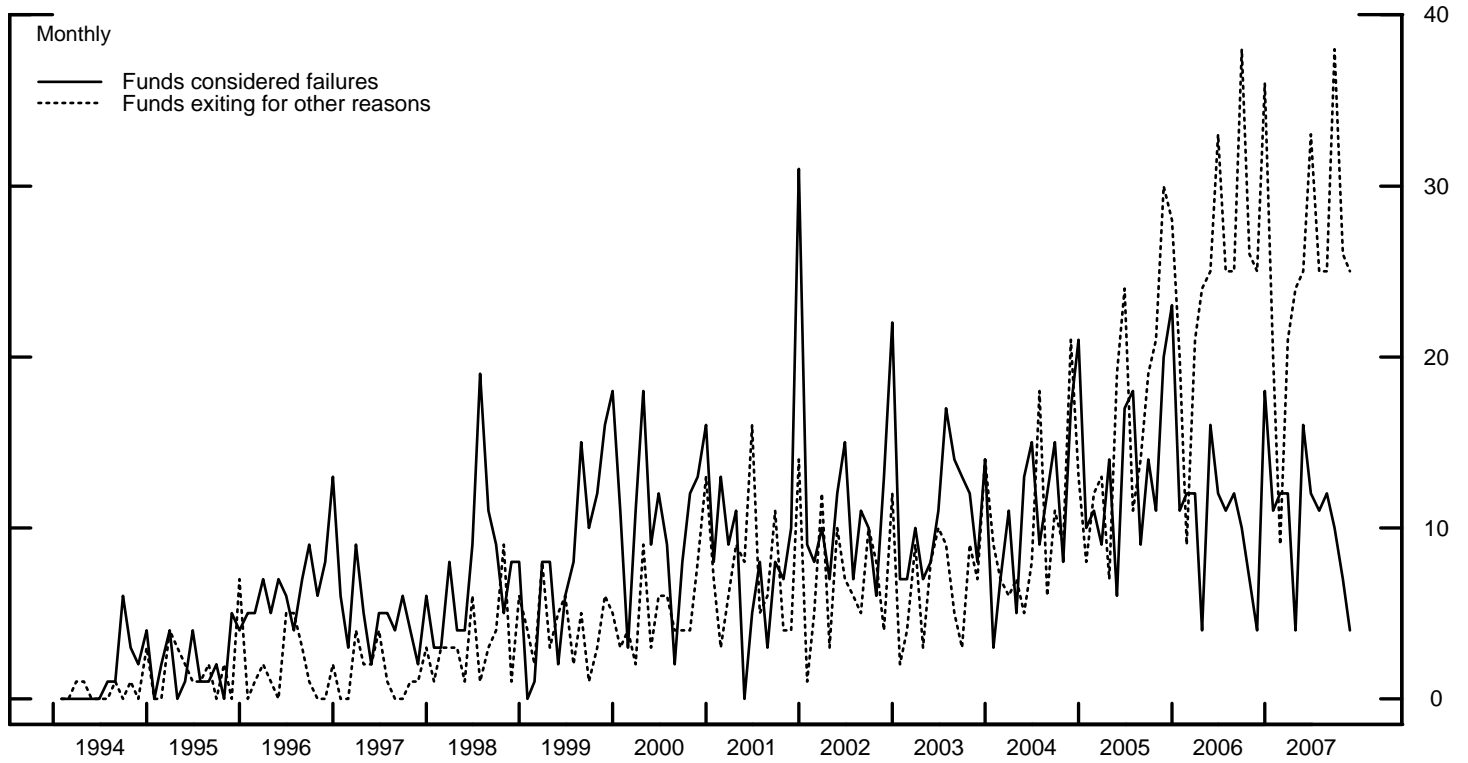
Source. TASS database.

Figure 2
Selected coefficients from rolling-window regressions using individual hedge funds
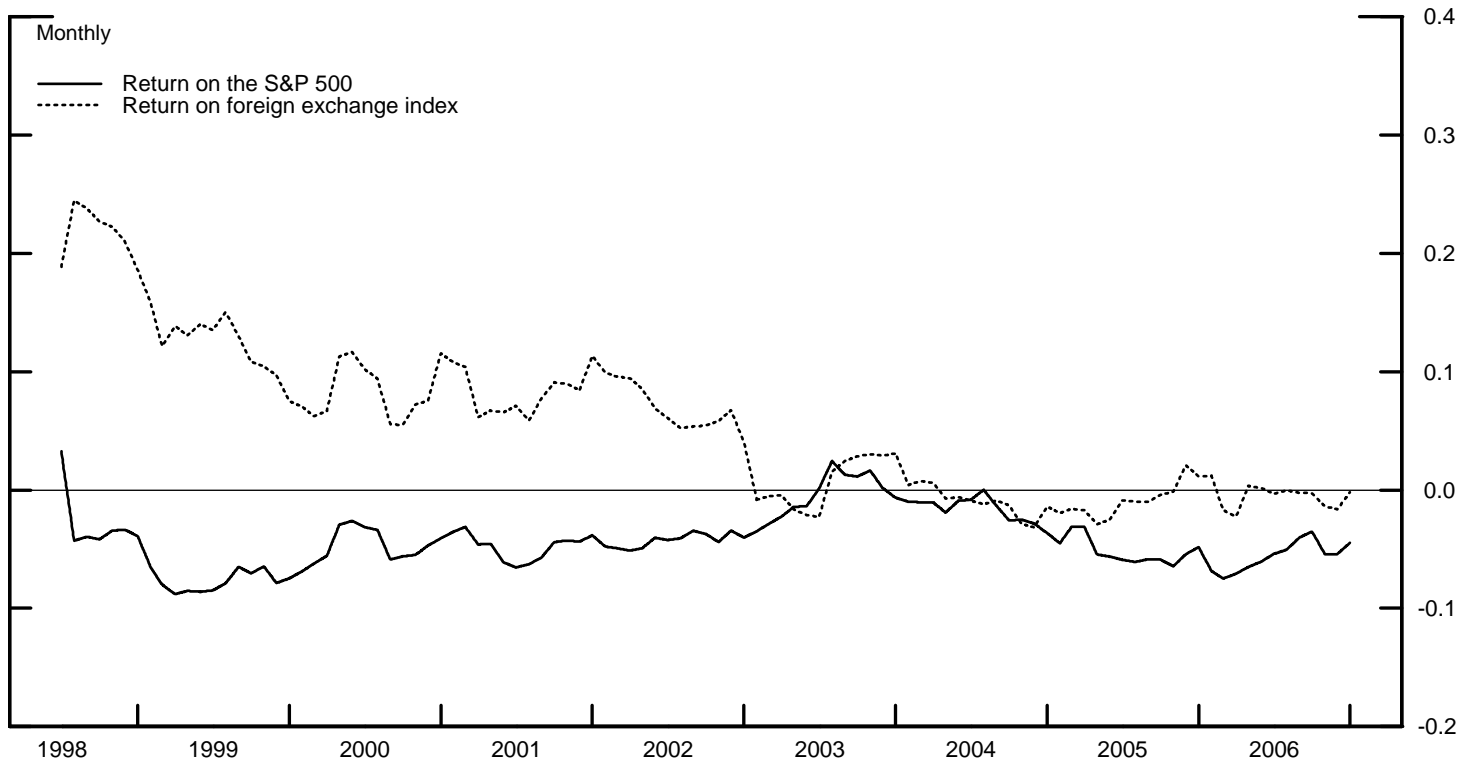
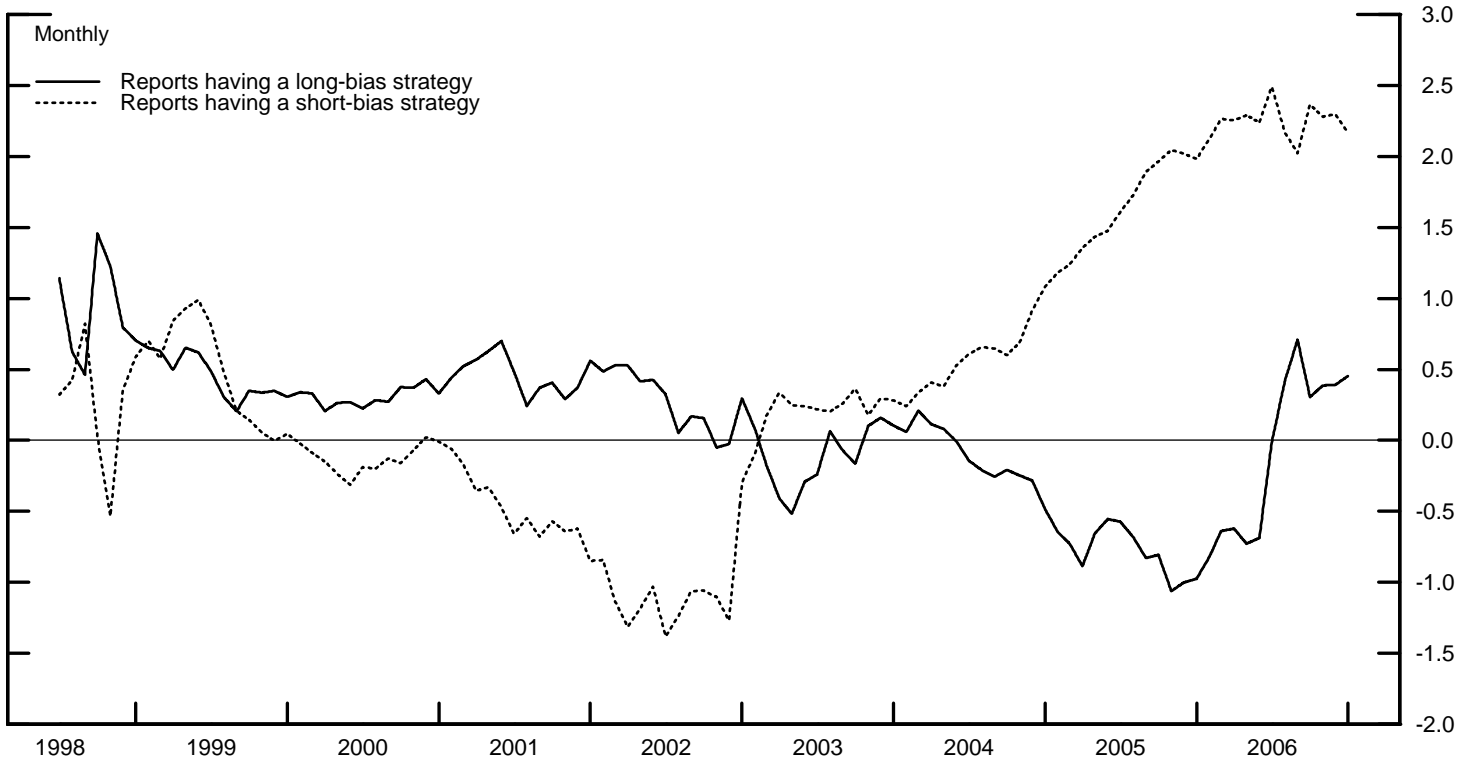Figure 2a - Coefficients on selected market returns

Monthly

——— Return on the S&P 500
·········· Return on foreign exchange index

Figure 2b - Coefficients on selected volatility related items

Monthly

——— Interaction of volatility of the S&P 500 and of hedge fund returns (left scale)
·········· Volatility of the S&P 500 (right scale)
– – – Volatility of foreign exchange index (right scale)
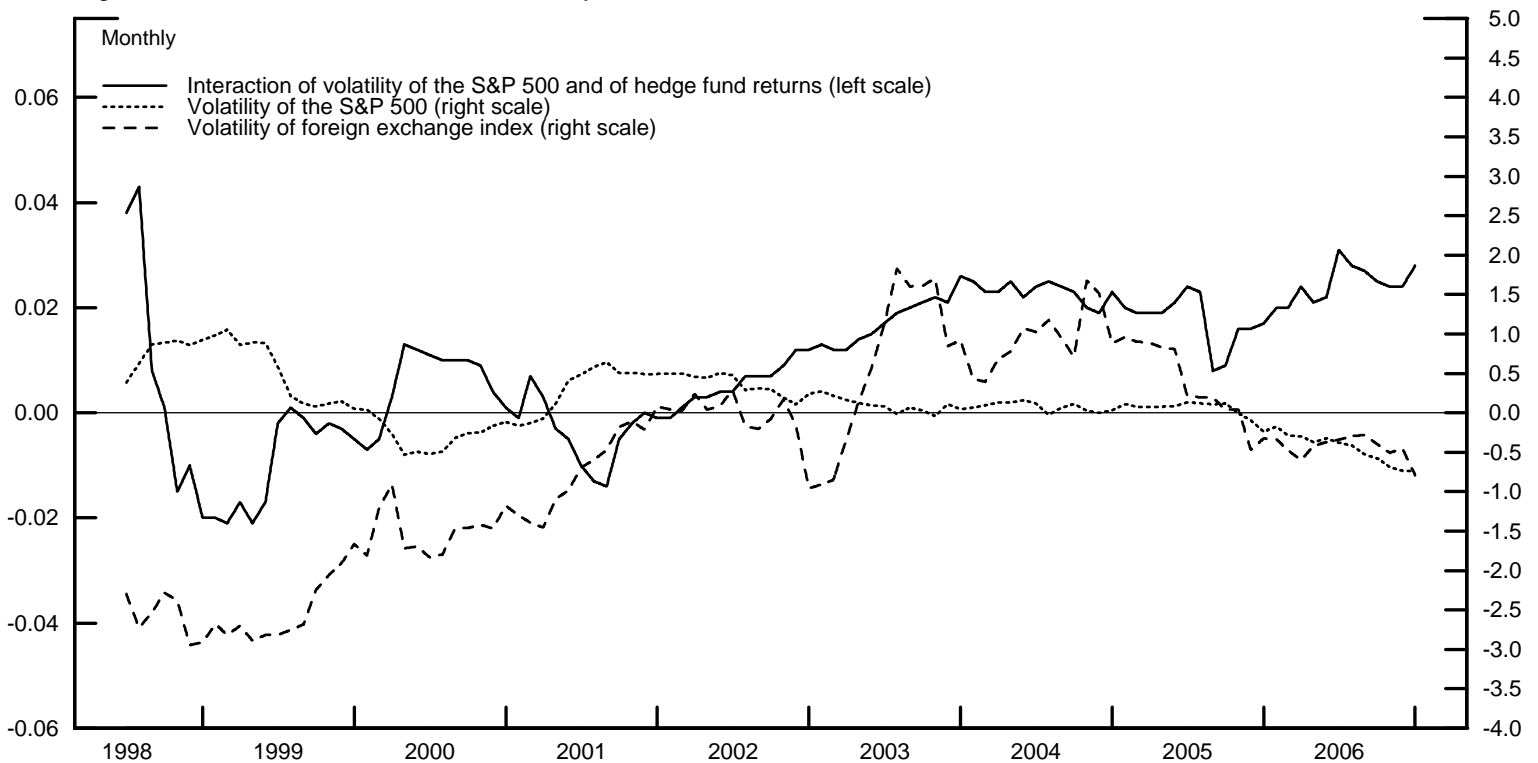
Figure 2
(continued)

Figure 2c - Coefficients on swap spreads and leverage use

Monthly

10-year swap spread (left scale)
Reports using leverage (right scale)
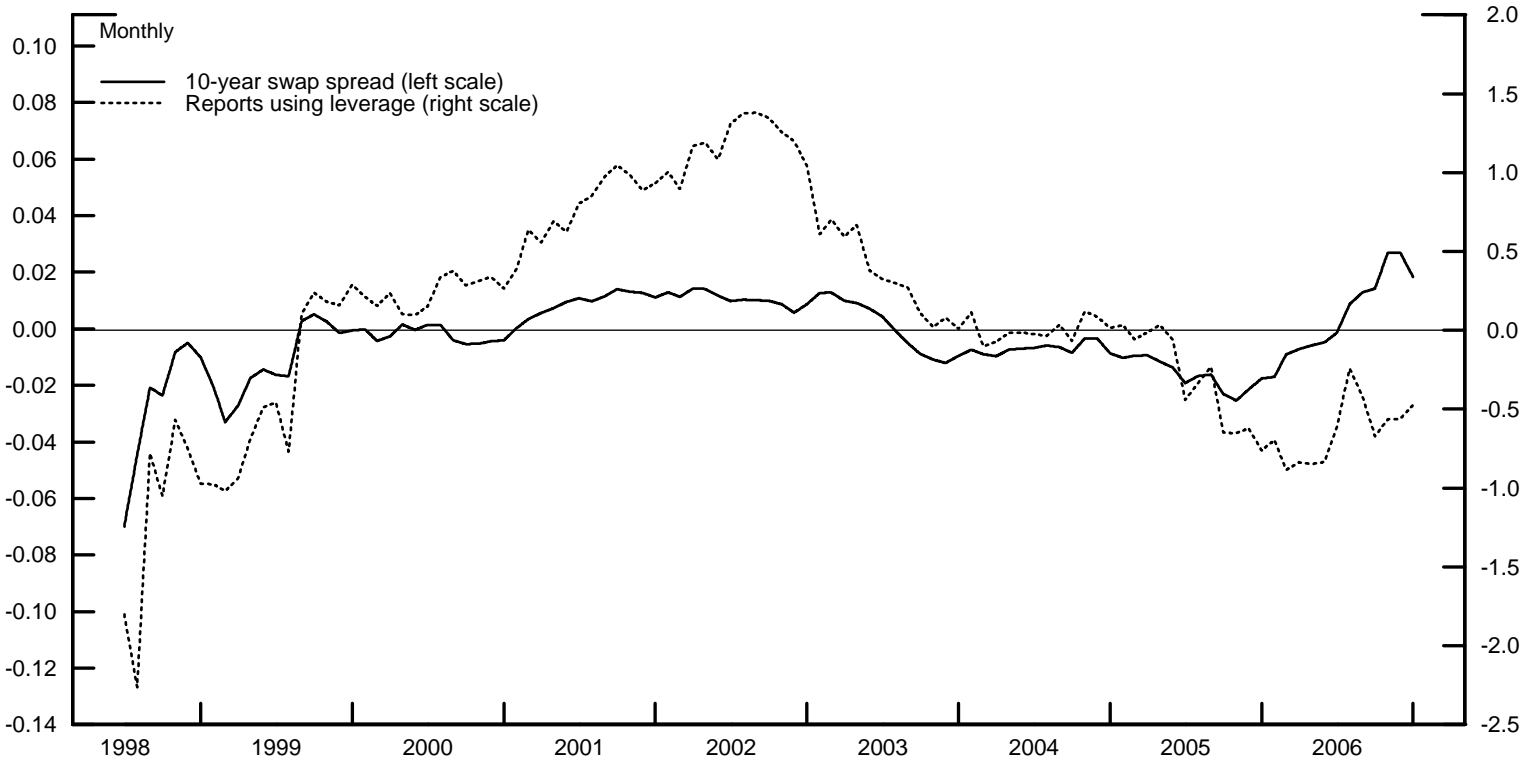
Figure 2d - Coefficients on selected strategies

Monthly

Reports having a long-bias strategy
Reports having a short-bias strategy

Figure 3
Selected coefficients from rolling-window regressions using industry aggregate data

Figure 3a - Coefficients on selected market returns

Figure 3b - Coefficients on selected market volatility measures
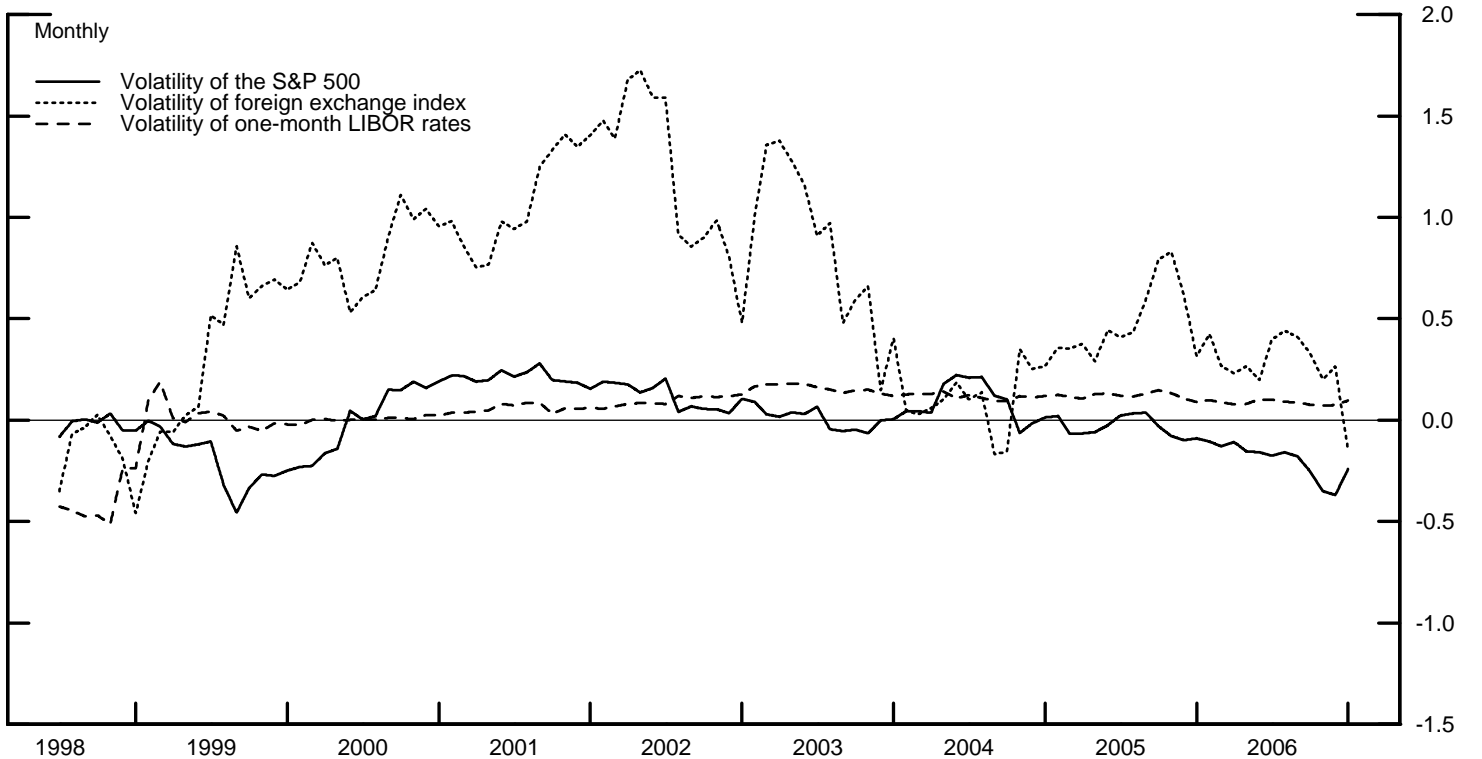
**Figure 3
(continued)**

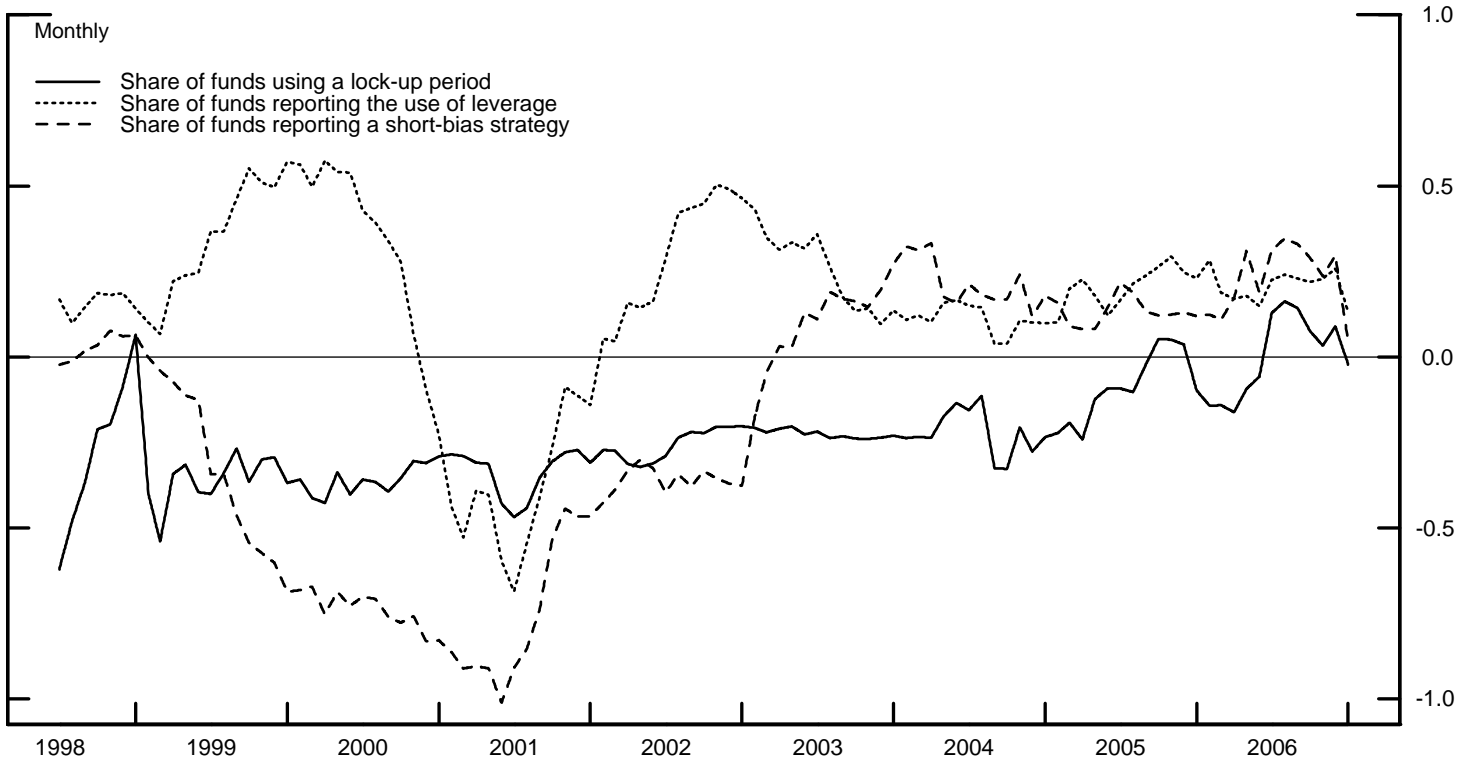Figure 3c - Coefficients on hedge fund characteristics and strategies

Monthly

——— Share of funds using a lock-up period
·········· Share of funds reporting the use of leverage
– – – Share of funds reporting a short-bias strategy

Figure 4
Actual and predicted number of failures based on individual hedge fund analysis
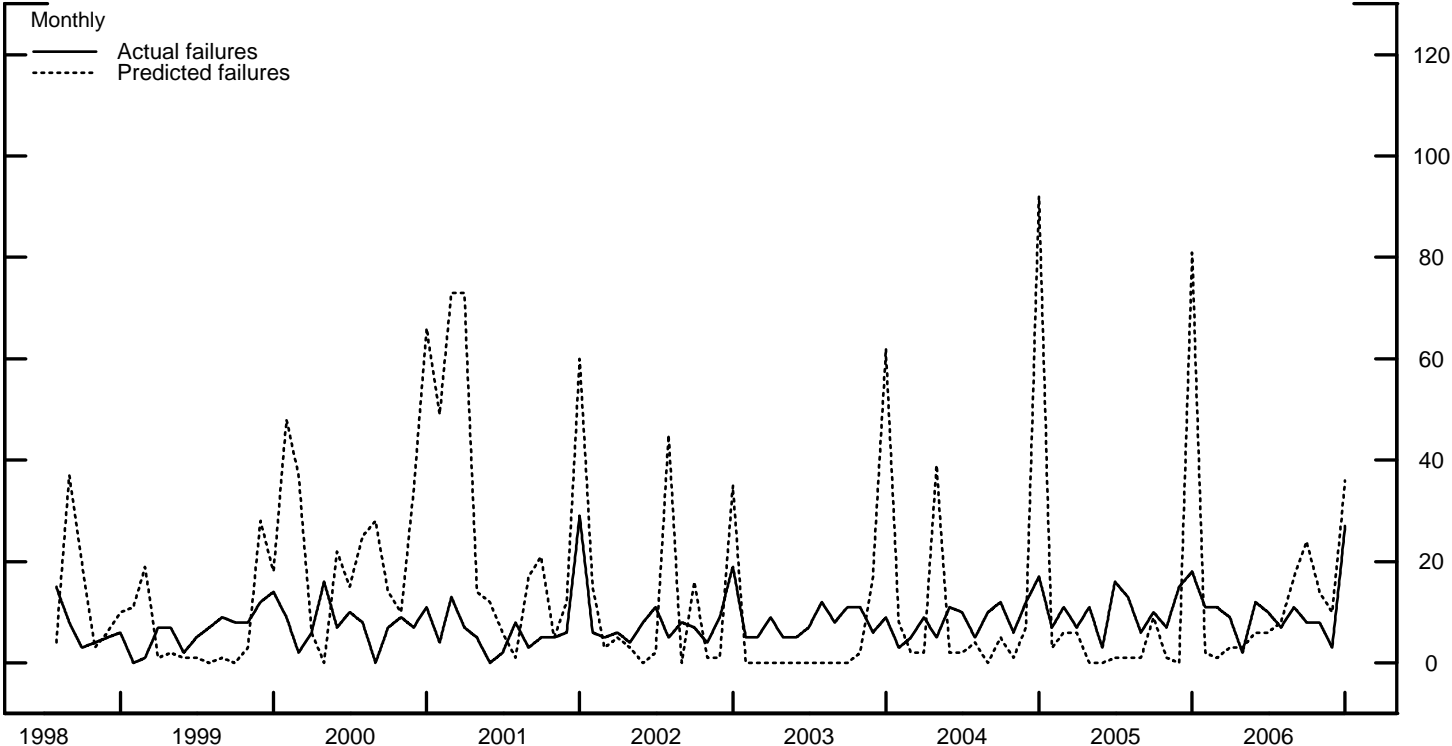
Figure 5
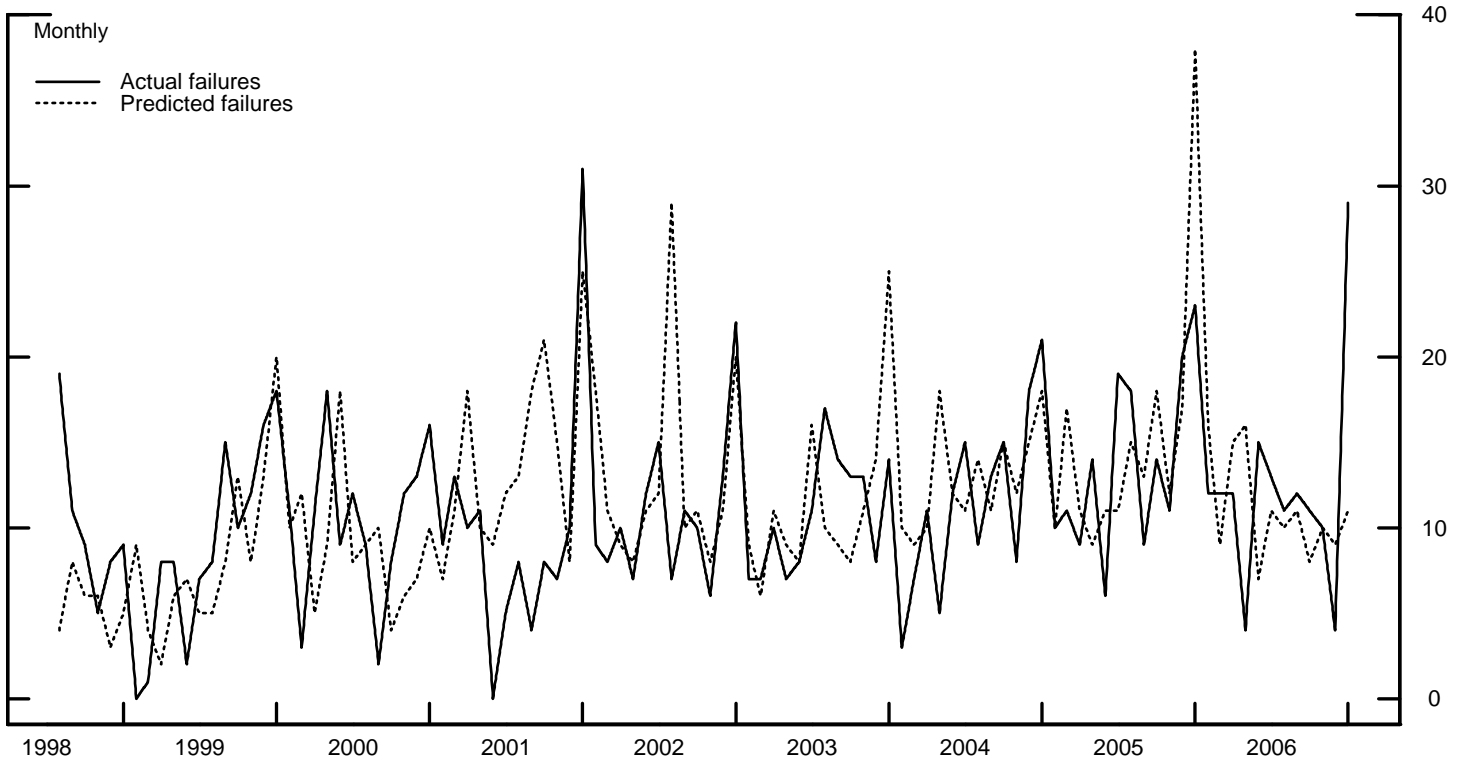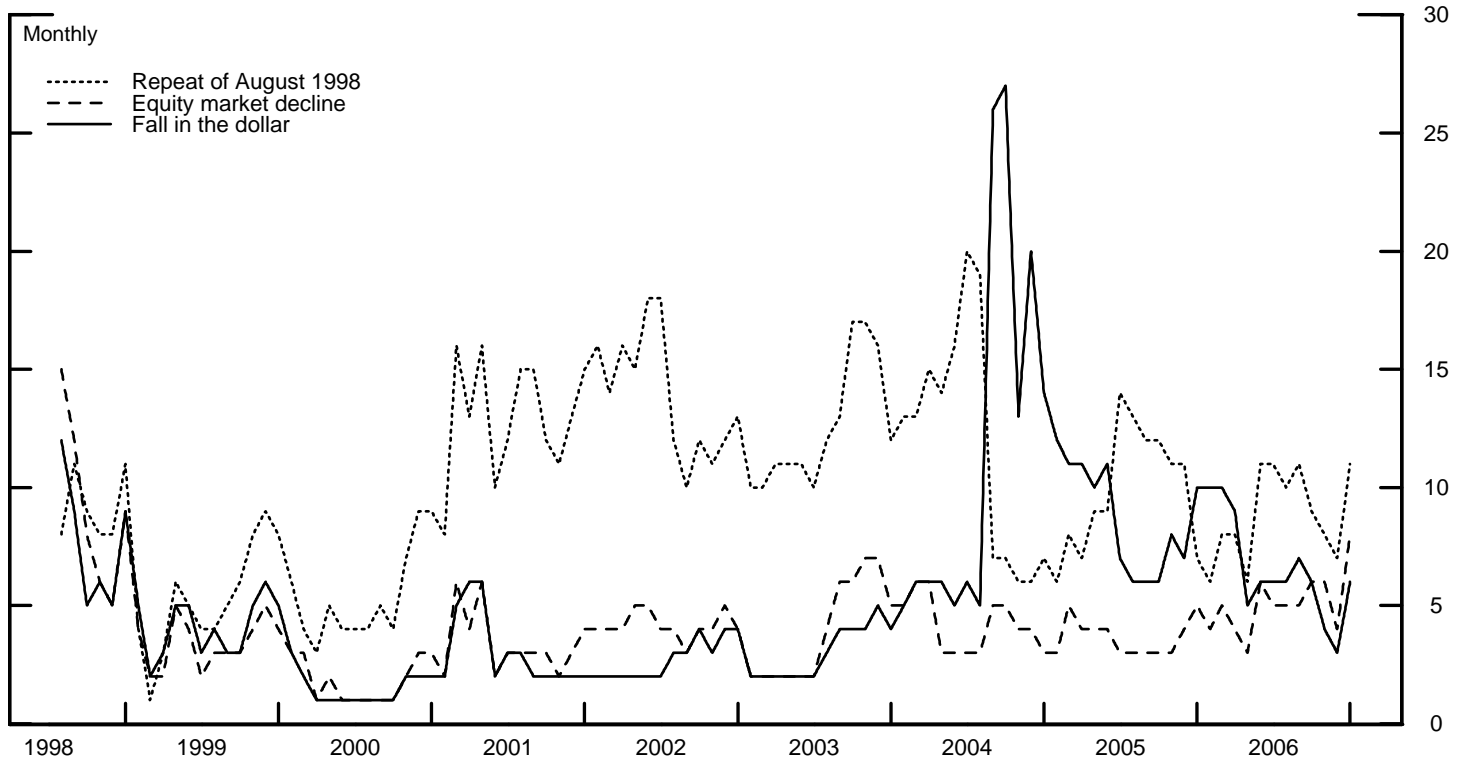**Actual and predicted number of failures based on industry aggregate analysis**

Figure 6
Predicted hedge fund failures under different stress scenarios based on industry aggregate regressions

Note. The average monthly number of failures from July 1998 to December 2006 is 10.65.