Do Hedge Funds Profit From Mutual-Fund Distress?

Joseph Chen
USC

Harrison Hong
Princeton University

Jeremy C. Stein
Harvard University and NBER

First draft: September 2007

Abstract: This paper explores the question of whether hedge funds engage in front-running strategies that exploit the predictable trades of others. One potential opportunity for front-running arises when distressed mutual funds—those suffering large outflows of assets under management—are forced to sell stocks they own. We document two pieces of evidence that are consistent with hedge funds taking advantage of this opportunity. First, in the time series, the average returns of long/short equity hedge funds are significantly higher in those months when a larger fraction of the mutual-fund sector is in distress. Second, at the individual-stock level, short interest is abnormally high in advance of sales by distressed mutual funds.

We are grateful for helpful feedback from Andrei Shleifer, seminar participants at the Federal Reserve Bank of New York, and students in Stein's Economics 1760 and 2728 classes.

I. Introduction

Consider an arbitrageur who learns that a big investor is about to sell a large amount of a particular stock, and who understands that this sale is likely to have a significant price impact. How might the arbitrageur take advantage of this knowledge? Broadly speaking, there are two types of trading strategies available to him. The first strategy, "liquidity provision", involves the arbitrageur buying the stock *after* the big investor has sold it and knocked down the price, and then holding as the price reverts towards its pre-sale value. The second strategy, "front-running", involves the arbitrageur shorting the stock *before* the big investor has had a chance to sell it, and then covering this short position immediately after the sale occurs.

While liquidity provision is undoubtedly a socially desirable activity, front-running is more controversial. Indeed, the potentially adverse consequences of front-running have been repeatedly pointed out by academics, practitioners and policymakers. DeLong et al (1990) demonstrate that front-running, while individually rational for the arbitrageurs who profit from it, can nevertheless push prices further away from fundamentals and increase volatility. Brunnermeier and Pedersen (2005) offer a similar analysis of what they call "predatory trading", and present several anecdotal accounts of cases where such activity appears to have played an important role. Perhaps the best-known of these stories comes from the meltdown of Long Term Capital Management (LTCM) in the fall of 1998; it is widely believed that LTCM's initial troubles were magnified by the actions of front-runners.

Whatever its implications for market efficiency, it should be noted that there is nothing illegal about front-running. The information that allows arbitrageurs to predict the trades of other investors may well come from public sources.[1] This is not to say that there are not also

[1] To take one possibility, it may be that certain high-frequency statistical arbitrage strategies are profitable in part because they succeed in forecasting imminent order flow.

shadier ways to play the game. For example, attention has recently focused on a particular type of front-running, one that relies on inside information leaked by brokers to their favored hedge-fund clients. As reported by the *New York Times* in February of 2007:

> "The Securities and Exchange Commission has begun a broad examination into whether Wall Street bank employees are leaking information about big trades to favored clients, like hedge funds, in an effort to curry favor with those clients…Knowledge about a large trade, like the sale of a big block of stock by the mutual fund giant Fidelity, would tell a trader which way the stock would move…Large mutual fund companies have often complained in the past that Wall Street brokerage firms were front-running their trades….But the latest S.E.C. investigation appears to have a new twist: Rather than examine whether a bank is trading ahead of its own client by using knowledge of the customers trade, the scope of the investigation will allow regulators to see if banks tip their valued customers who then go trade at another bank, making the paper trail harder to detect."

In spite of all the interest in front-running, both in its legal and illegal forms, there is little large-sample evidence that speaks to its general prevalence in financial markets. This is not surprising, given the limited disclosure requirements faced by the sorts of big institutional players—hedge funds in particular—who might be thought of as potential front-runners. For example, hedge funds with more than $100M in assets have to disclose their long equity positions on a quarterly basis in 13-F filings, but there is no comparable disclosure of their short positions, which is a major drawback, given that front-running is likely to involve shorting. And there is no systematic information on hedge funds' positions in other asset classes, where front-running is often alleged to have occurred (e.g., emerging-market bonds in the LTCM case).

Given these data limitations, we take an indirect approach to the problem. Rather than trying to observe hedge funds in the act of front-running itself, we begin our investigation by asking whether, in the time series, hedge funds earn higher returns in those periods when there appear to be more good opportunities for front-running. By analogy, if one suspected a group of police officers of taking bribes from drug dealers, but was unable to observe the act of bribery directly, it might be informative to ask whether those officers who patrolled the areas with the highest levels of drug activity also owned the most expensive houses and cars.

This approach requires us to develop a proxy for time-variation in the front-running opportunity set. Here we build directly on recent work by Coval and Stafford (2007), who study "fire sales" by distressed mutual funds. Coval and Stafford show that when a given stock is simultaneously owned by several distressed funds (i.e., funds that have recently suffered big outflows of assets under management), that stock is likely to be subject to unusually heavy selling pressure and a corresponding drop in price. Moreover, these fire sales can to some extent be predicted ahead of time, since mutual-fund distress is largely a function of poor past performance. Indeed, using only real-time public information, Coval and Stafford are able to construct a hypothetical trading strategy that front-runs mutual-fund fire sales—i.e., that takes short positions in those stocks most likely to be dumped by distressed mutual funds—and that earns significant abnormal returns, on the order of ten percent per year.[2]

Coval and Stafford (2007) use their hypothetical front-running strategy as a way of quantifying the predictable price-pressure effects associated with mutual-fund fire sales. However, they stop short of asking whether anybody in the real world actually plays this strategy. This is where we pick up the story. Our basic premise is the following. If, as Coval and Stafford suggest, mutual-fund distress does in fact create opportunities for front-running, and if hedge funds in the aggregate are front-runners, then we should see them earning higher returns in those periods when there are more distressed mutual funds.

This conjecture is strongly supported by the data. In the time series, the monthly returns of long-short equity hedge funds are significantly positively related to the contemporaneous

[2] Frazzini and Lamont (2005) also analyze the price-pressure effects associated with mutual-fund flows. However, unlike Coval and Stafford (2007), they do not investigate the possibility of front-running such flows.

aggregate outflows of distressed mutual funds. Moreover, the coefficient estimates imply noteworthy economic magnitudes. Although the precise details vary with our specifications, a one-standard deviation increase in mutual-fund distress is typically associated with a 30 to 40 basis point improvement in monthly hedge-fund returns.

Again, we stress that in spite of the statistical strength of these results, the indirect nature of our time-series approach means that it can provide only circumstantial evidence in favor of the proposition that hedge funds are active front-runners. A good deal of skepticism is clearly warranted. In particular, we can imagine two broad types of objections to the front-running interpretation. First, one might argue that our measure of mutual-fund distress is proxying for another factor that influences hedge-fund returns through a different channel. For example, mutual-fund redemptions might be higher in periods when the market is volatile, and market volatility might be directly beneficial to hedge funds for other reasons (e.g., it creates more mispricing and hence more stockpicking opportunities). Although we can try to control for such effects, our ability to do so is undoubtedly imperfect, which leaves the door open to other stories.

Second, even if it is the case that mutual-fund distress does have a causal impact on hedge-fund profitability, this could be because hedge funds do more in the way of socially valuable liquidity provision (i.e., more *buying* of fire-sale stocks) during times of heightened distress—as opposed to more front-running via short sales. One counter to this argument comes from the timing of the relationship. If hedge funds were providing liquidity to distressed mutual funds, one would expect them to earn higher returns in the several quarters *after* distress spikes up, since as Coval and Stafford (2007) show, the negative price impact associated with a fire sale reverses only gradually over a period of roughly 18 months. However, we find that hedge-fund returns rise approximately contemporaneously with mutual-fund distress. This fits better with a front-running story, since a front-runner would put on a short position before a fire sale, then close it out—and book his profit—at the time that the fire sale actually occurs.

Nevertheless, given both of these objections, the front-running hypothesis would clearly be on stronger ground if we had evidence that spoke more directly to the mechanism in question, i.e., if we could actually observe hedge funds short-selling stocks in advance of these stocks being subject to fire sales. Unfortunately, as noted above, there is no source for data on the short positions of hedge funds. However, data on *total* outstanding short interest from all sources is readily available at the individual-stock level. Using this data, we show that if a stock is subject to a fire sale in a particular quarter, (say January-March 2006) short interest in that stock is abnormally high in the month before the quarter begins (December 2005 in this example); this is in the context of a regression that includes stock-level fixed effects as well as a number of other controls. Thus it appears as if *somebody* is playing the Coval-Stafford (2007) strategy.

Overall, then, we offer two complementary pieces of evidence. First, at the aggregate level, hedge funds earn significantly higher returns when more mutual funds are in distress. This is circumstantially consistent with front-running being an important source of hedge-fund profitability, but also admits other interpretations. Second, at the individual-stock level, short interest tends to be elevated before a stock is subject to fire selling by distressed mutual funds. This is more directly suggestive of an active front-running mechanism, but by itself does not pin down what class of trader is doing the front-running.

The rest of the paper is organized as follows. Section II briefly discusses related work. In Section III, we examine the time-series relationship between mutual-fund distress and hedge-fund performance. In Section IV, we look at stock-level data, and ask whether short interest is abnormally high in advance of fire sales by distressed mutual funds. Section V concludes.

II. Related Literature

While there is much anecdotal discussion of front-running, there are few systematic empirical studies of this phenomenon. The one exception we know of is an interesting piece by Cai (2003), who uses a unique dataset of audit trail transactions to examine the trading behavior of market makers in the Treasury bond futures market when LTCM faced binding margin constraints in 1998. Cai finds that market makers engaged in front-running against customer orders coming from a particular clearing firm—orders that closely matched various features of LTCM's trades through Bear Stearns. The market makers traded on their own accounts in the same direction as the customers of this clearing firm did, but one or two minutes beforehand.

There is a large literature on the determinants of hedge-fund returns. An important strand of this work emphasizes loading on tail risks as a source of hedge-fund returns. In an early study, Fung and Hsieh (1997) show that the distributional properties of hedge-fund returns can differ significantly from those of mutual funds. For instance, trend-following strategies (Fung and Hsieh (2001)) and risk-arbitrage strategies (Mitchell and Pulvino (2001)) have the sort of highly nonlinear risk-return characteristics associated with the writing of options.

Agarwal and Naik (2004) extend this analysis to a wide variety of hedge fund styles. They find that tail risk, as proxied by the returns to S&P 500 index options, is important for explaining the returns of several hedge fund styles.[3] From our perspective, however, it turns out that tail risk is less of an issue. Agarwal and Naik show that the returns on long-short equity funds—the focus of our paper—can largely be explained by the Fama-French (1993) three-factor

[3] Most of the aforementioned studies look at the returns of various hedge-fund indices. But there is also evidence using individual fund return data, which shows that those funds that take on high left-tail risk outperform those funds with less risk exposure (Bali, Gokcan, and Liang (2007)).

model, a finding which we confirm below.[4] Moreover, the nonlinear risks associated with writing options play a statistically insignificant role for this particular style.

Another important consideration when looking at hedge-fund returns is the ability of funds to smooth their reported performance (Asness, Krail and Liew (2001) and Getmansky, Lo and Makarov (2004)). This implies that it can be important to account for past market movements in explaining current fund returns, particularly for styles that trade relatively illiquid securities, or that are otherwise non-transparent. Most recently, a number of studies point out that contagion risk might also be important for explaining hedge-fund returns (Boyson, Stahel, and Stulz (2006), Chan, Getmansky, Haas, and Lo (2006), Adrian and Brunnermeier (2007)).

In the spirit of this prior work, one contribution of our paper is to put forth a new factor—namely aggregate mutual-fund distress—that helps to explain the time series of hedge-fund returns. Whether or not one believes the front-running interpretation that we attach to our time-series results, the mutual-fund distress factor appears to be a robust and economically important determinant of the returns to long-short equity hedge funds. Moreover, at a minimum, it is a factor that can be said to be well-motivated by a particular economic theory.

III. Mutual-Fund Distress and Hedge-Fund Returns: Time-Series Evidence

A. Data Sources

1. Hedge-fund returns

Our data on hedge-fund returns come from two providers: Credit Suisse/Tremont (formerly Tremont Advisory Shareholder Services, or TASS); and Hedge Fund Research Inc., henceforth HFRI. Each provider computes numerous sub-indices, corresponding to a variety of

[4] Gatev, Goetzmann, and Rouwenhorst (2006) find that the Fama-French (1993) factors are also important for explaining the profitability of pairs-trading strategies.

different hedge-fund strategies. Given that our interest is in funds that trade in equities, and that can take short positions, we focus primarily on the Long/Short Equity index from CS/Tremont, and on the Equity Hedge index from HFRI. However, in the spirit of a placebo check, we also experiment with fixed income and global macro indices from each provider.[5] The premise is that funds in these latter categories are less likely to be active in the stock market, so their returns should not be as sensitive to distress on the part of equity mutual funds.

The principal difference between the CS/Tremont and HFRI indices is that the former are value-weighted, while the latter are equal-weighted. More specifically, the CS/Tremont indices are based on the value-weighted returns of the largest funds in their universe, funds that in each case collectively comprise at least 85 percent of the assets under management in the given category. The HFRI indices, by contrast, equal-weight the funds in their universe, which is subject to the restriction that to be eligible for the HFRI universe, a fund must have at least $50 million under management, or have been actively trading for at least twelve months.

As is well known, hedge-fund reporting to these providers is voluntary, so no single provider offers a comprehensive picture of the returns of all hedge funds.[6] Nevertheless, there is reason to believe that, taken together, the CS/Tremont and the HFRI data capture a substantial fraction of the hedge-fund universe. For example, working with a larger dataset that includes four providers (our two plus CISDM and MSCI), Agarwal et al (2007) note that as of year-end 2002, 63 percent of the funds in their sample were covered by either CS/Tremont or HFRI.

[5] As of August 2007, the composite CS/Tremont index contained 456 funds. Of these, by far the largest number were in the Long/Short Equity index, which had 167 funds. The fixed income index was composed of 34 funds, and the global macro index contained 23 funds.

[6] There are several papers that compare the indices produced by different vendors (see e.g. Agarwal and Naik (2005)), and some research that compares the indices with the returns of individual funds (Malkiel and Saha (2005)). In addition, there is some evidence that the CS/Tremont indices appear to be the least affected by various biases, perhaps because of their value-weighted nature (Malkiel and Saha (2005)).

Moreover, the overlap in the coverage of CS/Tremont and HFRI is modest: only 8 percent of the funds in the Agarwal et al sample are covered by both. This suggests that using both of these providers gives us meaningful incremental information.[7]

Our sample period runs from January 1994 to December 2006. Agarwal et al (2007) and others have argued that it is desirable to focus on the post-1994 period, since the data from 1994 onwards tends to include better coverage of defunct funds, and hence is less subject to survivorship bias. Moreover, the CS/Tremont data are only available beginning in 1994.[8]

This is not to claim that survivorship bias is completely eliminated in our sample period. However, such bias is arguably not as problematic for us as it can be in other contexts, since we do not seek to make statements about the absolute average returns to hedge funds—i.e., we do not address the question of whether they have unconditionally positive alphas.[9] Rather, we are interested in how their returns covary with a particular factor, namely the extent of distress in the mutual-fund sector. It is less obvious how a bias in the data towards surviving funds would distort our inferences about this covariance.

Table 1 presents some basic information about the monthly means, standard deviations, and correlations of the returns on the indices that we examine. Over the 1994-2006 sample period, the equal-weighted HFRI Equity Hedge index has a somewhat higher mean monthly

---

[7] We have also examined data from a third provider, Barclay. Like with HFRI, the Barclay indices are equal-weighted. However, they are only available beginning in 1997. Over this shorter sample period, the Barclay Equity Long/Short index produces results very similar to those we obtain below using the HFRI Equity Hedge index, so we do not report them separately.

[8] The HFRI data go back to 1990, but again, data-quality concerns are more pronounced pre-1994.

[9] The impact of survivorship bias on measured performance is analyzed by Brown, Goetzmann, and Ibbotson (1999). The related problems of termination and self-selection biases are studied by Ackermann, McEnally, and Ravenscraft (1999).

return than the value-weighted CS/Tremont Long/Short Equity index, 1.15% vs. 1.00%.[10] It also has a lower standard deviation, 2.53% vs. 2.90%. But perhaps most relevant for our purposes, these two indices have a very high correlation coefficient of 0.91. This gives us some confidence that, whatever their idiosyncrasies, they capture an essential common component of performance among long/short equity hedge funds.

2. Measures of mutual-fund distress

To measure mutual-fund distress, we begin with a sample of funds classified as "equity" funds using the objective codes in the CRSP Mutual-Fund Database. This screen leads us to exclude bond funds, money market funds, sector funds, international funds and balanced funds. To make it into our sample, a fund must also be identified in the MFLINKS database of WRDS. In cases where there are multiple fund share classes, we aggregate these classes into one fund, on a value-weighted basis.

Next, for each mutual fund i in each period t, we calculate $\text{FLOW}_{i,t}$, which is the percentage flow into the fund over the period. It is defined as:

$$\text{FLOW}_{i,t} = (\text{TNA}_{i,t} - (1 + r_{i,t})\text{TNA}_{i,t-1})/\text{TNA}_{i,t-1}, \tag{1}$$

where $\text{TNA}_{i,t-1}$ is the total net assets under management at the end of the previous period, and $r_{i,t}$ is the return (net of fees and expenses) over the period. We compute $\text{FLOW}_{i,t}$ at both the monthly and quarterly frequencies.

[10] This difference in mean returns could potentially reflect a greater degree of survivorship bias among smaller hedge funds, which play a bigger role in the equal-weighted HFRI indices.

At either frequency, a fund is considered to be in distress if it experiences percentage outflows greater than some threshold level. Table 2 gives a sense of how many funds are classified as distressed, depending on the threshold that we use. For example, if we use a monthly threshold of 4%, we label 7.9% of funds as distressed in a typical month, and these funds on average represent 2.4% of assets under management among the funds in our sample. (This difference reflects the fact that small funds have more volatile flows and hence are more likely to become distressed than large funds.) In what follows, we use a monthly threshold of 4% as our baseline definition of distress, but we also show that our results are robust to a wide range of alternative cutoffs.[11]

Once we have defined a set of distressed funds in each period, we create two measures of aggregate distress. The first, "equal-weight outflows from distressed funds" is an equal-weighted average of: i) the absolute value of percentage outflows (i.e., the absolute value of $FLOW_{i,t}$) from those mutual funds in distress in period t; and ii) zero for those mutual funds not in distress in period t. The second, "asset-weight outflows from distressed funds" is an assets-under-management-weighted average of: i) the absolute value of percentage outflows from those mutual funds in distress in period t; and ii) zero for mutual funds not in distress in period t.[12]

[11] Yan (2006) documents that over the period 1992-2001, the median equity mutual fund held a cash balance equal to 3.68% of assets. Thus for a typical fund, an outflow of 4% in a month would necessarily lead to some forced liquidations of its stockholdings.

[12] For the purposes of these calculations (and after we have already classified funds as distressed or not) we winsorize $FLOW_{i,t}$ at its 1% and 99% values within each period. We do so because there are a handful of extreme outliers in the flow numbers, including some cases where measured outflows from a fund exceed 100%. Per equation (1), this is presumably due in part to a mismeasurement of the fund's return $r_{i,t}$. However, our results are qualitatively similar—albeit a bit noisier—if we do not winsorize at all.

Note that our sign convention is that more positive values of these measures are associated with greater mutual-fund distress.[13]

Of the two measures, the latter, asset-weighted one is perhaps more immediately intuitive: it simply captures total dollar outflows from all distressed funds, scaled by the current size of the mutual-fund sector. Nevertheless, we believe that the equal-weight measure also has some conceptual appeal, particularly to the extent that small distressed funds offer proportionally more opportunities for front-running than large distressed funds. For example, since small funds tend to hold fewer stocks than large funds, they have less choice of what to unload when they get into trouble, and hence their trades may be easier for a front-runner to predict. By putting relatively more weight on the outflows of such small funds, the equal-weight distress measure arguably does a better job of incorporating this effect.

Figure 1 plots these two aggregate distress measures on a monthly basis over the period 1994-2006, using a 4% threshold to define distress. While the equal-weight measure is considerably more volatile, the two are very closely correlated, with a correlation coefficient of 0.859. Thus it should come as no surprise that the results that we present below are not sensitive to which of the two measures we use.

B. Results

1. Baseline specification

Panels A and B of Table 3 present the results from our baseline time-series specification, using the value-weighted CS/Tremont Long/Short Equity index, and the equal-weighted HFRI

[13]An alternative approach to measuring aggregate distress is simply to count—on either an equal-weighted or value-weighted basis—the fraction of funds that are distressed at any point in time. We view this approach as somewhat less desirable, as it amounts to focusing only on the extensive distress margin, and ignoring the intensive margin—i.e., it ignores the size of the outflows from distressed funds. Nevertheless, it leads to results that are similar to those we report below.

Equity Hedge index, respectively. Consider first Panel A, which focuses on the CS/Tremont index. In column (1), we warm up with a conventional performance-attribution regression, in which the monthly returns on the index from January 1994 through December 2006 are regressed against four familiar factors: EMKT, the excess return on the value-weighted market portfolio; SMB, the return on a portfolio that is long small stocks and short large stocks; HML, the return on a portfolio that is long high book-to-market stocks and short low book-to-market stocks; and WML, the return on a portfolio that is long past twelve-month winners and short past twelve-month losers. Of these factors, EMKT, SMB and WML come in strongly positive and significant, and collectively they explain an impressive amount of the variation of the returns to the Long/Short Equity index: the simple R-squared of the regression is 81.2%. This is consistent with prior work (Agarwal and Naik (2004)) which finds that for long-short equity funds, linear stock-market factors are the most important explanatory variables, with non-linear option-like factors playing a statistically insignificant role.

In column (2), we add to these four factors the contemporaneously-measured monthly variable DISTRESS, which is just "equal-weight outflows from distressed funds", as described above, using a monthly threshold level of 4%. The coefficient on DISTRESS is 1.70, and is statistically significant, with a t-stat of 3.17. To get a sense of the economic magnitude of this effect, note that the standard deviation of the DISTRESS variable is 0.232%, which implies that a one-standard-deviation increase in DISTRESS raises monthly hedge-fund returns by 39.4 basis points, or almost five percentage points on an annualized basis.

In column (3), we keep all else the same as column (2), but add also POSFLOW, which is the mirror image of DISTRESS—i.e., it captures equal-weighted inflows to those mutual funds that have positive inflows of greater than 4%. The motivation for including this variable also comes from Coval and Stafford (2007), who note that mutual funds experiencing large inflows often tend to mechanically scale up their existing positions, rather than diversifying into new holdings. Thus, Coval and Stafford suggest, large inflows may also give rise to predictable price pressure—a phenomenon they refer to as "fire purchases"—and hence to front-running opportunities. As it turns out, however, the coefficient on POSFLOW, while of the expected positive sign, is much smaller than that on DISTRESS, and is statistically insignificant.

Columns (4) and (5) mimic columns (2) and (3), except that the DISTRESS and POSFLOW variables are now computed based on flows over the quarter that runs up through the contemporaneous month, using a threshold level of 8%. For example, the hedge-fund return for the month of December is now regressed against DISTRESS and POSFLOW measures based on flows over the three months October, November and December. As can be seen, the results are very similar. The quarterly DISTRESS variable is again positive and significant, while the quarterly POSFLOW variable remains positive and insignificant. Moreover, the quantitative impact of a one-standard-deviation increase in quarterly DISTRESS on monthly hedge-fund returns is 35.1 basis points, very similar to the 39.4 basis-point figure obtained with the monthly DISTRESS measure.

The fact that the monthly version of DISTRESS is roughly as informative for hedge-fund returns as the quarterly version suggests that aggregate mutual-fund distress translates almost immediately (i.e., within the month) into higher hedge-fund returns, with more distant realizations of distress having little incremental explanatory power. As discussed above, this is consistent with a front-running interpretation, since a front-runner presumably closes out his position and takes his profit at the moment that a fire sale occurs.

Panel B replicates everything in Panel A, but using the equal-weighted HFRI Equity Hedge index instead of the value-weighted CS/Tremont index. The basic conclusions that emerge are generally quite similar, though a couple of noteworthy distinctions stand out. First, using an equal-weighted index reduces the noise in measured hedge-fund returns, leading to uniformly higher R-squareds and t-statistics. For example, in column (2), the coefficient on DISTRESS is now 2.01 with a t-stat of 4.21, and the R-squared is 88.1%, as opposed to its value of 82.8% in the corresponding column (2) of Panel A.

Second, with these more precise estimates, the coefficient on POSFLOW in column (3) now becomes statistically significant, although it remains much smaller, at 0.462, than the coefficient on DISTRESS.   Thus the HFRI data offer some support for the proposition that there may also be front-running opportunities associated with large inflows into mutual funds. Nevertheless, it would seem that the magnitude of this effect is not nearly as large as that associated with outflows from distressed funds—a conclusion which seems quite plausible.

2. Additional controls

In Panels C and D of Table 3, we add a variety of additional controls to the regressions from Panels A and B. We begin with the specification seen in column (3) of Panels A and B, that which includes the four market factors (EMKT, SMB, HML and WML), as well as the monthly versions of DISTRESS and POSFLOW. To this specification we add: i) lagged values of EMKT, SMB, HML, and WML (in column 1 of Panels C and D); ii) MKTVOL, the standard deviation of daily market returns in the given month (in column 2); iii) XVOL, the cross-sectional standard deviation of monthly individual-stock returns in the given month (in column 3); iv) TIME and TIME squared, where TIME is the numbers of years since the start of the sample period (in column 4); and v) DEC, a dummy variable that takes on the value of one in the month of December (in column 5).

The lagged values of the EMKT, SMB, HML, and WML are motivated by prior work which shows that measured hedge-fund returns can be sluggish in adjusting to market-wide price movements, perhaps due to smoothing of reported performance by fund managers (Asness, Krail, and Liew (2001) and Getmansky, Lo, and Makarov (2004)). And indeed, the returns to both the CS/Tremont and HFRI indices show significant loadings on lagged values of EMKT. The MKTVOL and XVOL variables represent an (admittedly imperfect) attempt to control for the possibility that mutual-fund distress is more likely to occur when markets are going through periods of high volatility. The TIME and TIME squared terms are meant to take out any low-frequency time trends in the data. And finally, the DEC dummy is added in light of Agarwal et al (2007), who uncover a December seasonal in hedge fund returns—an effect that they attribute to managers' efforts to inflate year-end performance. Their finding is particularly relevant for us, since mutual-fund outflows, and hence our DISTRESS variable, also tend to spike up in December; this seasonality is readily apparent in Figure 1.

As it turns out, none of these added controls materially affects our key results. For example, in Panel C, which uses the CS/Tremont Long/Short Equity index, the coefficient on DISTRESS ranges from 1.49 to 1.95 across the five columns (and remains significant in each case); these figures compare with the value of 1.71 in the less heavily-controlled version of the same regression in column (3) of Panel A. In Panel D, which uses the HFRI Equity Hedge index, the coefficient on DISTRESS ranges from 1.82 to 2.21 across the five columns; these figures compare with the value of 2.03 in column (3) of Panel B.

3. Results for fixed income and global macro hedge funds

In Panels E and F of Table 3, we re-run our baseline specifications using fixed income indices (Panel E) and global macro indices (Panel F) from both CS/Tremont and HFRI. These regressions can be thought of as a placebo check on our results. In particular, given that fixed income and global macro funds are less likely to be active traders of equities, we should expect their returns to be less strongly influenced by distress among equity mutual funds.[14] And, as can be seen, there is no evidence of a systematic positive relationship between the DISTRESS variable and hedge-fund returns in either fixed income or global macro. Across all the specifications in Panels E and F, the coefficient on DISTRESS is never statistically significant, and is actually negative in three out of eight cases.

4. Varying measures of mutual-fund distress

All of the results thus far are based on just a couple of versions of our mutual-fund distress measures. We have always been equal-weighting the outflows of distressed funds, and have been consistently using either a monthly distress threshold of 4% or a quarterly distress threshold of 8%. In Table 4, we explore a wide range of variations with respect to these choices. In order to present a lot of information compactly, each column in Table 4 shows a univariate regression of monthly hedge-fund alpha on a particular measure of mutual-fund distress, where the monthly alpha is the residual from a regression of index returns on the four factors EMKT, SMB, HML, and WML.

[14] Of course, we cannot rule out that funds in these categories do some equity trading. Indeed, the returns to both HFRI indices load significantly on the stock-market factors EMKT, SMB, and HML, and the HFRI global macro index also loads on WML. These four factors explain 43.4% of the variation in the HFRI fixed income index, and 36.8% of the variation in the HFRI global macro index. The HFRI fixed income index (unlike the CS/Tremont fixed income index) includes convertible bond funds, which could help to explain its exposure to stock-market factors.

Using this format, we tabulate the regression coefficients on: i) both equal-weighted and asset-weighted distress measures; ii) monthly measures with distress thresholds ranging in one-percent increments from 2% to 6%; and iii) quarterly measures with distress thresholds ranging in two-percent increments from 2% to 10%. Altogether, these combinations yield 20 different measures of distress. Panel A of Table 4 uses the CS/Tremont Long/Short Equity index to create our dependent variable, and Panel B uses the HFRI Equity Hedge index.

When looking at the results in Table 4, it should be borne in mind that the coefficients on two different distress measures are not directly numerically comparable to one another, as, they can have very different standard deviations. Thus to ease comparability, we report below each coefficient the implied effect of a one-standard deviation change in the given distress measure. With this metric, it can be seen that the results are generally of a consistent magnitude across the whole range of distress measures.

In Panel A, with the CS/Tremont index, a one-standard-deviation increase in distress raises monthly hedge fund alphas by between 23 and 32 basis points, depending on the distress measure used. In Panel B, with the HFRI index, there is a little more variability across the distress measures, with the economic impact of a one-standard deviation shock ranging from 19 basis points to 43 basis points. Also with the HFRI index, we tend to see somewhat stronger effects when the distress measure is based on more extreme thresholds, i.e., when the threshold is set at 4% or higher in the monthly case, or 8% or higher in the quarterly case. Nevertheless, the overall picture that emerges is one of uniformity across the various distress measures. Of course, this should not be too surprising, as these measures are all highly correlated with one another in the time series.

5. A graphical illustration

Figures 2 and 3 illustrate two of the univariate regressions shown in Table 4. In Figure 2, we take the CS/Tremont index alphas, and the equal-weight monthly measure of distress based on a 4% threshold, and use these data to create both a scatterplot, as well as a graph that shows the joint time-series evolution of the two variables. In Figure 3, we repeat all of this, using instead the alphas from the HFRI index. As can be seen—especially from the scatterplots—the regression results that we report appear to capture a central tendency of the data, as opposed to just a handful of extreme outliers.

IV. Is Short Interest Higher Before Fire Sales by Distressed Mutual Funds?

A. Data and Variable Construction

Our data on monthly short interest for NYSE, AMEX and NASDAQ stocks are obtained from Bloomberg. We use this data to construct short interest ratios for each stock in each month. Observations on short interest represent positions that close on the first business day on or after the 15th of the month. Hence we approximate the short interest ratio by dividing total short interest by shares outstanding on the closest available day to the 15th of each month. Because the resulting raw short interest ratio, denoted by SR, is strongly right-skewed, in our regressions we use as a dependent variable a log transform LSR, which is given by LSR = log(SR + 0.01%), and which is more symmetrically distributed than SR.

Our key right-hand side variable is a measure of fire-selling by distressed mutual funds. We construct this measure as follows. First, for each quarter ending in March, June, September or December, and for each stock in our universe, we calculate the number of shares bought or sold by every mutual fund in the CDA/Spectrum database that reports holdings at both the beginning and end of the quarter. (These changes in shareholdings control for stock splits.) Next, we define a mutual fund as distressed at the 8% level if it has had outflows of greater than 8% over the quarter; from Table 2, this definition encompasses 11.7% of funds and 3.9% of fund assets in a typical quarter. The variable FIRESALE{8} is then defined for each stock as the sum of all shares sold by distressed funds in a quarter, divided by shares outstanding.

Finally, we denote by FIRESALE{8,90} an indicator that takes on the value one whenever the continuous variable FIRESALE{8} exceeds its 90th percentile value, and that takes on the value zero otherwise. FIRESALE{8,90} is our baseline measure of whether a stock is subject to a fire sale in a given quarter. Note that we use the entire panel unconditionally to determine the 90th percentile cutoff, which means that, according to our definition, there may be more fire sales in some periods than others. In alternative specifications, we also use variables we denote as FIRESALE{8,95}, FIRESALE{6,90} and FIRESALE{10,90}. These variables are constructed analogously, but using either different percentile breakpoints in the FIRESALE{8} distribution, or different thresholds for determining mutual-fund distress.

When we examine the impact of sales by distressed mutual funds, we want to be careful to distinguish this from any impact of sales by other, non-distressed mutual funds. Thus a crucial control is SELL, which is simply the total gross number of shares sold in a quarter by *all* mutual funds, divided by shares outstanding at the end of the quarter. Similarly, BUY is the total gross number of shares bought in a quarter by all mutual funds, divided by shares outstanding.

In addition to these variables, our regressions include a number of other controls that have been found in previous work (e.g., D'Avolio (2002), Asquith et al (2005), and Savor and Gamboa-Cavazos (2005)) to be significant determinants of short interest. These include institutional ownership, firm size, turnover, book-to-market, past returns, and the presence of convertible bonds in the firm's capital structure.

Our institutional ownership measure, IHOLD, is based on the CDA Spectrum Database of 13-F filings by large institutional investors, defined as those managing at least $100 million dollars in assets. Specifically, IHOLD is the fraction of a company's shares that are held by 13-F institutions, measured at the end of each calendar quarter.

The remaining controls are based on data from the Center for Research in Security Prices (CRSP) and COMPUSTAT.[15] With respect to firm size, rather than simply including a linear size control, we are more expansive, and use a set of 20 dummy variables corresponding to demi-deciles of the NYSE market-cap distribution in each period. We do so because the relationship between short interest and firm size is highly non-linear. In particular, short interest has an inverted-U shape when plotted against size: it is low among the very smallest micro cap stocks, then rises sharply with size through the first two deciles of the size distribution, before flattening out and eventually declining with size through the last two deciles of the size distribution

Our turnover measure, TURN, is a firm's average turnover in a quarter. BM is a firm's book value divided by its market capitalization at the end of its most recent fiscal year. PRET is a firm's stock return over the past twelve months. CONVERT is a dummy that equals one if a firm has convertible debt outstanding at the end of its most recent fiscal year, and zero otherwise.

Table 5 displays the full-panel means and standard deviations of all of the variables described above.

[15] To be included in our sample, a firm must have the requisite financial data from both CRSP and COMPUSTAT, which include book value, market capitalization, and twelve months of past returns. We also follow other studies in focusing on stocks with CRSP share codes of 10 or 11, i.e., common stocks of U.S. firms that are listed on the NYSE, AMEX or NASDAQ.

B. Results

Table 6 presents our stock-level regression results, which as before, cover the sample period 1994-2006. Recall that we have quarterly observations of the FIRESALE proxies, as well as of the SELL and BUY variables. The way the regressions are specified, if the FIRESALE, SELL and BUY measures are based on mutual-fund activity in a given stock over a given quarter (say January-March 2006), the dependent variable LSR corresponds to short interest in the stock on about the 15th of the month before the quarter begins (December 2005 in this example).[16] The controls IHOLD, TURN, BM, and CONVERT all reflect data from before the quarter begins (i.e., data from up through December 31, 2005). And PRET is based on returns over the twelve months ending one month before the quarter begins (i.e., returns from November 30, 2004 to November 30, 2005).

In addition to the 20 size dummies, and the controls IHOLD, TURN, BM, PRET, and CONVERT, all the regressions also include fixed effects for each quarter, as well as stock fixed effects. The presence of the stock fixed effects implies that we are basing our identification solely on within-stock variation in short interest over time. This fits most naturally with the economic story we have in mind. In particular, if a stock is going to experience a fire sale over the quarter January-March 2006, we expect it to have unusually high short interest—relative to its own typical levels—in December of 2005. Nevertheless, in untabulated regressions, we have also experimented with removing the stock fixed effects, while maintaining all of the other controls. This leads to results that are similar to those we report in Table 6, albeit a little stronger both statistically and economically.

[16] Thus, even though we observe short interest monthly, only every third month's value of short interest is used in the regressions in Table 6.

In column (1) of Table 6, we use the FIRESALE{8,90} indicator as our measure of fire-selling. The coefficient on this indicator is 0.182, with a t-statistic of 14.76 (all standard errors are clustered at the industry level using the Fama-French (1997) 48-industry classification). The quantitative interpretation is straightforward: when a stock is to be subject to a fire sale in the next quarter, its contemporaneous value of LSR is elevated by 0.182, which means that the raw (unlogged) short ratio is 20% higher than normal. At the sample-wide mean short ratio of 2.85%, this translates into an 0.62 percentage-point increase in short interest. Thus in addition to being statistically significant, the impact of the FIRESALE{8,90} variable on short-selling would seem to be of a magnitude that is economically interesting. As one simple benchmark, this impact is slightly less than half that associated with having one or more convertible bonds outstanding: the coefficient on the CONVERT indicator is 0.44.

The coefficients on the SELL and BUY variables are both significantly positive, at 6.90 and 3.10 respectively. Given that these variables capture gross selling and buying by mutual funds, the results suggest two conclusions. First, short interest rises in advance of more intense gross trading activity by mutual funds. Second, the fact that the coefficient on SELL is more than double that on BUY means that short interest is higher in a given stock when there is impending *net selling* by mutual funds in that stock. This finding can be given a number of interpretations, but one possibility is that net selling by mutual funds reflects some real information about fundamentals, and that whoever is taking short positions is acting on that same information in a somewhat more timely fashion.

In light of this story, it is important to stress that the coefficient on FIRESALE{8,90} reflects an *incremental* impact of selling by distressed mutual funds, above and beyond the impact of selling by all mutual funds (which is embodied in SELL). Thus our results for the

FIRESALE{8,90} variable cannot be explained away simply by saying that short-sellers are responding to the same information as mutual funds in general; this effect will be absorbed by the SELL and BUY controls. Rather, there seems to be something special about sales by distressed mutual funds.

The other controls in the regression have the signs that one would expect based on previous work. Short interest is increasing in turnover and institutional ownership, and as already noted, is higher when the firm in question has convertible debt outstanding. Short sellers also appear to be tilting in the right direction with respect to book-to-market and momentum, as the coefficients on BM and PRET are significantly negative. Collectively, all the variables—including the fixed effects—explain a large fraction of the variation in LSR: the adjusted R-squared of the regression is 74.6%.

Directly underneath the principal regression in column (1) of Table 6, we report the results from a variant in which all the controls are the same, but in which the FIRESALE{8,90} variable is interacted with SMALL, MID, and LARGE, which are dummies that equal one if a stock belongs in NYSE deciles 1-2 (SMALL), 3-6 (MID), and 7-10 (LARGE), respectively. The goal here is to decompose our full-sample results by broad market-cap categories. For brevity, we do not reproduce the coefficients on the controls, and focus only on the key interaction terms.

The coefficient on FIRESALE{8,90}*SMALL is 0.292, with a t-statistic of 19.68; the coefficient on FIRESALE{8,90}*MID is 0.103, with a t-statistic of 4.65; and the coefficient on FIRESALE{8,90}*LARGE is 0.016, with a t-statistic of 0.92. Thus the effects of future fire sales on short interest are strongest among small-cap stocks, continue to be economically and statistically significant among mid-cap stocks, and are virtually non-existent among large-cap stocks. This is not an implausible result, particularly if one believes that small stocks are likely to be less liquid, and hence vulnerable to more price pressure for a given amount of fire-selling. If so, it would be more attractive for a front-runner to take a short position in a small stock in advance of a fire sale, all else equal.

Columns (2)-(4) of Table 6 redo the analysis of column (1), with the FIRESALE{8,95}, FIRESALE{6,90}, and FIRESALE{10,90} indicators taking the place of FIRESALE{8,90}. As can be seen, the overall results are very similar. Thus our conclusions do not appear to be sensitive to modest changes in the thresholds used to define a fire sale.

Finally, in column (5), we use FIRESALE{8}, which is not an indicator, but rather a continuous variable measuring total gross selling of a stock by all distressed mutual funds. (As in the baseline specification, distressed funds are still defined as those with outflows of greater than 8% in the quarter.) While it might be argued that this continuous measure is in some ways less appropriate for capturing the extreme nature of a fire sale, it does have one nice feature: it is denominated in the same units as the SELL and BUY controls. Therefore it allows for a direct and intuitive comparison of their magnitudes. As can be seen, the coefficient on FIRESALE{8} is 20.08 (with a t-statistic of 3.96), while the coefficient on SELL is 8.15 (with a t-statistic of 8.08). This means that an impending sale by a distressed mutual fund has an impact on short interest that is more than three times the impact of an impending sale of the same size by a non-distressed mutual fund.[17]

V. Conclusions

Rather than restate our results, we close with a couple of further qualifications regarding how these results should be interpreted. First, even if one accepts the proposition that hedge

[17] Note that the total impact of a sale by a distressed fund is obtained by summing the coefficients on SELL and on FIRESALE{8}.

funds are engaging in the general kind of front-running that we describe, we cannot speak to *how* they are implementing it—i.e., to what kind of data, either public or private, they are using to construct their trading strategies. For example, it is possible that some funds are using a public-sources methodology very similar to that laid out by Coval and Stafford (2007): studying 13-F filings to get a picture of mutual funds' holdings, and trying to forecast which ones will become distressed based on past performance. On the other hand, it could be that some funds are relying on illegal inside information from their brokers to tell them precisely when a fire sale is coming. This more refined information set would naturally lead to higher trading profits on average. Nevertheless, as long as there is a greater supply of such inside information when more mutual funds are in distress, this mechanism would also generate patterns like those we observe. Thus we have nothing to say about whether any front-running done by hedge funds is of the legal or illegal variety.

Finally, and more subtly, even if front-running hedge funds earn higher returns as a result of mutual funds being in distress, it does not necessarily follow that these incremental returns are *at the expense of* mutual funds. This point is most clearly illustrated with a simple example. Consider a stock that is trading at $100/share at time 0. At time 1, a hedge fund gets an advance tip that a distressed mutual fund will be selling 100 shares at time 2. These shares will have to be absorbed by the risk-averse "public", which will cause the price to fall to $98. If the hedge fund does not front-run, the entire price decline is delayed until time 2. Alternatively, suppose the hedge-fund front-runs by short-selling 50 shares to the public at time 1, which drives the price down to $99 at this time. If the hedge fund covers its position at time 2, and if the mutual fund's selling decision is unaffected by the time-1 price movement, the price at time 2 will still be $98, since all of the mutual fund's 100-share sale is again ultimately absorbed by the public.

In this example, the hedge fund clearly profits by front-running (it sells 50 shares for $99 and buys them back at $98), but the distressed mutual fund is no worse off, since it sells its 100 shares for $98 at time 2 in either case. Rather, it is the public that is harmed by front-running, since instead of getting to buy 100 shares for $98, the public buys 50 shares for $99 at time 1 and another 50 shares for $98 at time 2. Intuitively, by using its inside information about the impending fire sale, the hedge fund is able to exploit public investors, who, not knowing the fire sale is coming, are content to buy at $99 at time 1. As a result, the public earns less from liquidity provision than it otherwise would.

None of this is meant to argue that a distressed mutual fund *cannot* be hurt by a front-runner with advance knowledge of its trades; indeed, it is easy to construct alternative scenarios where the mutual fund does suffer.[18] Still, it is important to recognize that distressed mutual funds and would-be front-runners are not engaged in a bilateral zero-sum game. From a methodological perspective, this implies that, e.g., one would probably not want to try to make inferences about the extent of front-running in a given market environment by looking at whether mutual funds continue to underperform their benchmarks once they encounter distress.[19] A strategy of front-running distressed mutual funds can be profitable even if the front-running itself does not further exacerbate their distress.

[18] Following DeLong et al (1990), the key to the mutual fund being harmed in an example like the one above is that its own trades be endogenously linked to the interim price at time 1. If a price decline at time 1 makes the mutual fund have to sell more than it had originally planned at time 2—say because the poor mark-to-market performance between time 0 and time 1 increases time-2 outflows—then the mutual fund suffers directly from front-running.

[19] It is known from the work of Carhart (1997) that there is some degree of asymmetric persistence among the worst-performing funds—losers tend to stay losers more than winners tend to stay winners. The logic developed above suggests that asymmetries of this sort, while they might appear suggestive, are not likely to be reliable indicators front-running activity.

References

Ackermann, Carl, Richard McEnally, and David Ravenscraft, 1999, The Performance of Hedge Funds: Risk, Return, and Incentives, *Journal of Finance* 54, 833-874.

Adrian, Tobias, and Markus Brunnermeier, 2007, Hedge Fund Tail Risk, Princeton University Working Paper.

Agarwal, Vikas, Naveen Daniel, and Narayan Y. Naik, 2007, Why is Santa So Kind to Hedge Funds? The December Return Puzzle!, Georgia State University Working Paper.

Agarwal, Vikas, and Narayan Y. Naik, 2004, Risks and Portfolio Decisions Involving Hedge Funds, *Review of Financial Studies* 17, 63-98.

Agarwal, Vikas, and Narayan Y. Naik, 2005, Hedge Funds, *Foundations and Trends in Finance* 1, 103-170.

Anderson, Jenny, 2006, S.E.C. is Looking at Stock Trading, *New York Times*, February 6.

Asness, Clifford S., Robert Krail, and John M. Liew, 2001, Do Hedge Funds Hedge?, *Journal of Portfolio Management* 28, 6-19.

Asquith, Paul, Parag A. Pathak, and Jay R. Ritter, 2005, Short Interest, Institutional Ownership and Stock Returns, *Journal of Financial Economics* 78, 243-276.

Bali, Turan G., Suleyman Gokcan, and Bing Liang, 2007, Value at Risk and the Cross-Section of Hedge Fund Returns, *Journal of Banking and Finance* 31, 1135-1166

Boyson, Nicole M., Christof W. Stahel, and René M. Stulz, 2006, Is There Hedge Fund Contagion?, NBER Working Paper 12090.

Brown, Stephen J., William N. Goetzmann, and Roger G. Ibbotson, 1999, Offshore Hedge Funds: Survival and Performance 1989-1995, *Journal of Business* 72, 91-117.

Brunnermeier, Markus, and Lasse H. Pedersen, 2005, Predatory Trading, *Journal of Finance* 60, 1825-1863.

Cai, Fang, 2003, Was There Front Running During the LTCM Crisis?, Board of Governors of the Federal Reserve System Working Paper.

Carhart, Mark M., 1997, On Persistence in Mutual Fund Performance, *Journal of Finance* 52, 57-82.

Chan, Nicholas, Mila Getmansky, Shane M. Haas, and Andrew Lo, 2006, Systemic Risk and Hedge Funds, in Mark Carey and René Stulz eds., *The Risks of Financial Institutions*, University of Chicago Press.

Coval, Joshua, and Erik Stafford, 2007, Asset Fire Sales (and Purchases) in Equity Markets, *Journal of Financial Economics,* forthcoming.

D'Avolio, Gene, 2002, The Market for Borrowing Stock, *Journal of Financial Economics* 66, 271-300.

Delong, J. Bradford, Andrei Shleifer, Lawrence H. Summers, and Robert Waldmann, 1990, Positive Feedback Investment Strategies and Destabilizing Rational Speculation, *Journal of Finance* 45, 379-395.

Fama, Eugene F., and Kenneth R. French, 1993, Common Risk Factors in the Returns on Stocks and Bonds, *Journal of Financial Economics* 33, 3-56.

Fama, Eugene F., and Kenneth R. French, 1997, Industry Costs of Equity, *Journal of Financial Economics* 43, 153-193.

Frazzini, Andrea, and Owen Lamont, 2005, Dumb Money: Mutual Fund Flows and the Cross-section of Stock Returns, Yale University Working Paper.

Fung, William, and David A. Hsieh, 1997, Empirical Characteristics of Dynamic Trading Strategies: The Case of Hedge, *Review of Financial Studies* 10, 275-302.

Fung, William, David A. Hsieh, 2001, The Risk in Hedge Fund Strategies: Theory and Evidence from Trend Followers, *Review of Financial Studies* 14, 313-341.

Gatev, Evan, William Goetzmann and K. Geert Rouwenhorst, 2006, Pairs Trading: Performance of a Relative Value Strategy, *Review of Financial Studie*s 19, 797-827.

Getmansky, Mila, Andrew Lo, and Igor Makarov, 2004, An Econometric Model of Serial Correlation and Illiquidity in Hedge Fund Returns, *Journal of Financial Economics* 74, 529-609.

Malkiel, Burton G., and Atanu Saha, 2005, Hedge Funds: Risk and Return, *Financial Analysts Journal* 61, 80-88.

Mitchell, Mark and Todd Pulvino, 2001, Characteristics of Risk and Return in Risk Arbitrage, *Journal of Finance* 56, 2135-2175.

Newey, Whitney, and Kenneth West, 1987, A Simple Positive Semi-definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix, *Econometrica* 55, 703-708.

Savor, Pavel and Mario Gamboa-Cavazos, 2005, Holding on to Your Shorts: When do Short Sellers Retreat? University of Pennsylvania Working Paper.

Yan, Xuemin, 2006, The Determinants and Implications of Mutual Fund Cash Holdings: Theory and Evidence, *Financial Management* 35, 67-91.

Table 1: Summary Statistics for Hedge-Fund Indices

This table reports summary statistics on monthly returns of hedge fund indices from both Credit Suisse/Tremont and Hedge Fund Research Inc. From each provider, we collect returns on a long/short equity index, a fixed income index and a global macro index. Returns of CS/Tremont indices are value-weighted, and returns of HFRI indices are equal-weighted. The sample period is from January 1994 to December 2006.

	Monthly Returns		Correlation					
	Mean	St.Dev.	Matrix					
CS/Tremont Long/Short Equity	1.00%	2.90%	1.00					
CS/Tremont Fixed Income Arbitrage	0.53%	1.06%	0.21	1.00				
CS/Tremont Global Macro	1.11%	3.10%	0.43	0.45	1.00			
HFRI Equity Hedge	1.15%	2.53%	0.91	0.18	0.33	1.00		
HFRI Fixed Income (Total)	0.68%	0.85%	0.55	0.66	0.50	0.57	1.00	
HFRI Global Macro	0.82%	2.04%	0.69	0.40	0.73	0.62	0.58	1.00

Table 2: Summary Statistics for Mutual-Fund Distress Measures

This table reports summary statistics for our measures of mutual-fund distress. Each month, we calculate the percentage flow into each equity mutual fund over the past month and over the past quarter. In either case, a mutual fund is considered to be in distress if it experiences an outflow greater than a given percentage threshold. "Equal-weight fraction of distressed funds" is the fraction of mutual funds in distress in a given month. "Asset-weight fraction of distressed funds" is the fraction of total fund assets that are in distressed funds in a given month. "Equal-weight outflows from distressed funds" is an equal-weighted average of: i) the absolute value of percentage outflows from mutual funds in distress; and ii) zero for mutual funds not in distress. "Asset-weight outflows from distressed funds" is an assets-under-management-weighted average of: i) the absolute value of percentage outflows from mutual funds in distress; and ii) zero for mutual funds not in distress. In all cases, more positive values of these measures are associated with greater mutual-fund distress. Panel A presents the time-series averages for our four measures, with distress defined based on monthly flows. In Panel B, distress is defined based on quarterly flows. The sample period is from January 1994 to December 2006.

Panel A: Average values of mutual-fund distress measures based on monthly flows

Distress Threshold	2%	3%	4%	5%	6%	7%	8%
Equal-weight fraction of distressed funds	16.8%	11.0%	7.9%	6.2%	5.0%	4.2%	3.6%
Asset-weight fraction of distressed funds	7.9%	4.0%	2.4%	1.7%	1.2%	0.9%	0.7%
Equal-weight outflows from distressed funds	0.61%	0.47%	0.36%	0.28%	0.23%	0.18%	0.15%
Asset-weight outflows from distressed funds	0.27%	0.18%	0.12%	0.09%	0.07%	0.05%	0.04%

Panel B: Average values of mutual-fund distress measures based on quarterly flows

Distress Threshold	4%	6%	8%	10%	12%	14%	16%
Equal-weight fraction of distressed funds	23.4%	16.1%	11.7%	9.0%	7.3%	6.1%	5.3%
Asset-weight fraction of distressed funds	13.1%	6.9%	3.9%	2.4%	1.7%	1.1%	0.8%
Equal-weight outflows from distressed funds	1.78%	1.41%	1.10%	0.86%	0.68%	0.53%	0.43%
Asset-weight outflows from distressed funds	0.94%	0.63%	0.43%	0.30%	0.22%	0.15%	0.11%

Table 3: Hedge-Fund Returns and Mutual-Fund Distress, 1994-2006

This table shows time-series regressions of the monthly returns to various hedge fund indices on our monthly measures of mutual-fund distress, along with a number of other factors. EMKT is the excess return on the value-weighted market portfolio, SMB is the return on a portfolio that is long small stocks and short large stocks, HML is the return on a portfolio that is long high book-to-market stocks and short low book-to-market stocks, and WML is the return on a portfolio that is long past twelve-month winners and short past twelve-month losers. DISTRESS is "Equal-weight outflows from distressed funds", as defined in Table 2, using either a monthly threshold level of 4% or a quarterly threshold level of 8%. POSFLOW is the positive mirror image of DISTRESS, i.e., the equal-weighted average of percentage inflows into those funds experiencing inflows greater than the threshold levels. LAG( ) indicates the previous month's value of the factor at hand. MKTVOL is the standard deviation of daily returns on a value-weighted market portfolio in a given month. XVOL is the cross-sectional standard deviation of monthly returns among all listed stocks. TIME is the number of years since the beginning of our sample. DEC is a dummy variable that takes on the value one in the month of December. In Panels A and C, the dependent variable is the return on the CS/Tremont Long/Short Equity Index. In Panels B and D, the dependent variable is the return on the HFRI Equity Hedge Index. In Panel E, the dependent variables are the returns on fixed income hedge-fund indices. In Panel F, the dependent variables are the returns on global macro hedge-fund indices. In all specifications, the sample period is January 1994 to December 2006, and the t-statistics, shown in parentheses, are adjusted for serial correlation using a Newey-West (1987) estimator with three lags.

Panel A: CS/Tremont (Value-Weight) Long/Short Equity Index

	(1)	(2)	(3)	(4)	(5)
Constant x 100	0.17	-0.44	-0.64	-0.47	-0.55
	(1.45)	(2.25)	(2.45)	(2.06)	(1.65)
EMKT	0.492	0.489	0.482	0.487	0.485
	(13.62)	(12.71)	(12.23)	(13.11)	(13.19)
SMB	0.216	0.227	0.227	0.214	0.214
	(6.31)	(6.88)	(6.91)	(6.62)	(6.64)
HML	-0.018	0.006	0.006	-0.009	-0.010
	(0.39)	(0.17)	(0.16)	(0.23)	(0.24)
WML	0.220	0.204	0.204	0.217	0.216
	(7.46)	(8.06)	(8.11)	(8.44)	(8.36)
DISTRESS		1.703	1.707		
EW Monthly 4%		(3.17)	(3.16)		
POSFLOW			0.125		
EW Monthly 4%			(0.83)		
DISTRESS				0.584	0.578
EW Quarterly 8%				(2.89)	(2.84)
POSFLOW					0.015
EW Quarterly 8%					(0.32)
R-squared	81.2%	82.8%	82.9%	82.5%	82.5%

Panel B: HFRI (Equal-Weight) Equity Hedge Index

	(1)	(2)	(3)	(4)	(5)
Constant x 100	0.42	-0.30	-1.02	-0.34	-1.11
	(4.22)	(1.53)	(4.89)	(1.63)	(6.11)
EMKT	0.458	0.454	0.428	0.452	0.436
	(23.13)	(24.03)	(21.54)	(23.78)	(21.40)
SMB	0.240	0.254	0.251	0.238	0.239
	(7.40)	(10.39)	(10.54)	(9.14)	(9.44)
HML	0.016	0.045	0.044	0.026	0.020
	(0.46)	(1.80)	(1.98)	(1.05)	(0.77)
WML	0.089	0.071	0.070	0.086	0.080
	(3.80)	(4.20)	(4.45)	(4.95)	(4.87)
DISTRESS		2.014	2.027		
EW Monthly 4%		(4.21)	(4.90)		
POSFLOW			0.462		
EW Monthly 4%			(3.46)		
DISTRESS				0.698	0.642
EW Quarterly 8%				(4.20)	(4.87)
POSFLOW					0.151
EW Quarterly 8%					(4.14)
R-squared	85.3%	88.1%	89.7%	87.7%	89.4%

Panel C: Robustness, CS/Tremont (Value-Weight) Long/Short Equity Index

	(1)	(2)	(3)	(4)	(5)
Constant x 100	-0.56	-0.24	-0.76	-1.34	-0.61
	(2.24)	(0.66)	(1.88)	(2.93)	(2.23)
EMKT	0.485	0.461	0.482	0.474	0.477
	(12.49)	(10.50)	(12.25)	(11.98)	(11.59)
LAG(EMKT)	0.100				
	(3.63)				
SMB	0.208	0.219	0.221	0.213	0.224
	(6.06)	(6.61)	(5.93)	(6.15)	(6.87)
LAG(SMB)	0.018				
	(0.61)				
HML	-0.018	-0.005	0.008	-0.009	-0.001
	(0.41)	(0.14)	(0.22)	(0.23)	(0.02)
LAG(HML)	0.070				
	(1.98)				
WML	0.216	0.195	0.206	0.207	0.202
	(8.46)	(7.08)	(7.80)	(8.36)	(7.94)
LAG(WML)	0.027				
	(1.36)				
DISTRESS	1.629	1.952	1.606	1.538	1.487
EW Monthly 4%	(3.27)	(3.52)	(3.24)	(2.68)	(2.14)
POSFLOW	0.021	0.096	0.110	0.295	0.147
EW Monthly 4%	(0.14)	(0.61)	(0.68)	(1.69)	(0.98)
MKTVOL		-0.449			
		(1.64)			
XVOL			0.010		
			(0.43)		
TIME				0.001	
				(0.97)	
$TIME^2$				-0.000	
				(0.54)	
DEC x 100					0.34
					(0.66)
R-squared	84.1%	83.2%	82.9%	83.2%	82.9%

Panel D: Robustness, HFRI (Equal-Weight) Equity Hedge Index

	(1)	(2)	(3)	(4)	(5)
Constant x 100	-0.91	-0.72	-1.29	-0.85	-1.02
	(4.25)	(2.85)	(5.59)	(2.28)	(4.92)
EMKT	0.426	0.413	0.430	0.430	0.429
	(21.01)	(20.35)	(21.71)	(20.18)	(20.99)
LAG(EMKT)	0.046				
	(2.64)				
SMB	0.245	0.246	0.241	0.254	0.252
	(10.07)	(10.36)	(9.53)	(10.07)	(10.44)
LAG(SMB)	0.018				
	(0.93)				
HML	0.030	0.035	0.048	0.047	0.045
	(1.23)	(1.59)	(2.24)	(2.09)	(1.93)
LAG(HML)	0.009				
	(0.34)				
WML	0.074	0.063	0.075	0.069	0.070
	(4.37)	(3.77)	(4.54)	(4.41)	(4.42)
LAG(WML)	0.014				
	(1.00)				
DISTRESS	1.889	2.208	1.815	2.083	2.060
EW Monthly 4%	(4.70)	(5.00)	(4.61)	(4.93)	(4.35)
POSFLOW	0.397	0.440	0.430	0.431	0.459
EW Monthly 4%	(2.96)	(3.21)	(3.04)	(2.71)	(3.27)
MKTVOL		-0.333			
		(1.99)			
XVOL			0.021		
			(1.66)		
TIME				-0.000	
				(0.53)	
$TIME^2$				0.000	
				(0.44)	
DEC x 100					-0.05
					(0.17)
R-squared	90.3%	90.0%	89.9%	89.8%	89.7%

Panel E: Fixed Income Hedge-Fund Indices

	CS/Tremont		HFRI	
	(1)	(2)	(3)	(4)
Constant x 100	-0.17	-0.08	-0.01	0.20
	(0.62)	(0.24)	(0.06)	(0.88)
EMKT	0.030	0.034	0.092	0.098
	(1.15)	(1.35)	(4.88)	(5.45)
SMB	0.046	0.045	0.088	0.088
	(1.59)	(1.53)	(4.26)	(4.17)
HML	0.069	0.064	0.056	0.052
	(1.70)	(1.61)	(2.19)	(2.01)
WML	0.014	0.016	-0.007	-0.005
	(0.78)	(0.84)	(0.45)	(0.33)
DISTRESS	0.320		0.209	
EW Monthly 4%	(0.87)		(0.83)	
POSFLOW	0.125		0.127	
EW Monthly 4%	(1.15)		(1.92)	
DISTRESS		0.061		-0.038
EW Quarterly 8%		(0.42)		(0.35)
POSFLOW		0.028		0.018
EW Quarterly 8%		(0.70)		(0.81)
R-squared	9.1%	8.5%	44.6%	43.6%

Panel F: Global Macro Hedge Fund Indices

	CS/Tremont		HFRI	
	(1)	(2)	(3)	(4)
Constant x 100	-0.21	0.66	-0.47	0.38
	(0.33)	(0.93)	(1.28)	(0.90)
EMKT	0.272	0.293	0.254	0.269
	(3.20)	(3.44)	(4.97)	(5.24)
SMB	0.063	0.069	0.142	0.136
	(0.76)	(0.82)	(3.53)	(3.51)
HML	0.183	0.175	0.124	0.108
	(1.91)	(1.82)	(2.50)	(2.20)
WML	0.158	0.159	0.082	0.094
	(2.44)	(2.45)	(2.49)	(2.71)
DISTRESS	-0.092		1.089	
EW Monthly 4%	(0.08)		(1.69)	
POSFLOW	0.414		0.177	
EW Monthly 4%	(1.18)		(0.89)	
DISTRESS		-0.565		-0.067
EWQuarterly 8%		(1.73)		(0.29)
POSFLOW		0.065		-0.022
EW Quarterly 8%		(0.70)		(0.36)
R-squared	20.9%	21.2%	38.5%	36.9%

Table 4: Hedge-Fund Alphas and Varying Measures of Mutual-Fund Distress, 1994-2006

This table shows univariate regressions of monthly hedge-fund alphas on various measures of mutual-fund distress. First, the alphas are constructed by regressing hedge-fund returns on the following four factors: EMKT, the excess return on the value-weighted market portfolio; SMB, the return on a portfolio that is long small stocks and short large stocks; HML, the return on a portfolio that is long high book-to-market stocks and short low book-to-market stocks; and WML, the return on a portfolio that is long past twelve-month winners and short past twelve-month losers. These alphas are then regressed against the DISTRESS measure, which takes on the following variations. "Equal-weighted distress" is an equal-weighted average of: i) the absolute value of outflows from mutual funds in distress; and ii) zero for mutual funds not in distress, using monthly threshold levels from 2% to 6% and quarterly threshold levels from 2% to 10%. "Asset-weighted distress measure" is an assets-under-management-weighted average of: i) the absolute value of outflows from mutual funds in distress; and ii) zero for mutual funds not in distress, using monthly threshold levels from 2% to 6% and quarterly threshold levels from 2% to 10%. In Panel A, the dependent variable is the alpha of the CS/Tremont Long/Short Equity Index. In Panel B, the dependent variable is the alpha of the HFRI Equity Hedge Index. For each specification, we report the coefficient on DISTRESS, the impact on alpha of a one-standard-deviation change in DISTRESS, the OLS t-statistic, and an unadjusted R^2.

Panel A: CS/Tremont (Value-Weight) Long/Short Equity Index

	Regressions using monthly distress measures									
	Equal-weighted distress measures					Asset-weighted distress measures				
Threshold	2%	3%	4%	5%	6%	2%	3%	4%	5%	6%
Coefficient	1.071	1.211	1.395	1.604	1.869	1.391	1.743	2.373	3.222	4.300
Impact of 1 SD	0.32%	0.32%	0.32%	0.32%	0.32%	0.26%	0.26%	0.26%	0.28%	0.28%
OLS t-stat	(2.83)	(2.85)	(2.89)	(2.85)	(2.81)	(2.34)	(2.31)	(2.34)	(2.51)	(2.52)
R-squared	6.1%	6.2%	6.4%	6.2%	6.0%	4.2%	4.0%	4.1%	4.7%	4.8%

	Regressions using quarterly distress measures									
	Equal-weighted distress measures					Asset-weighted distress measures				
Threshold	2%	4%	6%	8%	10%	2%	4%	6%	8%	10%
Coefficient	0.397	0.422	0.464	0.522	0.575	0.436	0.542	0.536	0.673	0.897
Impact of 1 SD	0.30%	0.31%	0.31%	0.31%	0.30%	0.23%	0.27%	0.24%	0.24%	0.25%
OLS t-stat	(2.65)	(2.75)	(2.77)	(2.79)	(2.71)	(2.09)	(2.41)	(2.14)	(2.16)	(2.21)
R-squared	5.3%	5.8%	5.8%	5.9%	5.6%	3.3%	4.4%	3.5%	3.6%	3.7%

Panel B: HFRI (Equal-Weight) Equity Hedge Index

	Regressions using monthly distress measures									
	Equal-weighted distress measures					Asset-weighted distress measures				
Threshold	2%	3%	4%	5%	6%	2%	3%	4%	5%	6%
Coefficient	1.184	1.510	1.785	2.083	2.462	1.508	2.249	3.261	3.864	4.543
Impact of 1 SD	0.35%	0.40%	0.41%	0.42%	0.42%	0.29%	0.33%	0.36%	0.34%	0.30%
OLS t-stat	(3.97)	(4.51)	(4.69)	(4.71)	(4.70)	(3.23)	(3.78)	(4.09)	(3.82)	(3.38)
R-squared	11.9%	15.4%	16.7%	16.8%	16.7%	7.9%	10.8%	12.7%	11.0%	8.7%

	Regressions using quarterly distress measures									
	Equal-weighted distress measures					Asset-weighted distress measures				
Threshold	2%	4%	6%	8%	10%	2%	4%	6%	8%	10%
Coefficient	0.345	0.410	0.533	0.664	0.790	0.344	0.541	0.758	1.152	1.558
Impact of 1 SD	0.26%	0.30%	0.36%	0.40%	0.42%	0.19%	0.27%	0.34%	0.42%	0.43%
OLS t-stat	(2.92)	(3.39)	(4.04)	(4.51)	(4.73)	(2.10)	(3.06)	(3.85)	(4.70)	(4.88)
R-squared	6.4%	8.7%	12.4%	15.4%	17.0%	3.3%	7.1%	11.2%	16.7%	18.0%

Table 5: Summary Statistics for Short Interest, Fire Sales and Stock-Level Covariates

This table reports the means and standard deviations for short interest, fire sales, and other stock level-covariates. LSR is the log of the short interest ratio for a stock (short interest as percentage of shares outstanding) plus 0.01%, measured the month before the start of every calendar quarter. FIRESALE{8} is total selling of a stock by all distressed mutual funds within a quarter as a percentage of shares outstanding, where a mutual fund is considered to be distressed if it experiences an outflow greater than 8% over the quarter. SELL is total selling of a stock by all mutual funds within a quarter as a percentage of shares outstanding. BUY is total purchases of a stock by all mutual funds within a quarter as a percentage of shares outstanding. TURN is turnover in the previous quarter. IHOLD is the percentage of shares outstanding held by institutional investors. BM is a stock's book-to-market ratio as of the most recent fiscal year end. PRET is past 12-month return. CONVERT is an indicator that equals one if the firm has one or more convertible bonds outstanding. TURN, BM and PRET are winsorized at 1% and 99% levels within each quarter. The sample covers 1994Q1 to 2006Q4.

	LSR	FIRESALE{8}	SELL	BUY	TURN	IHOLD	BM	PRET	CONVERT
Mean	-5.08	0.0152%	0.16%	0.48%	37.3%	44.8%	0.60	18.9%	9.9%
Std. Dev.	2.16	0.0716%	0.36%	0.85%	43.5%	32.3%	0.53	83.3%	

Table 6: Short Interest and Fire Sales, 1994-2006

This table displays regressions of LSR, the log of the short interest ratio plus 0.01%, measured the month before the start of every calendar quarter, on various measures of selling by mutual funds. The independent variables include the following. FIRESALE{8} is total selling by distressed mutual funds within a quarter as a percentage of shares outstanding, where a mutual fund is considered to be distressed if it experiences an outflow greater than 8% over the quarter. FIRESALE{8,90} and FIRESALE{8,95} are indicator functions that equal one if FIRESALE{8} is greater than the 90^{th} or 95^{th} percentiles of the distribution. FIRESALE{6,90} and FIRESALE{10,90} are defined analogously, using distress thresholds of 6% and 10% instead of 8%. The control variables, SELL, BUY, TURN, IHOLD, BM, PRET and CONVERT are defined in the previous table. Below the main regression in each column, we also report coefficient estimates from a separate regression where that column's FIRESALE variable is interacted with SMALL, MID, and LARGE, which are dummies that equal one if a stock belongs in NYSE size deciles 1-2 (SMALL), 3-6 (MID), and 7-10 (LARGE), respectively. All specifications also have 20 size dummies corresponding to NYSE demi-deciles, as well as stock fixed effects and time effects. Standard errors are clustered at the industry level, using the Fama-French (1997) 48-industry classification, and are shown in parentheses. The panel covers 1994Q1 to 2006Q4.

	FIRESALE {8,90}	FIRESALE {8,95}	FIRESALE {6,90}	FIRESALE {10,90}	FIRESALE {8}
FIRESALE	0.182	0.131	0.155	0.182	20.076
	(14.76)	(9.31)	(10.41)	(12.40)	(3.96)
SELL	6.90	7.73	6.52	7.40	8.15
	(6.44)	(7.45)	(6.12)	(6.96)	(8.08)
BUY	3.10	3.18	3.13	3.09	3.19
	(6.45)	(6.54)	(6.56)	(6.44)	(6.49)
TURN	1.04	1.04	1.04	1.04	1.04
	(18.37)	(18.35)	(18.36)	(18.41)	(18.31)
IHOLD	0.99	1.00	0.99	0.99	1.01
	(13.60)	(13.68)	(13.62)	(13.60)	(13.68)
BM	-0.24	-0.24	-0.24	-0.24	-0.24
	(9.20)	(9.20)	(9.18)	(9.22)	(9.19)
PRET	-0.10	-0.10	-0.10	-0.10	-0.10
	(7.37)	(7.37)	(7.37)	(7.38)	(7.37)
CONVERT	0.44	0.43	0.43	0.44	0.43
	(12.45)	(12.41)	(12.44)	(12.43)	(12.38)
20 Size Dummies	Yes	Yes	Yes	Yes	Yes
Stock Fixed Effects	Yes	Yes	Yes	Yes	Yes
Time Effects	Yes	Yes	Yes	Yes	Yes
Adj R-sq	74.6%	74.5%	74.6%	74.6%	74.5%
Number of Obs	176329	176329	176329	176329	176329
FIRESALE	0.292	0.171	0.253	0.299	20.565
* SMALL	(19.68)	(12.23)	(13.48)	(17.35)	(2.84)
FIRESALE	0.103	0.105	0.092	0.105	27.268
* MID	(4.65)	(4.22)	(3.78)	(3.89)	(3.44)
FIRESALE	0.016	0.058	-0.011	0.003	5.714
* LARGE	(0.92)	(1.95)	(0.55)	(0.18)	(0.63)

Figure 1: Plots of Mutual Fund Distress Measures, 1994-2006

This figure graphs our two monthly mutual-fund distress measures from January 1994 to December 2006. Each month, we calculate the percentage flow into each equity mutual fund. A mutual fund is considered to be in distress if it experiences a monthly outflow greater than 4%. "Equal-weight outflows from distressed funds" is an equal-weighted average of: i) the absolute value of percentage outflows from mutual funds in distress; and ii) zero for mutual funds not in distress. "Asset-weight outflows from distressed funds" is an assets-under-management-weighted average of: i) the absolute value of percentage outflows from mutual funds in distress; and ii) zero for mutual funds not in distress.

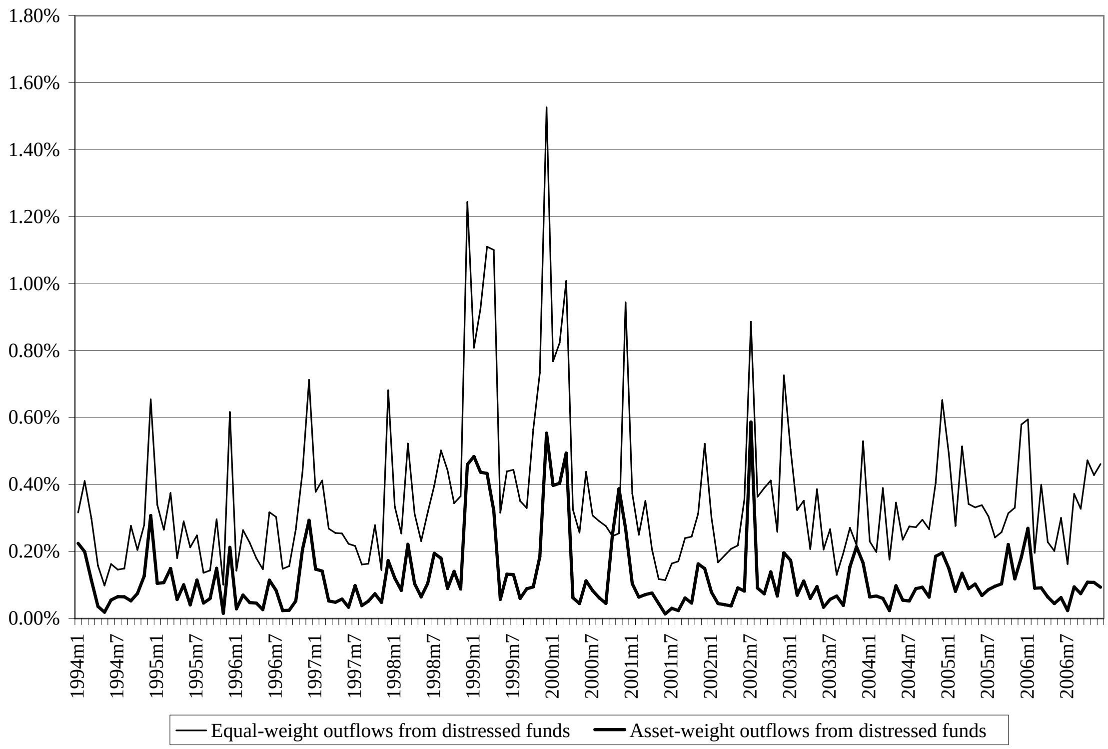
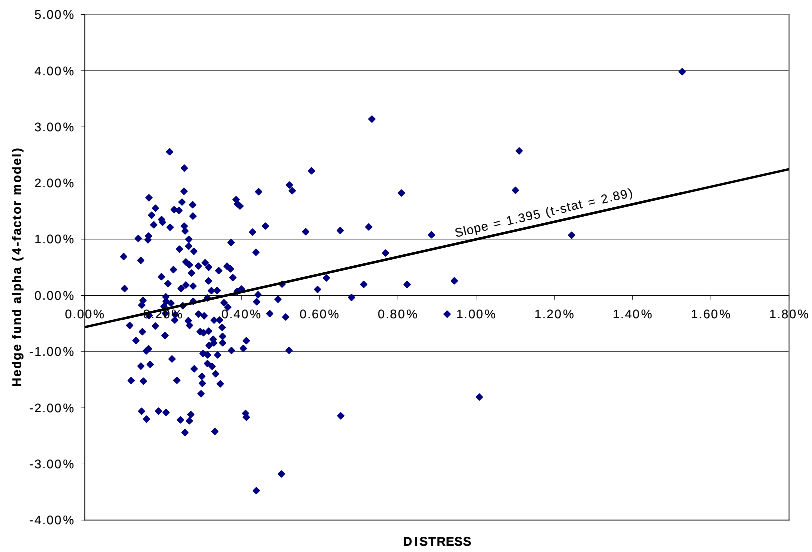


Figure 2: Alphas on CS/Tremont Long/Short Equity Index vs. Mutual-Fund Distress

These figures show the relationship between the alphas on the CS/Tremont Long/Short Equity Index and a measure of mutual-fund distress. The alphas are constructed monthly by regressing hedge-fund returns on the following four factors: EMKT, SMB, HML, and WML. The DISTRESS variable is monthly equal-weight outflows from distressed funds using a threshold level of 4%. Panel A shows the two series in scatter-plot form, with the fitted regression line included. Panel B shows the same two series separately as a function of calendar time.

Panel A: Scatterplot



Panel B: Time Series

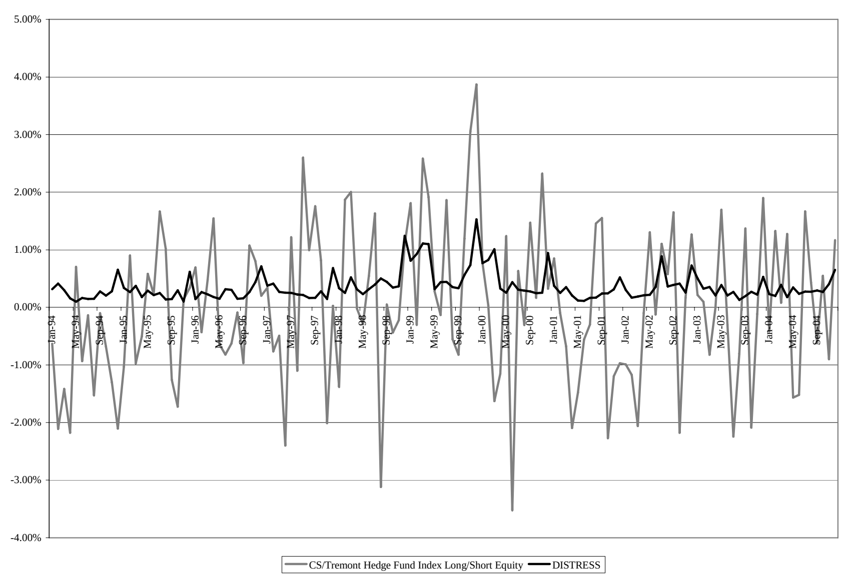
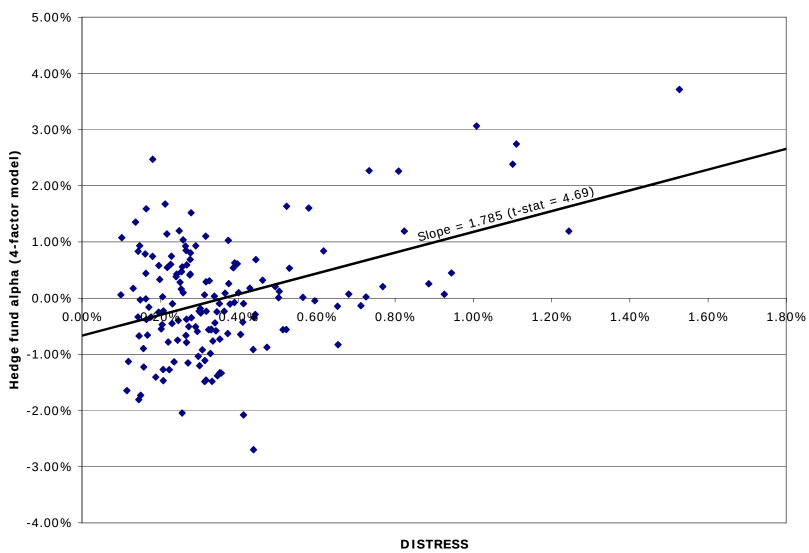


Figure 3: Alphas on HFRI Equity Hedge Index vs. Mutual-Fund Distress

These figures show the relationship between the alphas on the HFRI Equity Hedge Index and a measure of mutual-fund distress. The alphas are constructed monthly by regressing hedge-fund returns on the following four factors: EMKT, SMB, HML, and WML. The DISTRESS variable is monthly equal-weight outflows from distressed funds using a threshold level of 4%. Panel A shows the two series in scatter-plot form, with the fitted regression line included. Panel B shows the same two series separately as a function of calendar time.

Panel A: Scatterplot



Panel B: Time Series