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ABSTRACT

Using hedge fund indices representing eight different styles, we find strong evidence of contagion within the hedge fund sector: controlling for a number of risk factors, the average probability that a hedge fund style index has extreme poor performance (lower 10% tail) increases from 2% to 21% as the number of other hedge fund style indices with extreme poor performance increases from zero to seven. We investigate how changes in funding and asset liquidity intensify this contagion, and find that the likelihood of contagion is high when prime brokerage firms have poor performance (which would be expected to affect hedge fund funding liquidity adversely) and when stock market liquidity (a proxy for asset liquidity) is low. Finally, we examine whether extreme poor performance in the stock, bond, and currency markets is more likely when contagion in the hedge fund sector is high. We find no evidence that contagion in the hedge fund sector is associated with extreme poor performance in the stock and bond markets, but find significant evidence that performance in the currency market is worse when hedge fund contagion is high, consistent with the effects of an unwinding of carry trades.

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Figure 1 shows that, strikingly, many hedge fund indices performed extremely poorly on the same dates even though the indices correspond to very different hedge fund styles. Why would a hedge fund index of long-short equity funds perform poorly when an index of distressed securities funds has poor performance? It could be that this simultaneous occurrence of poor returns across hedge fund styles is just due to bad luck. Alternatively, poor returns for one type of hedge fund may make it more likely that other types of hedge funds have poor returns. The finance and economics literatures often use the term contagion to describe a situation where, to borrow the language of Bekaert, Harvey, and Ng (2005), there is excess correlation and poor performance spreads across countries, asset classes, or investment strategies for reasons not related to correlations in fundamentals.[1]

In this paper, we investigate whether hedge fund styles suffer from contagion, in the sense that extremely poor returns on traditional asset classes or on other hedge fund styles lead to extremely poor returns for a hedge fund style that cannot be explained by normal correlation or by traditional hedge fund risk factors. We find no systematic evidence of contagion from the main markets to individual hedge fund indices, but we provide strong evidence of contagion across hedge fund styles. We show that this hedge fund contagion is most severe when asset and funding liquidity are low. Next, we investigate whether greater hedge fund contagion is associated with extremely poor performance in the traditional asset classes. We find evidence that hedge fund contagion is associated with extremely poor performance of the currency markets (which is consistent with an unwinding of carry trades), but not of the stock and bond markets.

Whether hedge fund styles suffer from contagion is an important issue for investors, risk managers, and regulators. For investors, if contagion is present, linear measures of dependence such as correlation do not capture the dependence in extremely poor returns, so that the diversification benefits associated

[1] The contagion literature has its origins in the international finance literature that focuses on emerging market and currency crises. As discussed by Dornbush, Park, and Claessens (2000), there are many definitions of contagion.

with investing in different hedge fund styles are likely overstated when based on historical correlations.[2] During periods of contagion, correlations are unusually high compared to historical correlations since poor returns occur across assets regardless of their historical correlations – a phenomenon that Chan, Getmansky, Haas, and Lo (2005) call phase-locking and that Duffie, Eckner, Horel, and Saita (2006) call frailty. With contagion, therefore, risk management models that rely on historical correlations can fail dramatically because they understate risk during periods of contagion. Finally, the existence of hedge fund contagion raises concerns about hedge funds creating systemic risk. If contagion is not present, the probability that different hedge fund styles will perform extremely poorly at the same time is low, and therefore, it is unlikely that the hedge fund sector as a whole would suddenly become financially fragile.[3] However, if there is contagion, extremely poor performance could be pervasive across the whole hedge fund sector, which could seriously endanger banks and investment banks with exposure to hedge funds. This issue becomes even more important if the contagion is not confined to the hedge fund sector, but spreads from the hedge fund sector to the main financial markets.

A small number of papers investigate contagion-related issues for hedge funds. Chan, Getmansky, Haas, and Lo (2005) analyze the systemic risk of hedge funds using regression models that allow for nonlinearities in the relation between hedge fund returns and main market returns as well as regression models that allow for regime shifts. Their analysis reveals a positive correlation between bank returns (measured using a broad-based bank index from CRSP) and hedge fund returns after controlling for a nonlinear relation between the S&P 500 return and hedge fund returns. They suggest as an explanation for this finding the use of hedge fund strategies by banks' proprietary trading desks. Khandani and Lo (2007) investigate the factors that led to large losses in long/short equity funds (i.e., quant funds) during August 2007 and hypothesize that these losses were caused by a rapid unwinding of trades on a proprietary-trading desk or large hedge fund due to losses in unrelated strategies. Their paper therefore

[2] In addition, studies have shown that hedge fund returns do not follow a normal distribution, that they tend to be heavily skewed, and that their correlations with some risk factors are not stationary. It is well-known that correlation is a poor measure of dependence under such conditions (see, e.g., Embrechts, McNeil, and Straumann, 2002).
[3] If returns follow a multivariate normal distribution, the joint probability of returns being in the tails of the distribution becomes vanishingly small as the size of the tail threshold increases (see Longin and Solnik (2001)).

provides an example where hedge fund contagion results from forced liquidations in funds that are active in different styles. Billio, Getmansky, and Pelizzon (2007) examine hedge fund risk exposures in a regime-switching model. They show that when volatility is high the four strategies they examine have exposure to proxies for liquidity and credit risk. Finally, Adrian and Brunnermeier (2008) use quantile regressions to document the increase in a measure of the risk of hedge funds, i.e., value-at-risk (VaR), conditional on other hedge fund styles experiencing financial distress. They explain within-sector hedge fund VaR contagion using various factors including volatility, credit spreads, repo spreads, and returns on the main markets.

To investigate contagion, we use monthly hedge fund index return data from HFR (Hedge Fund Research) for eight different hedge fund styles.[4] We focus on the lower 10% return tail events (i.e., the bottom 10% of the entire time series of returns).[5] Using the logit regression methodology to estimate contagion (see Eichengreen, Rose, and Wyplosz (1996) and Bae, Karolyi, and Stulz (2003)), we estimate how the probability of an extreme negative return for a hedge fund style index (i.e., a "tail event") is related to the occurrence of an extreme negative return on the main market indices – stock market, currency, and fixed income – and to the number of other hedge fund style indices that have negative tail events. We use as independent variables the returns of the main markets and the hedge fund style indices to allow for the impact of correlation on the likelihood of occurrence of extreme negative returns, as well as a number of other control variables. To account for contagion from the main markets, we use indicator variables for the occurrence of extreme negative returns in these markets, and to account for contagion across hedge funds we use a variable called *COUNT,* which ranges in value from zero to seven and is defined as the number of other hedge fund styles that have negative tail events in a given month. In interpreting our results, a positive and significant coefficient on any of the main market indicator variables or on the *COUNT* variable is evidence of contagion.

[4] In addition, we perform robustness tests using published indices from CSFB/Tremont (www.hedgeindex.com). Results using these alternate indices are consistent with the results we document.

[5] Because hedge fund indices exhibit autocorrelation, we standardize the hedge fund returns (and all other variables used in the paper) using AR-GARCH models to control for autocorrelation and volatility clustering. The residuals from these models are then used in our analyses. For further detail on the standardization, see the Data section.

We perform eight regressions, one for each hedge fund style. We find no consistent evidence of contagion from the main markets to the hedge fund style indices, but find strong evidence of contagion within the hedge fund sector. Specifically, the coefficient on the *COUNT* variable is positive and significant at the 10% level or better in six of the eight regressions, indicating a high level of contagion between hedge fund styles. The economic significance of this contagion is large. If all the explanatory variables are set to their mean values except for *COUNT*, the average probability that a style index has a return in the lower 10% tail increases from 1.8% to 20.9% as *COUNT* increases from zero to seven.

After documenting the existence of contagion between hedge fund styles, we investigate its possible causes. An obvious concern is that the indices we use misclassify funds. Such misclassification would not likely explain contagion, however – it would simply explain greater correlation. To further address this concern, we perform robustness tests of all our results using a different set of hedge fund indices from CSFB/Tremont and find consistent results. The second possible explanation is related to the well-known result from hedge fund research (Fung and Hsieh (1997, 1999, 2001, 2004), Mitchell and Pulvino (2001), and Agarwal and Naik (2004)) that hedge fund returns have option-like properties, so it could be that our finding of contagion within the hedge fund sector is spurious and caused by nonlinearities in hedge fund returns. Hence, we perform additional regressions controlling for non-linear factors and for volatility in the main markets, and find that our results remain unaffected.

After rejecting these explanations for our findings, we turn to economic explanations of contagion. Khandani and Lo (2007) highlight a natural mechanism of contagion for hedge fund styles, namely that some funds are active across multiple styles (multi-strategy funds), so that poor performance in one style leads them to liquidate positions in other styles, thereby putting pressure on prices in these styles and possibly creating mark-to-market losses for funds specialized in these styles if liquidity is low.[6] For the mechanism they highlight to be strong, it would seem that asset liquidity must be low – i.e., it is not possible to sell financial assets quickly without a discount. Further, a fund that performs poorly in one

[6] It is important to note that we exclude multi-strategy funds for the obvious reason that using these funds in an analysis cannot capture contagion across hedge fund styles, since by definition, these funds use a number of different trading styles. Therefore, we focus on single-strategy hedge fund styles.

strategy will have to liquidate across strategies only to the extent that it faces funding constraints, so that the transmission mechanism also requires limited funding liquidity.

The role of asset liquidity and funding liquidity as amplifying contagion mechanisms is modeled by Brunnermeier and Pedersen (2008). They provide a theoretical model in which asset liquidity and funding liquidity interact. An adverse shock to asset liquidity reduces the ability of financial intermediaries to finance their asset holdings due to higher margin requirements resulting from the decrease in asset liquidity. Hedge fund losses in one style can reduce both funding liquidity and asset liquidity for hedge funds of all styles. Losses in hedge funds reduce their ability to provide liquidity to the markets, which leads to lower asset liquidity. Lower asset liquidity reduces the credit available to hedge funds and forces them to reduce their leverage, but the resulting liquidations lead to mark-to-market losses and hence further reductions in credit availability.

Reductions in funding liquidity for the hedge fund sector can occur for reasons that have nothing to do with hedge funds, for example because of regulatory tightening or an unexpected increase in risk in financial markets, but they can also result from hedge fund losses. A sharp reduction in funding liquidity can lead to liquidations across the hedge fund sector, a reduction in asset liquidity, and mark-to-market losses that cannot be explained by traditional risk factors for hedge fund returns. For a reduction in funding liquidity to take place because of poor returns in a hedge fund style, the losses in one hedge fund style must directly affect the providers of funding to hedge funds and/or affect their willingness to lend to hedge funds. Prime brokers are direct lenders to hedge funds. Shocks to the capital of prime brokers forces them to contract lending to hedge funds, thereby reducing funding liquidity for these funds. To capture the impact of shocks to funding liquidity for hedge funds, we therefore create a prime broker stock index, PBI, as our main proxy for funding liquidity. To evaluate the role of asset liquidity as a channel of contagion, we use Amihud's (2002) stock market liquidity variable. This measure is calculated as the average of the daily ratio of absolute stock return to dollar volume across stocks. It may be interpreted as the daily price response associated with one dollar of trading volume, and thus, is a rough measure of price impact.

Our proxies for low liquidity are associated with increased contagion. For example, in periods when asset liquidity is low (as proxied by Amihud's measure), an average of 3.14 hedge fund styles have extreme negative returns, as compared with 0.70 hedge fund styles when asset liquidity is not low. Results are similar for the PBI index, our proxy for low funding liquidity. Even more impressively, in periods when both asset liquidity and funding liquidity are low, the average number of hedge fund styles with extreme negative returns goes to 4.33, as compared with 0.70 hedge fund styles when both asset liquidity and funding liquidity are not low. This strong relation between asset and funding liquidity and the number of styles with extreme negative returns is still present in a Poisson regression framework where we control for determinants of hedge fund style returns.[7]

Finally, given the strong contagion within the hedge fund sector, the last section of the paper explores whether hedge fund contagion is associated with extremely poor performance in the main markets. Using logit regressions, we find evidence of poor performance in the currency market, but not in the stock and bond markets, when hedge fund contagion is high. This finding is related to recent work on the impact of carry trades on the currency market. We show that extreme dollar depreciation is associated with poor hedge fund returns. Research on carry trades suggests that the unwinding of these trades is associated with appreciation of the yen and other currencies (relative to the dollar) in which hedge funds borrow with these trades.[8] Plantin and Shin (2008) develop a model where the unwinding of carry trades is associated with de-leveraging of hedge funds because of a reduction in funding liquidity. While this research is consistent with the contagion we document, our empirical work cannot distinguish between unwinding caused by currency movements versus currency movements caused by unwinding.

The paper is organized as follows. In Section I we describe the data for the hedge fund index returns and the explanatory variables. Section II uses HFR monthly hedge fund indices and documents contagion in extremely poor returns within the hedge fund sector. Section III examines possible economic

[7] Chan, Getmansky, Haas, and Lo (2005) show that hedge fund returns are correlated with bank returns. The funding tail dependence we uncover between the PBI index and hedge fund style returns holds up in regressions which control for the level of bank returns, so that it is a distinct phenomenon from the one they describe.
[8] See, for example, Becker and Clifton (2007).

explanations for contagion using proxies for funding illiquidity and asset illiquidity. Section IV examines whether hedge fund contagion is associated with extremely poor performance in the main markets. We attempt to interpret our results and conclude in Section V.

I. Data

The hedge fund style returns are the monthly style index returns provided by Hedge Fund Research (HFR). The returns are net of fees and are equally-weighted averages of fund returns. The indices include both domestic and offshore funds. This data extends from January 1990 to August 2007 for a total of 212 monthly observations. The indices consist of eight single strategy indices: Convertible Arbitrage, Distressed Securities, Equity Hedge, Equity Market Neutral, Event Driven, Global Macro, Merger Arbitrage, and Relative Value Arbitrage.[9] They include over 1,600 funds, with no required minimum track record or asset size. Additionally, these indices are not investible; that is, they include funds that are closed to new investors. To address backfilling and survivorship bias, when a fund is added to an index, the index is not recomputed with past returns of that fund. Similarly, when a fund is dropped from an index, past returns of the index are left unchanged.[10]

In our study, we investigate contagion between the main financial markets and eight hedge fund styles as well as within the hedge fund sector across the eight hedge fund styles. The main financial markets are the stock market, the fixed-income market, and the currency market. We use the return of the Russell 3000 index to proxy for the return of the stock market, the return on the Lehman Brothers bond index (LB bond index hereafter) to proxy for the return of the fixed-income market, and the change in the

[9] See Appendix A for definitions of each style category.

[10] As noted earlier, we perform robustness tests for all our analyses using the published CSFB/Tremont hedge fund indices (www.hedgeindex.com). One possible issue with the HFR data is that the indices are equally-weighted with no size requirement, so they might give too much weight to small funds. By contrast, the published CSFB/Tremont indices have a minimum $50 million size requirement and are value-weighted. However, because of survivorship bias, the CSFB/Tremont indices only cover the period beginning in 1994. The results for tests using these alternative indices are generally consistent with the HFR results.

trade-weighted US dollar exchange index published by the Board of Governors of the US Federal Reserve System (FRB dollar index in what follows) to proxy for the return of the currency market.[11]

Table I provides summary statistics and correlations for the hedge fund indices and broad markets. The data indicate relatively high positive unconditional correlations between the eight hedge fund indices. Additionally, the correlations with the Russell 3000 index are large and positive for all of the hedge fund indices. The correlations with the FRB dollar index (the currency index) are low or negative, and correlations with the LB Bond index are all positive, although generally not statistically significant.

Six of the eight hedge fund indices exhibit autocorrelation as shown in Panel 2, and the Ljung-Box tests reject the hypothesis of no autocorrelation for the first six lags for these indices. These results are generally consistent with Getmansky, Lo, and Makarov (2004) and others in prior literature. Finally, the normality tests as shown in Panel 3 are rejected for seven of the eight indices. These results are consistent with Embrechts, McNeil, and Straumann (2002).

Since hedge fund returns are autocorrelated, we standardize the hedge fund returns (and all other variables used in the paper) using AR-GARCH models to control for autocorrelation and volatility clustering. The residuals from these models are then used in our analyses.[12] The approach of filtering a time-series with a GARCH process and using the residuals in the analysis has been proposed in the risk management literature in applications of conditional extreme value theory (EVT) for financial time-series. In particular, McNeil, Frey, and Embrechts (2005) suggest using GARCH models to obtain a time-series for which extreme observations are not clustered and, hence, are suitable to estimate the tail distribution based on Generalized Pareto Distributions (GDP). Our filtering procedures of the original series with AR-GARCH processes can be viewed in light of these EVT applications where we remove clustering of extreme events that are due to periods of heightened volatilities.

The relatively high correlations we observe among hedge fund indices and between hedge fund indices and market indices indicate the importance of controlling for correlation in our contagion tests to

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[11] The source for these indices is Thomson Financial's DataStream.

[12] Ljung-Box tests on these residuals indicate that using AR(1)-GARCH(1,1) processes is sufficient to remove the autocorrelation except for the equity market neutral style where we use an ARMA(2,2)-GARCH(1,1) model.

ensure that we do not mistake for contagion the normal workings of correlation. With our definition of contagion, normal correlation between hedge fund indices and between hedge fund indices and market indices does not represent contagion. We control for the relationship between hedge fund returns and market returns in our tests by including the returns on the main market factors as well as the returns on the other hedge fund indices as explanatory variables. Thus, our approach is carefully constructed to test for contagion over and above the linear relationship implied by these relatively high correlations.

II. Tests of contagion using HFR index data

Our data encompasses a number of market crises including the Asian and Mexican currency crises and the failure of Long Term Capital Management. We use a lower 10% cutoff of the overall distribution of returns to identify "extreme" or "tail" negative returns. With such a cutoff, we have 21 "tail" observations for each style. Had we chosen a 5% cutoff instead, we would have only ten observations per style.

II.1. Existing approaches

There is a large literature on contagion in emerging markets.[13] A major part of this literature focuses on testing whether correlations increase in troubled periods. This approach has been controversial. We avoid this approach for three reasons. First, as Baig and Goldfajn (2002) and Forbes and Rigobon (2002) argue, there are statistical difficulties involved in testing changes in correlations across different regimes. Second, using correlations is problematic in this type of test, as correlations are linear measures of association that are not appropriate to investigate behavior during extreme market conditions, while the approach we use specifically focuses on nonlinearities in return distributions. Third, correlations are particularly ill-suited for evaluating contagion for hedge funds because these funds often pursue strategies with non-linear payoffs.

[13] For surveys, see Karolyi (2003), Dungey and Fry (2004), de Bandt and Hartmann (2000), and Pesaran and Pick (2004).

An alternative approach would be to employ extreme value theory (EVT) as in Longin and Solnik (2001). Such an approach is implemented using monthly hedge fund indices by Geman and Kharoubi (2003) and Bacmann and Gawron (2004). Geman and Kharoubi (2003) find that, though above-threshold correlations between hedge fund returns and the S&P 500 index go asymptotically to zero for positive returns as the threshold increases, this is not the case for negative returns. Bacmann and Gawron (2004) find no asymptotic dependence of hedge funds and bonds, but find some dependence of hedge funds and stocks which disappears when August 1998 is removed from the sample. While EVT and the use of copulas makes it possible to examine tail dependence without using correlations, such an approach requires the choice of a copula function and can easily give too much weight to extremely rare observations. Further, it does not permit explicit conditioning on additional risk factors and, hence, makes it difficult to explore the determinants of contagion.

The third approach involves allowing explicitly for nonlinearities and for different return distributions in troubled times. Chan, Getmansky, Haas, and Lo (2005) follow this approach in a study of the systemic risk of hedge funds.[14] They use models that include non-linear exposures to various markets such as squared and cubed returns on the S&P 500 index and also apply regime-switching models to hedge fund returns. We allow for nonlinearities in exposures to risk factors as well. However, we do not parameterize the tail dependencies for the same reason that we do not use copulas: our approach makes it less likely that we will give too much weight to rare observations.

The last approach uses quantile regressions. Adrian and Brunnermeier (2008) use this approach to document that hedge funds' value-at-risk (VaR) increases conditional on other styles being in distress and predictable spillover effects into the banking sector. Their result measures risk contagion rather than returns contagion as it shows how the VaR for an index is affected by conditions in other hedge fund styles and main markets.

[14] Billio, Getmansky, and Pelizzon (2007) also use regime-switching models to study the systemic risk of hedge funds.

We use a logit model to test for contagion from main markets to hedge funds and within the hedge fund industry, following Eichengreen, Rose, and Wyplosz (1996) and Bae, Karolyi, and Stulz (2003). This model allows conditioning on additional risk factors and does not parameterize the tail dependencies.

II.2. Contagion between monthly hedge fund and market indices, and between hedge fund indices

We wish to identify the extent to which hedge fund indices are subject to contagion. The dependent variable in our basic regression specification is an indicator variable set to one if the hedge fund index under study has a return in the bottom 10% of all returns for that index, and zero otherwise. Independent variables include the three main market indices: the Russell 3000, the LB bond index, and the FRB dollar index. Additionally included are returns on the other seven hedge fund indices, measured as an equally-weighted index of these indices. We also include indicator variables for extreme returns in the main market indices (set to one if the return for that month is in the bottom 10% of all returns for the index). A positive and significant coefficient on a market indicator variable is interpreted as evidence of contagion from the main markets. Finally, we create the "*COUNT*" variable. The *COUNT* variable is the aggregated indicator variable for the other seven hedge fund indices, and is set to 0 if none of the other indices has an extreme return for the month, one if one of the other indices has an extreme return for the month, and so on up to a maximum value of seven when all seven of the other indices have extreme returns for the month. A positive and significant coefficient on this variable indicates contagion within the hedge fund sector. Figure 2 shows the *COUNT* variable over time. As expected, *COUNT* is at its maximum at the time of the Long Term Capital crisis and at the start of the more recent subprime crisis. Finally, our tests are robust to including separately the returns and indicator variables for the other hedge fund indices (rather than our more parsimonious approach which aggregates this data.)

Results are presented in Table II. Focusing first on the continuous variables, there are no distinctive patterns in the coefficients on equities, bonds, or currencies, indicating no consistent relationship between 10% tail returns in hedge funds and the performance of broad markets. The coefficients on the equally-weighted hedge fund index are also insignificant. For the indicator variables, the coefficients on the main markets are mostly insignificant and yield inconsistent signs. Of the 24 indicator variables, 15 are negative, of which three are statistically significant, and nine are positive, of which three are statistically significant. These results provide no evidence of systematic contagion between the main markets and hedge funds. By contrast, the results for the *COUNT* variable provide strong evidence of contagion within the hedge fund industry. Seven of the eight coefficients on the *COUNT* variable are positive and of these seven, six are statistically significant at least at the 10% probability level. Importantly, this evidence is obtained when controlling for the equally-weighted returns of the other hedge fund styles indices, so that we fully allow correlation to play its role.

Since Fung and Hsieh (1997), it is well-known that hedge funds pursue strategies with highly non-linear payoffs.[15] It could therefore be the case that strategies with non-linear payoffs explain the occurrence of extreme returns for hedge fund styles, and that the contagion we find is simply due to the fact that non-linear strategies employed by hedge funds have correlated payoffs when the underlying assets have extreme returns. In this case, the trading strategies of hedge funds would explain the contagion we observe. To control for these non-linearities, we follow Fung and Hsieh (2001 and 2004) and control for additional risk factors using asset-based factors that are designed to mimic the returns of certain types of hedge fund strategies. Five of these factors are from Fung and Hsieh (2001). These factors are modeled as "Primitive Trend-Following Strategies" (PFTS), or "lookback straddles." Simply stated, a lookback straddle strategy assumes that an investor owns both a lookback call option, which gives an investor the right to buy an asset at its lowest price over the life of the option and a lookback put option, which gives an investor the right to sell an asset at its highest price over the life of the option. Fung and Hsieh construct lookback straddles on bonds, currencies, commodities, short-term interest rates, and equities.[16]

We also use three additional asset-based factors, as suggested by Fung and Hsieh (2004). These are a size-spread factor, calculated as the Wilshire Small Cap 1750 minus Wilshire Large Cap 750 monthly return, a bond factor, calculated as the change in the 10-year treasury constant maturity yield from month-

[15] See, for example, Fung and Hsieh (1997, 1999, 2001, 2004), Ackermann, McEnally and Ravenscraft (1999), Liang (1999), Mitchell and Pulvino (2001), and Agarwal and Naik (2000, 2004).

[16] We thank David Hsieh for providing us these returns for the period January, 1990 to August, 2007.

end to month-end, and a credit spread factor, calculated as the change in the monthly spread of Moody's Baa yield less the 10-year treasury constant maturity yield from month-end to month-end.[17] Finally, because it is likely that volatility in the main market indices we use could be related to extreme returns in our dependent variables, we include a measure of monthly volatility extracted from the univariate GARCH models for each of the main market factors used in Table II. We also include the return on the 3-month Treasury bill, and the negative portion of the S&P index return to proxy for a put option.

Table III adds these factors to the regressions from Table II. A problem that occurs with the inclusion of these additional factors is that the regressions sometimes fail to converge due to quasi-separability. Quasi-separation is not an uncommon problem in applications of discrete dependent variable models and is more likely to occur in settings with discrete explanatory variables, particularly in samples that are small relative to the number of explanatory variables. The issue is that if quasi-separation occurs, the maximum likelihood estimation procedure gives non-unique infinite parameter estimates with an unbounded dispersion matrix.[18]

Therefore, to test our hypotheses and control for these additional factors, we use a stepwise regression approach for each of the eight style regressions. Starting with the null model containing only the constant term, successive models are created, each using one more regressor than the prior model. The potential regressors are selected from the list of all explanatory variables excluding the *COUNT* variable. To choose which regressor to add to the model in this "forward step", each of the potential regressors is tested by separately including it in the current model. The regressor with the largest impact (based on a Lagrange multiplier test) is then included. After this new regressor is added, the statistical significance of each of the explanatory variables currently in the model is evaluated by calculating a Wald test for each of them. If a variable does not meet a (conservative) significance threshold p-value of 0.2 for the Wald

[17] The data for the size-spread factor are obtained from Wilshire, and the data for the bond and credit spread factors are obtained from the website of the Board of Governors of the Federal Reserve System. See the website of David Hsieh at http://faculty.fuqua.duke.edu/~dah7/HFRFData.htm for links to the Wilshire and Federal Reserve data.

[18] Quasi-separation occurs if there exists a parameter vector in the logit regression model that "almost" perfectly describes the binary response variable. Hence, in the maximization procedure, the log likelihood function value diminishes to a non-zero constant. For a concise exposition on quasi-separation see Albert and Anderson (1984).

test, the variable is removed. This "backward step" elimination process is repeated until all explanatory variables remaining in the model have a (Wald test) level of significance of at least 0.2. This iterative forward and backward procedure is then repeated for each potential regressor not yet included in the model. The process terminates if no further regressor can be added to the model, or if the regressor just entered into the model is the only regressor removed in the subsequent backward elimination.

The main benefit from this procedure is that quasi-separation is not an issue since the process starts with the null model. Further, for each hedge fund style, it produces a parsimonious model containing the most relevant explanatory variables for that style. After we have identified the "best" model for each style, we then include the *COUNT* variable. Thus, although the explanatory variables, carefully chosen through the stepwise process, are different for each of the eight hedge fund indices, we include the *COUNT* variable in all eight regressions so that we may test for contagion.

The results of Table III indicate that, despite the addition of many control variables to our regressions, all the coefficients on the *COUNT* variable are positive, and 5 of 8 are statistically significant at the 10% level or better, so that we still have strong evidence of contagion across hedge fund styles. Further, our conclusion that there is no systematic evidence of contagion between main markets and hedge fund styles does not change.

We now evaluate the economic significance of this contagion. The average return of a particular style is strongly related to the number of other styles that experience extremely poor returns. The difference in average returns for each style index when all other styles experience an extreme negative return compared to the average return when none of the other styles experiences an extreme return ranges from –1.80% to -7.15%. Using the estimates of Table III, and setting all the explanatory variables at their means except for *COUNT*, the average (median) probability that a style index has a return in the lower 10% tail increases from 1.77% (1.49%) to 20.90% (18.04%) as *COUNT* increases from zero to seven. This result is shown graphically, by index, in Figure 3. This Figure shows the probability of an extreme return for each hedge fund style index as the *COUNT* variable increases from zero to seven. The probability of an extreme return increases for all style indices as the *COUNT* variable increases. The increase is especially dramatic for the Distressed Securities, Equity Hedge, Equity Market Neutral, and the Global Macro styles. It is smaller for the Convertible Arbitrage, the Event Driven, the Merger Arbitrage, and the Relative Value styles.

Since we use hedge fund index data, a concern with our results is that hedge funds are misclassified in indices. In this case, we would find that performance of indices is similar because some hedge funds pursue the same strategies even though they are classified into different styles. However, while this explanation could lead to an increase in correlations across hedge fund indices, there is no reason to believe that this problem would cause contagion. In addition, as noted earlier, we repeat all our analyses using the CSFB/Tremont hedge fund indices. The results are consistent with those obtained using the HFR database. Hence, we reject this explanation.

In this section, we find no consistent evidence of contagion between hedge funds and the main markets, but significant evidence of contagion between hedge fund styles. In the next section, we investigate possible channels through which this contagion takes place.

III. Contagion Channels

Why would the poor performance of a hedge fund style affect adversely the performance of another, different, hedge fund style? Why would hedge fund styles experience poor returns simultaneously which cannot be explained by correlations across hedge fund styles? We discussed in the introduction the role of liquidations for multi-strategy funds emphasized by Khandani and Lo (2007), as well as the roles of funding and asset liquidity. In this section, we explore how funding and asset liquidity affect hedge fund contagion. Funding liquidity refers to the ease with which a trader can obtain funding. If funding liquidity shrinks, levered hedge funds have to reduce their leverage. As hedge funds reduce leverage, they provide less liquidity to the markets. As a consequence, these reductions in leverage adversely affect the prices of the assets they sell because the hedge fund sector is providing less liquidity. As prices fall because of price pressure, hedge funds have to liquidate more assets because of mark-to-market losses. These losses lead to more liquidations, which put more pressure on prices. This view of mechanisms of contagion follows directly from Brunnermeier and Pedersen (2008).

We now consider why losses in one hedge fund style could lead to a reduction in funding liquidity and hence lead to losses in other hedge fund styles. For a reduction in funding liquidity to take place, it must be that the losses in one hedge fund style either affect directly the providers of funding to hedge funds and/or affect the willingness of these providers to lend to hedge funds. The main providers of funding to hedge funds are their prime brokers. Hedge fund losses in one style can lead to losses for prime brokers for at least two reasons. First, prime brokers, like banks more generally, pursue proprietary trading strategies similar to those pursued by hedge funds. Chan, Getmansky, Haas, and Lo (2005) emphasize this phenomenon in the context of banks and use it to explain the nonlinear dependence between hedge fund returns and bank returns that they observe. Sometimes, therefore, one would expect prime brokers to have implemented the same trades as those that led to hedge fund losses.[19] Second, losses by hedge funds can become losses for prime brokers both because hedge funds are debtors of prime brokers (although this effect may be limited by extensive collateralization of trades), and because losses by hedge funds that reduce their level of trading diminish the income of prime brokers. As prime brokers suffer losses, they must decrease their lending, which leads to a contraction of funding liquidity for hedge funds.

We use several proxies to test the funding liquidity and asset liquidity channels of hedge fund contagion. Our first proxy is a prime broker stock index (*PBI*). We expect large decreases in *PBI* to be associated with a decrease of funding liquidity for hedge funds. The index consists of 11 prime brokerage firms: Goldman Sachs, Morgan Stanley, Bear Stearns, UBS AG, Bank of America, Citigroup, Merrill Lynch, Lehman Brothers, Credit Suisse, Deutsche Bank, and Bank of New York Mellon. The first three of these firms represent about 58% of the total prime brokerage industry based on a 2006 survey by

[19] An example of this channel is the loss of $480 million reported by Morgan Stanley from proprietary strategies in August 2007 when quantitative hedge funds also experienced large losses. See "Quants' tail of woes," by Jayne Jung, in *Risk*, October, 2008.

Lipper Hedge World.[20] In addition, the remaining eight prime brokers are cited as dominant players in the industry in several sources and also in discussions with industry participants.[21] We construct an equally-weighted index of the returns of the 11 brokers during the sample period. Some prime brokers were not publicly traded for the entire period, so they are included for the dates for which stock prices could be obtained. We used CRSP to gather the stock price data through 12/31/2006, and *Yahoo! Finance* to gather the data for 2007. All returns are adjusted for splits and dividends.

Our second proxy is the Datastream bank stock index (*BANK*). This index is an equally weighted index of the stock returns of large banks provided by Datastream. It includes primarily national commercial and regional banks; the only companies common to both the Datastream index and the Prime Broker Index are Bank of America and Citigroup. Since hedge funds use prime brokers as their primary source of lending, and since prime broker trading desks employ hedge fund strategies, we expect the prime broker index to be a better proxy for both asset and funding liquidity for hedge funds than the bank index. In their study of risk contagion, Adrian and Brunnermeier (2008) use a more narrow investment bank index consisting of Morgan Stanley, Merrill Lynch, Goldman Sachs, Bear Stearns and Lehman Brothers and show that certain hedge fund styles predict an increase in value-at-risk in the investment banking sector. By contrast, we focus on the impact that poor performance among prime brokers (as a proxy for funding and asset liquidity) has on poor performance in hedge funds. As noted earlier, Chan, Getmansky, Haas, and Lo (2005) use a more broad-based bank index consisting of the monthly return of an equally weighted portfolio of bank stocks in CRSP, but do not allow for a nonlinear effect of bank returns. Thus, their banking index includes prime brokers, commercial banks, and other banks. When banks perform poorly, they provide less credit, some of which goes to hedge funds. We therefore expect funding liquidity for hedge funds to worsen as banks perform poorly.

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[20] See Baum, Stephanie, "Prime Brokers Target Stars of Tomorrow," November 21, 2007 at http://www.financialnews-us.com/?page=ushome&contentid=2349214053.

[21] See, for example Barr, Allistair, "New Entrants Shake Up Prime Brokerage," June 23, 2006 http://www.marketwatch.com/news/story/Story.aspx?guid=%7B577A9928-FFB7-46ED-940A-E39D693EE55D%7D&siteid=, and Moore, Heidi, "Lehman Takes Aim at Prime Brokerage," September 29, 2006. http://www.financialnews-us.com/?page=ushome&contentid=1045562640

We also use two other proxies for funding liquidity. First, we use as a measure of tightness in the credit market the BAA-AAA credit spread. Second, we use the volume in the repo market. Low volume in the repo market could indicate a reduction in funding liquidity; for example, Kambhu (2006) finds a relationship between hedge fund distress and low repo market volume, and Adrian and Fleming (2005) argue that while not perfect, net repo volume reflects dealer leverage. Volume in the repo market is the difference between overnight repo and reverse overnight repo volume.[22] This variable is available only at the weekly frequency. We average the weekly observations for each month to get a monthly net volume measure, and then calculate the relative change in that measure to use as our independent variable.

As discussed in the introduction, liquidations by hedge funds will have a larger impact on hedge funds when asset liquidity is low. As hedge funds must sell holdings, they will liquidate even more assets if markets are illiquid because the liquidations push the asset prices down. We employ as a proxy for asset liquidity the liquidity measure of Amihud (2002).[23] This variable measures the daily price response associated with one dollar of trading volume, and serves as a rough measure of price impact. Although this measure is calculated for the stock market, the literature suggests that reduced liquidity in the stock market is associated with reduced liquidity in other markets.[24] Asset liquidity can also be a channel of contagion because hedge funds often provide liquidity to the markets. As these hedge funds perform poorly, their difficulties lead to a withdrawal of liquidity from the markets, leading other hedge funds to decrease their positions because of the decrease in liquidity and to experience mark-to-market losses because of price pressure.

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[22] We thank John Kambhu of the Federal Reserve Bank of New York for providing the data.

[23] Amihud's (2002) measure is calculated as follows: For each ordinary common stock on CRSP with listing on NYSE and positive share volume we calculate a daily measure of Absolute return/dollar volume from January 1, 1989 to December 31, 2007. We then calculate a monthly raw market-wide liquidity measure as the market cap weighted average of all individual daily measures but exclude the top and bottom 1% following Amihud (2002) to remove outliers. Then we normalize the raw measure as in Acharya and Pedersen (2005) by multiplying it by the lagged ratio of CRSP market cap/CRSP market cap at December, 1989 to create a stationary series, and from this series we calculate the relative change in market wide liquidity. Finally, we control for the impact of changes in the tick-size when the NYSE switched from 1/8 to 1/16 on June 24, 1997 and from 1/16 to $0.01 on January 29, 2001 and use as our final measure of the change in market-wide liquidity the residuals from a regression of the change in liquidity on the two tick-size change dummy variables.

[24] See, for example, Chordia, Sarkar, and Subramanyam (2005).

Finally, hedge fund outflows are used as a channel of contagion. If poor performance of hedge funds leads investors to request withdrawal of their funds, we expect that the hedge funds will liquidate assets in anticipation of withdrawals. These liquidations would lead to price pressure and mark-to-market losses if they are substantial. Since we do not have access to the HFR individual fund database, we calculate monthly net fund flows for hedge fund styles using the CSFB/Tremont hedge fund database for the entire period. These net fund flows are calculated for each hedge fund separately, and aggregated by fund style. We then calculate the monthly percentage change in net fund flows for the entire style index.[25] We consider both contemporaneous and one month ahead net fund flows. Typically, hedge funds do not allow investors to redeem within a month, so that next month's flows may contain redemptions requested during the current month. The obvious difficulty with interpreting flow variables is that large net outflows may result from poor returns.

Thus, we have six measures proxying for contagion channels: a prime broker index (*PBI*), and bank index (*BANK*), Amihud's (2002) illiquidity measure (*STKLIQ*), a credit spread index (*CRSPRD*), a measure of changes in repo volume (*REPO*), and contemporaneous and one month ahead net flows ($FLOW_t$ and $FLOW_{t+1}$) (where t stands for time in months).[26] Table IV presents summary statistics for these variables. For all variables, the number of observations is 212, the same as for the hedge fund indices, with the exception of the percent change in repo volume, which is only available since August 1994, for 157 observations. Most variables have significant dispersion between the 25th and 75th percentiles, and all variables have excess kurtosis. The correlations between the variables are generally low or even negative, with the exception of the correlation between the prime broker index and the bank index, which is 0.82. This correlation is not too surprising, since all the firms in these indices are in the

[25] The matching process from the CSFB/Tremont database to the HFR style indices is not one-to-one, due to different methodologies for classifying styles. To overcome this issue, we read the style descriptions from both CSFB/Tremont and HFR and use judgment to match as closely as possible. Additionally, as noted earlier, the CSFB/Tremont database has survivorship bias problems prior to 1994. However, we expect that this bias would cause aggregate outflows to be understated, not overstated, and thus, is a conservative measure of true fund outflows.

[26] We also use first difference in the repo spread over the 3 month T-bill rate and find similar results. Further, we separately use TED spreads as a measure of illiquidity and find that it does not provide explanatory power.

financial services industry. However, our results below indicate that there are important differences in the explanatory power of these two indices.

Our first tests are presented in Table V. Here, we create a new contagion variable *COUNT8* that ranges in value from zero to eight. It is set to zero if no hedge fund index has a 10% tail return during a month, one if one hedge fund index has a 10% tail return during a month, and so on, up to a maximum value of eight when all eight hedge fund indices have an extreme negative return. In addition, we create liquidity proxy dummy variables for each of the proxies, set to one if the proxy variable has a realization in the lowest decile of liquidity and zero otherwise. Hence, *PBI,* $FLOW_t$, $FLOW_{t+1,}$ *BANK*, and *REPO* are set to one if their realizations are in the bottom 10% of all respective values, and *STKLIQ* and *CRSPRD* are set to one if their realizations are in the top 10% of all respective values. We calculate the mean value of the *COUNT8* variable conditional on the realization (zero or one) of each liquidity proxy dummy variable, and perform t-tests for differences in means. A higher average for *COUNT8* when the liquidity dummy variable is one implies that more hedge funds styles perform poorly when liquidity is low, i.e., contagion is exacerbated when that measure of liquidity is low.

The results in Table V indicate that three liquidity proxies, *PBI*, *BANK*, and *STKLIQ*, are strongly related to contagion. The results are consistent with the predictions of Brunnermeier and Pedersen's (2008) model of funding and asset liquidity crises. For example, when *PBI* returns are in the bottom decile, an average of almost three hedge funds have extremely poor realizations in returns, compared to 0.59 hedge funds when PBI returns are not in the bottom decile. The other liquidity proxies are less helpful in predicting *COUNT8*. As further evidence of the importance of asset and funding liquidity, the *COUNT8* variable has a mean of 4.33 in the joint presence of poor asset liquidity (in the form of a top decile value of Amihud's measure) and of poor funding liquidity (in the form of a bottom decile value of the prime broker index return), and 0.70 otherwise. This evidence shows that hedge fund styles perform poorly when both funding liquidity and asset liquidity are poor at the same time, confirming the individual importance of these contagion channels.

III.2. The Poisson regression approach

The univariate results for the *COUNT8* variable, though striking, could be explained by correlation rather than by contagion, since we do not control for other risk factors. In this section, we use a Poisson regression model to show that this is not the case. This model is a generalized linear model with a "log" link function and Poisson distributed errors.[27] The model attributes to a count response variable Y a Poisson distribution whose expected value depends on predictor variables x in the following way: $\log E[Y_t \mid x_t] = \beta x_t$ where x_t is a vector of regressors during a given time period t, and Y_t is the observed event count (*COUNT8*) during the time period t.

If Y are independent observations with corresponding values x of the predictor variable, then β can be estimated by maximum likelihood if the number of distinct x values is at least 2. The Poisson regression is particularly appropriate when analyzing "count" data for rare events that occur during a period of time t, and thus, is appropriate for our study as the contagion events we model are rare events by construction. Some other benefits of using the Poisson regression are that it handles the integer property of observed event counts directly and works well when the number of possible outcomes is small, both of which apply to our data.[28]

To examine the impact that the contagion channel variables have on hedge fund contagion, continuous and indicator measures of the six liquidity proxy variables are separately included in the regressions with *COUNT8* as the dependent variable (for the *FLOW* proxy, both contemporaneous and next-month flows are included). The liquidity dummy variables for each of the proxies are set to one if the proxy variable has a realization in the lowest quartile of liquidity and zero otherwise. Note that this

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[27] We thank Bill Greene for suggesting the Poisson model. Much of the following discussion follows Hausman, Hall, and Griliches (1984).

[28] The Poisson regression has been used occasionally in finance applications; some examples include Hausmann, Hall, and Griliches (1984) who apply Poisson regressions to analyze the relationship between R&D and patent applications, and Hermalin and Weisbach (1988) and Lerner (1995), both of whom use a Poisson regression to model the addition and departure of board members after CEO turnover.

differs from the analysis in Table V, where the indicator variables use decile realizations. Using decile indicator variables in the multivariate setting creates multicollinearity problems in the regressions, so we must resort to using quartile indicator variables for these tests. A positive and significant coefficient on the contagion channel variable indicates that variable is associated with increased hedge fund contagion. Finally, all the control variables from Table III are included in the regressions, but are not reported for brevity.

The basic Poisson probability specification is:

$$\Pr\left(Y_t = n_t \mid x_t\right) = \frac{e^{-\exp(\beta x_t)} \exp(\beta_i x_t)^{n_t}}{n_t!} \tag{1}$$

In our monthly analysis, Y is *COUNT8*, t the month, and $n_t \in \{0, \ldots ,8\}$ based on the realization of the *COUNT8* variable during month t. The mean value of Y, $\exp(\beta x_t)$, depends on a vector of explanatory variables x_t, where the exponential function guarantees non-negativity. Maximum likelihood with a log-likelihood function is used to estimate the model, and our goodness of fit measure is McFadden's (1974) pseudo-R^2.

Results are presented in Table VI. Following McCullagh (1983) and McCullagh and Nelder (1989), we allow for overdispersion to overcome the shortcoming that the mean and variance in the standard Poisson approach must be the same, and estimate the parameters and standard errors using a quasi-likelihood function framework. All variables except the indicator variables have been standardized using an AR-GARCH process to remove autocorrelation and volatility clustering.

There are seven regression specifications; the first six include the liquidity proxies separately, while the final specification includes all the proxies. Because the contagion channel dummy variables are set to one when markets are illiquid, a positive and significant coefficient on the dummy variable indicates that this variable increases the likelihood of contagion within the hedge fund industry. The results of Table VI indicate that four of the liquidity proxies: *PBI*, *STKLIQ*, $FLOW_{t+1}$, and *CRSPRD* are statistically significant in explaining contagion within the hedge fund industry. Both *PBI* and *STKLIQ* are statistically significant at the 1% level, $FLOW_{t+1}$ is significant at the 5% level, and *CRSPRD* is significant at the 6%

level. These results are generally consistent with the univariate tests in Table V with the exception that once the additional control variable are included, the *BANK* index is no longer significant in explaining contagion. In addition, the multivariate results for $FLOW_{t+1}$ and *CRSPRD* are stronger than for the univariate results. These consistent results indicate that the same proxy variables are relevant, whether we use a 10% or 25% cutoff for illiquidity.

The regression that includes all the liquidity proxy variables indicates that the most significant proxy is asset liquidity, as proxied by *STKLIQ*, followed by funding liquidity, as proxied by *PBI*. *CRSPRD* and $FLOW_{t+1}$ are no longer significant at traditional levels when all six proxies are included (although both are significant at about the 11% level). Taken together, the results from Tables V and VI are strongly consistent with the "phase locking" behavior described by Chan, Getmansky, Haas, and Lo (2005) and the liquidity spirals modeled by Brunnermeier and Pedersen (2008). Finally, as a robustness check, we repeat these analyses using the CSFB/Tremont indices. These results are consistent with the results for the HFR indices. Together, these results provide strong evidence that funding and asset liquidity are channels through which contagion takes place.

IV. Contagion between Hedge Funds and Main Markets

Thus far, we have documented the existence of contagion within the hedge fund industry and explored the possible determinants of this contagion. In addition, our tests found no evidence of contagion between main markets and hedge fund styles (testing each hedge fund index separately). However, we have not yet examined whether contagion within the hedge fund industry is associated with extreme poor performance in the main markets. Establishing whether there is such a relation is important to assess the systemic risk posed by contagion within the hedge fund sector.

Using a logit regression approach, we investigate whether hedge fund contagion is associated with poor performance in the main markets. For each of the three main markets: stocks, bonds, and currencies, we perform regressions where the dependent variable is an indicator variable set to one if that market has an extreme negative return (10% tail event) and zero otherwise. The explanatory variables include the return on the 3-month T-bill, a measure of volatility on each of the main markets (as described in Section II), the continuous return on each of the three main markets, the equally-weighted return on the eight hedge fund indices, and the *COUNT8* variable (described in Section III). A positive and significant coefficient on the *COUNT8* variable indicates that hedge fund contagion is associated with poor performance in the main market index being tested.

Table VII presents results. There is no evidence of an association between hedge fund contagion and poor performance in either the stock or bond markets. However, there is strong evidence of a relationship for the currency market. Such an association could occur because of the importance of carry trades as a mechanism of financing for hedge funds. As emphasized by Plantain and Shin (2008), hedge funds can directly borrow in low interest rate currencies or indirectly borrow from banks that in turn finance themselves in low interest rate currencies.

We perform additional analyses in Table VIII. In these tests, we include all the explanatory variables from Table VII, and separately add the contagion channel variables from Table VI. We are interested in two questions: First, does including the contagion channel variables change our result that hedge fund contagion is associated with poor performance in the currency market? And second, do the contagion channel variables provide explanatory power for extreme returns in the main markets? Results in Table VIII indicate that the answer to the first question is negative. Regardless of the contagion channel variable included, the evidence of an association between hedge fund contagion and poor performance of the currency market remains. For the second question, there is some evidence that the contagion channel variables help to explain extreme poor performance in bond and currency markets.

For the bond market, poor returns in the bank index (*BANK*) are associated with poor returns in the bond index. This result is probably related to the fact that banks' assets typically have longer durations than their liabilities, so that they suffer from unexpected interest rate increases which also affect the bond index adversely. For the currency market, asset illiquidity (*STKLIQ*) is associated with poor returns in the currency market. This result implies a connection between stock market liquidity and performance of the currency market.

Finally, as a robustness check, we repeat these analyses using the CSFB/Tremont indices. These results are consistent with the results for the HFR indices; there is no correlation between hedge fund contagion and poor performance in the stock and bond markets, but such association exists with currency markets.

V. Implications and Conclusions

In this paper, we use logit and Poisson regression models to study contagion within the hedge fund industry as well as between hedge funds and the main markets. Specifically, we examine the co-incidence of extreme poor returns between hedge fund indices and broad markets, and also between hedge fund indices, taking carefully into account the known determinants of hedge fund returns.

We find no systematic evidence of contagion between broad markets and individual hedge fund styles after accounting for correlation between market factors and hedge fund returns. By contrast, we find extremely strong and consistent evidence of contagion between hedge fund styles. Importantly, our evidence of hedge fund style contagion is economically significant since the probability that a hedge fund style will have a negative tail return is an order of magnitude higher when several other hedge fund styles have negative tail returns.

We investigate the channels through which contagion takes place. The framework of Brunnermeier and Pedersen (2008) provides a roadmap for this investigation. The idea is that poor hedge fund performance in one style can weaken the financial intermediaries that provide credit to hedge funds and hence lead to a reduction in the credit extended to hedge funds and an increase in the cost of the credit extended, so that hedge funds in other styles have to reduce their leverage and liquidate assets. The hedge funds in these styles are hurt by the price impact effect of the asset liquidations, which forces them to liquidate more assets. Liquidations of hedge funds withdraw liquidity from the main markets, leading to a reduction in asset liquidity, which worsens the impact of asset liquidations and increases the mark-to-market losses of hedge funds, forcing them to liquidate more assets because of increased funding constraints. We use proxies for funding liquidity and asset liquidity to investigate the channels through which hedge fund contagion takes place. Our strongest contagion channels are the prime broker channel and the stock market liquidity channel, showing that both funding liquidity and asset liquidity appear to be important hedge fund contagion channels.

Finally, we examine whether contagion in the hedge fund industry is associated with poor performance in the main markets. We find no evidence that hedge fund contagion is associated with poor performance in stock and bond markets, but significant evidence that it is associated with poor performance in the currency markets. We view this evidence as consistent with the arguments advanced for the importance of the carry trade for hedge fund funding and of how poor performance in hedge funds can lead to unwinding of carry trades. However, further research exploring this mechanism more directly is needed.

Table I: Summary statistics of monthly returns on HFR indices and market factors: January, 1990 to August, 2007

Summary statistics for monthly data on eight HFR monthly hedge fund indices and three market factors used in the paper are reported below. The indices include Convertible Arbitrage, Distressed Securities, Event Driven, Equity Hedge, Equity Market Neutral, Merger Arbitrage, Global Macro, and Relative Value and are described more fully in Section II and Appendix A. The market factors are from Datastream and include the return on the Russell 3000 index, the change in the Federal Reserve Bank competitiveness-weighted dollar index (the FRB Dollar Index), and the daily return on the Lehman Brothers U.S. Bond Index. The number of observations is 212. Correlations between the variables and the autocorrelations as well as Jarque-Bera test statistics for normality are reported below the summary statistics. The second row in the autocorrelation table reports t-values in parentheses. Bold correlation results indicate significance at the 5% level.

Panel 1: Summary statistics and simple correlations

	HFR Hedge Fund Indices								**Main Market Factors**		
	Convertible Arbitrage	**Distressed Securities**	**Event Driven**	**Equity Hedge**	**Equity Market Neutral**	**Merger Arbitrage**	**Global Macro**	**Relative Value**	**Russell 3000 Index**	**Return on LB bond Index**	**Δ in FRB Dollar Index**
Number of observations	212	212	212	212	212	212	212	212	212	212	212
Mean	0.79%	1.18%	1.14%	1.31%	0.72%	0.83%	1.19%	0.94%	0.94%	0.58%	0.07%
Median	0.99%	1.14%	1.34%	1.35%	0.65%	1.04%	0.84%	0.92%	1.39%	0.66%	0.00%
10% quantile return	-0.49%	-0.45%	-0.78%	-1.88%	-0.27%	-0.30%	-1.24%	-0.20%	-3.83%	-0.85%	-2.14%
90% quantile return	1.78%	2.88%	3.12%	4.46%	1.91%	1.96%	3.98%	2.03%	6.05%	1.89%	2.56%
Standard deviation	1.00%	1.68%	1.83%	2.46%	0.88%	1.20%	2.31%	1.01%	4.01%	1.09%	1.81%
Skewness	-1.082	-0.631	-1.272	0.209	0.186	-2.504	0.405	-0.813	-0.585	-0.398	-0.190
Excess kurtosis	2.028	6.018	4.818	1.599	0.566	11.282	0.796	10.630	1.085	0.633	0.438
Correlations											
Convertible Arbitrage	1.00	**0.55**	**0.57**	**0.45**	**0.22**	**0.46**	**0.40**	**0.60**	**0.30**	0.18	**-0.03**
Distressed Securities		1.00	**0.79**	**0.59**	**0.20**	**0.52**	**0.47**	**0.68**	**0.44**	0.03	-0.06
Event Driven			1.00	**0.78**	**0.24**	**0.73**	**0.56**	**0.64**	**0.69**	0.06	-0.02
Equity Hedge				1.00	**0.38**	**0.50**	**0.60**	**0.54**	**0.72**	0.07	0.04
Equity Market Neutral					1.00	**0.25**	**0.28**	**0.28**	**0.16**	**0.19**	0.04
Merger Arbitrage						1.00	**0.32**	**0.47**	**0.50**	0.08	-0.02
Global Macro							1.00	**0.40**	**0.41**	**0.33**	-0.02
Relative Value								1.00	**0.39**	0.06	-0.06
Russell 3000 return									1.00	0.12	0.06
Return on LB bond Index										1.00	0.21
Δ in FRB Dollar Index											1.00

Panel 2: Autocorrelation test for significance at 6 lags

	Convertible Arbitrage	**Distressed Securities**	**Event Driven**	**Equity Hedge**	**Equity Market Neutral**	**Merger Arbitrage**	**Global Macro**	**Relative Value**
Ljung-Box test (1-6)	**80.41**	**57.68**	**19.57**	11.08	**34.76**	12.03	**14.15**	**27.41**
p-value	<.0001	<.0001	0.00	0.09	<.0001	0.06	0.03	0.00

Panel 3: Normality test

	Convertible Arbitrage	**Distressed Securities**	**Event Driven**	**Equity Hedge**	**Equity Market Neutral**	**Merger Arbitrage**	**Global Macro**	**Relative Value**
Jarque-Bera Test	**74.42**	**316.00**	**249.58**	**22.29**	3.64	**1285.21**	**10.68**	**969.71**
***p*-value**	<.0001	<.0001	<.0001	<.0001	0.16	<.0001	0.00	<.0001

Table II: Contagion of extreme events for HFR monthly hedge fund indices

The event of an extreme monthly negative return in each hedge fund style is separately modeled as the outcome of a binary variable and estimated as a Logit regression. A monthly return is classified as extreme and the dependent variable is set to 1 if it belongs to the bottom 10% of all returns of that style. The independent variables are described in Section II.2. The market contagion variables are set to 1 if the market of interest has an extreme poor return (bottom 10%) for the month. The *COUNT* variable takes a value from 0 to 7 and measures the number of other hedge fund indices that have bottom 10% tail returns for the month. Below the coefficients are the t-values in parentheses. R^2 MAX is the scaled coefficient of determination suggested by Nagelkerke (1991). Coefficients with ***, **, and * are statistically significant at the 1%, 5%, and 10% levels, respectively.

	Conv. Arbitrage	**Distressed Securities**	**Event Driven**	**Equity Hedge**	**Equity Market Neutral**	**Merger Arbitrage**	**Global Macro**	**Relative Value**
Constant	-3.276***	-4.283***	-4.092***	-2.770***	-5.740***	-3.101***	-3.426***	-2.864***
	(-10.04)	*(-10.61)*	*(-10.97)*	*(-10.15)*	*(-11.03)*	*(-10.86)*	*(-10.99)*	*(-10.62)*
Continuous Variables								
Russell 3000	-0.478	-0.625*	-0.765**	0.122	0.087	-0.299	-0.177	-0.130
	(-1.41)	*(-1.93)*	*(-2.12)*	*(0.38)*	*(0.26)*	*(-0.92)*	*(-0.51)*	*(-0.40)*
Return on LB bond index	-0.492	1.032***	-0.177	-0.369	1.283***	-0.574*	0.181	-0.5892**
	(-1.66)	*(3.21)*	*(-0.55)*	*(-1.33)*	*(3.88)*	*(-1.93)*	*(0.61)*	*(-1.96)*
Change in FRB dollar index	0.100	0.176	-1.043***	-0.183	-0.835***	0.226	-0.760***	-0.347
	(0.37)	*(0.68)*	*(-3.46)*	*(-0.66)*	*(-2.83)*	*(0.85)*	*(-2.58)*	*(-1.28)*
Equally Weighted Return on other hedge fund indices	-2.192***	-0.815	-1.468**	-0.630	-2.156***	-0.746	-1.204**	-1.430***
	(-3.24)	*(-1.45)*	*(-2.28)*	*(-1.42)*	*(-2.72)*	*(-1.34)*	*(-1.97)*	*(-2.41)*
Contagion Variables								
Market Indicator Variables								
Bottom 10% return in Russell 3000	-0.456	-0.875	1.119*	-0.425	2.294***	-0.771	0.928	0.297
	(-0.73)	*(-1.36)*	*(1.75)*	*(-0.58)*	*(3.66)*	*(-1.13)*	*(1.41)*	*(0.45)*
Bottom 10% return in Bond index	-1.378	0.744	-1.286	-0.766	-0.235	0.040	-0.117	-0.708
	(-1.58)	*(0.73)*	*(-1.38)*	*(-0.91)*	*(-0.25)*	*(0.05)*	*(-0.13)*	*(-0.89)*
Bottom 10% return in FRB index	0.561	2.065***	-1.327*	0.916	-1.640*	-0.380	-0.830	-2.172**
	(0.75)	*(2.80)*	*(-1.70)*	*(1.28)*	*(-1.94)*	*(-0.45)*	*(-1.08)*	*(-2.18)*
Other Hedge Fund Index Indicator Variable								
COUNT	-0.005	0.886***	0.307*	0.307*	1.136***	0.439***	0.331*	0.115
	(-0.03)	*(4.24)*	*(1.67)*	*(1.79)*	*(4.62)*	*(2.38)*	*(1.82)*	*(0.64)*
R^2 MAX	0.490	0.656	0.732	0.244	0.915	0.414	0.541	0.416

Table III: Contagion of Extreme Events for HFR Monthly Hedge Fund Indices Controlling for Non-linear and Other Factors

The event of an extreme monthly negative return in each hedge fund style is separately modeled as the outcome of a binary variable and estimated as a Logit regression. A monthly return is classified as extreme and the dependent variable is set to 1 if it belongs to the bottom 10% of all returns of that style. The independent variables are described in Section II.2. The market contagion variables are set to 1 if the market of interest has an extreme poor return (bottom 10%) for the month. The *COUNT* variable takes a value from 0 to 7 and measures the number of other hedge fund indices that have bottom 10% tail returns for the month. A stepwise regression is used to generate a parsimonious model before *COUNT* is added. See Section II.2 for more detail. Below the coefficients are the t-values in parentheses. R^2 MAX is the scaled coefficient of determination suggested by Nagelkerke (1991). Coefficients with ***, **, and * are statistically significant at the 1%, 5%, and 10% levels, respectively.

	Conv. Arbitrage	Distressed Securities	Event Driven	Equity Hedge	Equity Market Neutral	Merger Arbitrage	Global Macro	Relative Value
Constant	-3.942***	-4.703***	-5.042***	-3.816***	-7.349***	-4.496***	-4.173***	-2.930***
	(-10.48)	*(-11.04)*	*(-10.16)*	*(-10.01)*	*(-11.06)*	*(-10.06)*	*(-11.23)*	*(-11.22)*
Russell 3000 return	-1.577***	.	-2.047***	.	.	.	.	.
	(-4.19)	.	*(-6.04)*	.	.	.	.	.
Return on LB bond index	.	0.645***	.	2.789***	.	-2.693***	.	.
	.	*(2.65)*	.	*(3.62)*	.	*(-3.48)*	.	.
Change in FRB dollar index	.	.	-0.499***	.	.	.	-0.760***	.
	.	.	*(-2.55)*	.	.	.	*(-3.52)*	.
Eq. wtd. ret. on other HFR indices	-0.975	-0.729	-0.648	-0.737**	-2.657***	-0.584	-2.063***	-2.000***
	(-1.47)	*(-1.30)*	*(-0.99)*	*(-2.14)*	*(-3.47)*	*(-0.98)*	*(-3.50)*	*(-3.72)*
Return on 3 month T-bill	-15.396***	.	.	.	.	.	.	.
	(-3.99)	.	.	.	.	.	.	.
S&P volatility	-0.046***	0.025	.	.	.	0.070***	.	.
	(-2.72)	*(1.59)*	.	.	.	*(5.19)*	.	.
FRB dollar index volatility	.	.	.	0.230***	.	-0.215***	-0.163***	.
	.	.	.	*(2.71)*	.	*(-4.67)*	*(-2.91)*	.
LB bond index volatility	-0.267***	.	.	.	.	.	.	.
	(-3.85)	.	.	.	.	.	.	.
Return on negative portion of S&P	.	-0.279***	.	.	-0.632***	-0.297***	.	.
	.	*(-3.32)*	.	.	*(-6.52)*	*(-2.44)*	.	.
Size spread	-0.288***	-0.176***	-0.275***	.	-0.337***	-0.251***	.	.
	(-3.55)	*(-2.76)*	*(-3.35)*	.	*(-4.41)*	*(-3.50)*	.	.
Δ in 10-year constant maturity YTM	.	.	.	0.122***	-0.040***	-0.067***	.	.
	.	.	.	*(4.05)*	*(-5.06)*	*(-2.40)*	.	.
BAA-AAA spread	.	.	.	.	.	.	1.004***	.
	.	.	.	.	.	.	*(4.57)*	.
<u>Lookback Straddle factors</u>								
Lookback on bonds	.	.	.	.	.	.	.	.
	.	.	.	.	.	.	.	.
Lookback on currencies	.	.	.	-5.772***	.	.	.	.
	.	.	.	*(-3.60)*	.	.	.	.
Lookback on commodities	.	.	.	.	.	-6.016***	5.795***	.
	.	.	.	.	.	*(-3.75)*	*(4.33)*	.
Lookback on short term interest rates	2.437***	-2.885***	.	.	.	.	-2.851***	.
	(2.64)	*(-2.90)*	.	.	.	.	*(-2.70)*	.
Lookback on equities	.	.	-3.097***	.	.	.	.	.
	.	.	*(-3.74)*	.	.	.	.	.
<u>Contagion Variables</u>								
Market Indicator Variables								
Bottom 10% return in Russell 3000	.	.	.	.	.	-2.807***	.	.
	.	.	.	.	.	*(-3.58)*	.	.
Bottom 10% return in Bond index	.	.	.	.	.	.	.	.
	.	.	.	.	.	.	.	.
Bottom 10% return in FRB index	.	1.867***	.	1.865***	.	.	.	.
	.	*(3.42)*	.	*(3.67)*	.	.	.	.
<u>Other Hedge Fund Index Indicator Contagion Variable</u>								
COUNT	0.099	0.605***	0.293*	0.473***	0.822***	0.150	0.482***	0.020
	(0.57)	*(3.16)*	*(1.77)*	*(2.87)*	*(3.73)*	*(0.79)*	*(2.60)*	*(0.12)*
R^2 MAX	0.637	0.703	0.782	0.457	0.961	0.669	0.708	0.369

Table IV: Summary Statistics for Funding and Asset Liquidity Variables January, 1990 to August, 2007

Summary statistics for monthly data on six funding and asset liquidity variables used in the paper are described below. The variables include: the monthly percent change in the BAA-AAA rated bond credit spread, the percent change in the Amihud (2002) liquidity measure, the monthly percent change in repo volume, the monthly percent change in hedge fund flows as a percentage of assets (contemporaneous), the monthly returns from the Datastream bank index, and the monthly returns from the prime broker index. Further description of these variables is in Section III. The number of observations is 212. Correlations between the variables are reported below the summary statistics. Bold correlation results indicate significance at the 5% level.

	Credit Spread	Liquidity Measure	Repo Volume	Hedge Fund Flows, Contemporaneous	Bank Index	Prime Broker Index
Number of observations	212	212	157	212	212	212
Mean	0.066	-0.096%	1.307%	0.717%	1.285%	1.912%
Median	0.000	-1.323%	1.086%	0.833%	1.368%	1.942%
25^{th} percentile cutoff	-8.00	-13.747%	-0.198%	0.016%	-0.185%	-0.219%
75^{th} percentile cutoff	8.00	9.600%	0.359%	0.144%	0.494%	0.610%
Standard deviation	14.596	21.500%	0.434%	0.170%	0.557%	0.709%
Skewness	0.200	1.229	0.298	-2.127	-0.296	-0.274
Excess kurtosis	1.846	3.598	0.540	35.072	1.838	1.802
Correlations						
Percent Change in BAA-AAA Credit Spread	1.00	0.03	0.04	0.00	-0.04	**-0.21**
Percent Change in Amihud's Liquidity Measure		1.00	-0.11	-0.01	**-0.25**	**-0.22**
Percent Change in Repo Volume			1.00	-0.13	-0.05	-0.02
Percent Change in Contemporaneous H.F. Flows				1.00	-0.07	-0.11
Bank Index Equally-weighted Return					1.00	**0.82**
Prime Broker Index Equally-weighted Return						1.00

Table V: Conditional Means of *COUNT8* Variable

For each liquidity indicator variable (Prime Broker Index (*PBI*), Datastream Bank Index (*BANK*), Amihud's Liquidity Measure (*STKLIQ*), BAA-AAA Credit Spread (*CRSPRD*), Changes in Repo Volume (*REPO*), and flows from other hedge funds, both contemporaneous and one month forward ($FLOW_t$ and $FLOW_{t+1}$)), we calculate means of the *COUNT8* contagion variable at both realizations (0 and 1) of the indicator variable. See Section IV for detail on the construction of the liquidity indicator variables. A value of 1 in an indicator variable implies a high level of illiquidity. The value of *COUNT8* ranges from 0 to 8. It is set to 0 if no hedge fund index has a 10% negative tail return on a given date, 1 if one hedge fund index has a negative return, and so on up to a value of 8. t-tests for differences in means, using the Satterthwaite method to adjust for unequal variance, are reported in italics. Differences in means with ***, **, and * are statistically significant at the 1%, 5%, and 10% levels, respectively.

	Number	Mean of *COUNT8*
Indicator Variable = Bottom Decile Returns for Prime Broker Index (PBI)		
PBI = 0	189	0.59
PBI = 1	21	2.71
Difference in *COUNT8* Means: (PBI=1 less PBI=0)		2.11***
		(4.23)
Indicator Variable = Bottom Decile Returns for Bank Index (BANK)		
BANK = 0	189	0.58
BANK = 1	21	2.76
Difference in *COUNT8* Means: (BANK=1 less BANK=0)		2.22***
		(4.43)
Indicator Variable = Decile with Largest Amihud Liquidity Measure (STKLIQ)		
STKLIQ = 0	189	0.86
STKLIQ = 1	21	3.14
Difference in *COUNT8* Means: (STKLIQ=1 less STKLIQ=0)		2.28***
		(2.60)
Indicator Variable = Top Decile BAA-AAA Credit Spread (CRSPRD)		
CRSPRD= 0	189	0.72
CRSPRD= 1	21	1.52
Difference in *COUNT8* Means: (CRSPRD=1 less CRSPRD=0)		0.80
		(1.63)
Indicator Variable =Decile with Largest Decreases in Repo Volume (REPO)		
REPO = 0	141	0.80
REPO = 1	16	1.44
Difference in *COUNT8* Means: (REPO=1 less REPO=0)		*(1.27)*
Indicator Variable = Top Decile Fund Outflows (Contemporaneous) ($FLOW_t$)		
$FLOW_t = 0$	189	0.83
$FLOW_t = 1$	21	0.57
Difference in *COUNT8* Means: ($FLOW_t$=1 less $FLOW_t$=0)		-0.26
		(-0.84)
Indicator Variable = Top Decile Fund Outflows ($FLOW_{t+1}$)		
$FLOW_{t+1} = 0$	189	0.70
$FLOW_{t+1} = 1$	21	1.43
Difference in *COUNT8* Means: ($FLOW_{t+1}$=1 less $FLOW_{t+1}$=0)		0.73
		(1.39)
Indicator Variable = Top Decile STKLIQ *and* Bottom Decile PBI		
PBI * STKLIQ = 0	204	0.696
PBI * STKLIQ = 1	6	4.333
Difference in *COUNT8* Means: ([PBI * STKLIQ] = 1 less [PBI * STKLIQ] = 0)		3.637***
		(6.15)

Table VI: Contagion Regressions Including Liquidity Proxies

The co-occurrence of extreme monthly negative returns in hedge fund style indices is modeled as the outcome of a variable (*COUNT8)* that takes the values of 0 to 8 and is estimated as a Poisson regression. A value of 0 indicates that no hedge fund style index has an extreme negative return during a given month, a value of 1 indicates that 1 hedge fund style index has an extreme negative return during a given month, and so on up to a maximum value of 8. A monthly return is classified as extreme if it belongs to the bottom 10% of all returns of that style. The independent control variables are described in Section II.2, and include all the variables in Table III, and are excluded below for brevity. In addition, the regressions also include the continuous and indicator values for the liquidity variables, Prime Broker Index (*PBI*), Bank Index (*BANK*), Amihud's (2002) Liquidity Measure (*STKLIQ*), BAA-AAA Credit Spread (*CRSPRD*), Changes in Repo Volume (*REPO*), and flows from other hedge funds, both contemporaneous and one month in the future ($FLOW_t$ and $FLOW_{t+1}$). The liquidity indicator variables are set to 1 when liquidity is in the lowest quartile. t-values are shown below the coefficients in parentheses. The pseudo R^2 is McFadden's likelihood ratio index. Coefficients with ***, **, and * are statistically significant at the 1%, 5%, and 10% levels, respectively.

Dependent Variable: COUNT8

	Liquidity Proxy = PBI	Liquidity Proxy = BANK	Liquidity Proxy = STKLIQ	Liquidity Proxy = CRSPRD	Liquidity Proxy = REPO	Liquidity Proxy = $FLOW_t$ and $FLOW_{t+1}$	ALL Liquidity Proxies Included
Constant	-1.411***	-1.199***	-1.462***	-1.246***	-1.185***	-1.410***	-2.102***
	(-7.13)	*(-6.32)*	*(-7.25)*	*(-6.46)*	*(-4.82)*	*(-6.38)*	*(-5.89)*
Liquidity Proxies: Continuous							
PBI	0.262						0.235
	(1.42)						*(0.70)*
BANK		0.238					-0.026
		(1.60)					*(-0.09)*
STKLIQ			-0.246**				-0.168
			(-2.01)				*(-1.03)*
CRSPRD				-0.053			-0.188
				(-0.34)			*(-0.83)*
REPO					-0.215		-0.161
					(-1.04)		*(-0.71)*
$FLOW_t$						0.133	0.333**
						(0.99)	*(1.95)*
$FLOW_{t+1}$						-0.033	0.063
						(-0.22)	*(0.31)*
Liquidity Proxies: Indicator							
PBI	1.161***						0.633*
	(3.80)						*(1.70)*
BANK		0.186					-0.167
		(0.69)					*(-0.48)*
STKLIQ			1.172***				0.847**
			(4.05)				*(2.15)*
CRSPRD				0.566*			0.572
				(1.82)			*(1.63)*
REPO					-0.512		-0.340
					(-1.27)		*(-0.81)*
$FLOW_t$						0.209	0.582
						(0.69)	*(1.62)*
$FLOW_{t+1}$						0.626**	0.650
						(2.10)	*(1.63)*
Pseudo R^2	0.646	0.616	0.651	0.618	0.790	0.634	0.843

Table VII: Contagion of Extreme Events from Hedge Funds to Main Markets

The event of an extreme monthly negative return in a main market (stock, bond, and currency) is separately modeled as the outcome of a binary variable and estimated as a Logit regression. A monthly return is classified as extreme and the dependent variable is set to 1 if it belongs to the bottom 10% of all returns of that style. The independent variables are described in Section III. The *COUNT8* variable takes a value from 0 to 8 and measures the number of hedge fund indices that have bottom 10% tail returns for the month. Below the coefficients are the t-values in parentheses. R^2 MAX is the scaled coefficient of determination suggested by Nagelkerke (1991). Coefficients with ***, **, and * are statistically significant at the 1%, 5%, and 10% levels, respectively.

	Stock Market: Russell 3000	**Bond Market: Lehman Brothers Bond Index**	**Currency Market: FRB Dollar-Weighted Index**
Constant	-3.822***	-2.323***	-2.932***
	(-11.10)	*(-9.75)*	*(-9.79)*
Return on 3 month T-bill	2.917	-10.489***	-6.064
	(0.96)	*(-2.59)*	*(-1.60)*
S&P volatility	0.069***	0.012	-0.050***
	(5.63)	*(0.82)*	*(-2.94)*
FRB dollar index volatility	-0.008	-0.092*	-0.009
	(-0.11)	*(-1.82)*	*(-0.16)*
LB bond index volatility	0.062	-0.020	0.070
	(0.54)	*(-0.23)*	*(0.66)*
Return on Russell 3000	NA	-0.237	-0.719***
	NA	*(-0.74)*	*(-2.15)*
Return on Lehman Brothers bond index	0.088	NA	0.444***
	(0.44)	NA	*(-2.26)*
Return on FRB Dollar-weighted index	0.154	-0.394*	NA
	(0.67)	*(-1.94)*	NA
Equally weighted return on hedge fund indices	-2.175***	-0.020	1.470***
	(-3.15)	*(-0.45)*	*(3.41)*
Hedge Fund Index Indicator Contagion Variable			
COUNT8	-0.051	-0.13	0.55***
	(-0.29)	*(-0.75)*	*(3.20)*
R^2 MAX	0.650	0.135	0.204

Table VIII: Channel Variables and Contagion of Extreme Events from Hedge Funds to Main Markets

The event of an extreme monthly negative return in a main market (stock, bond, and currency) is separately modeled as the outcome of a binary variable and estimated as a Logit regression. A monthly return is classified as extreme and the dependent variable is set to 1 if it belongs to the bottom 10% of all returns of that style. The independent variables are described in Section III. The *COUNT8* variable takes a value from 0 to 8 and measures the number of hedge fund indices that have bottom 10% tail returns for the month. In addition, the regressions also include the continuous and indicator values for the liquidity variables, Prime Broker Index (*PBI*), Bank Index (*BANK),* Amihud's (2002) Liquidity Measure (*STKLIQ*), BAA-AAA Credit Spread (*CRSPRD*), Changes in Repo Volume (*REPO*), and flows from other hedge funds, both contemporaneous and one month in the future ($FLOW_t$ and $FLOW_{t+1}$). The liquidity indicator variables are set to 1 when liquidity is in the lowest quartile. For brevity, only coefficients on the *COUNT8* and liquidity variables are reported. t-values are shown below the coefficients in parentheses. R^2 MAX is a scaled coefficient of determination suggested by Nagelkerke (1991). Coefficients with ***, **, and * are statistically significant at the 1%, 5%, and 10% levels, respectively.

Panel A: Liquidity Variable is Prime Broker Index (PBI)

	Stock Market: Russell 3000	**Bond Market: Lehman Brothers Bond Index**	**Currency Market: FRB Dollar-Weighted Index**
Hedge Fund Index Indicator Contagion Variable			
COUNT8	0.013	-0.163	0.560***
	(0.07)	*(-0.86)*	*(3.12)*
Liquidity Variable			
PBI: Continuous	-1.716***	-0.276	1.327***
	(-3.68)	*(-0.72)*	*(3.54)*
PBI: Indicator	1.382	0.162	0.777
	(1.63)	*(0.25)*	*(1.05)*
R^2 MAX	0.803	0.141	0.287

Panel B: Liquidity Variable is Bank Index (BANK)

	Stock Market: Russell 3000	**Bond Market: Lehman Brothers Bond Index**	**Currency Market: FRB Dollar-Weighted Index**
Hedge Fund Index Indicator Contagion Variable			
COUNT8	0.232	-0.189	0.554***
	(1.29)	*(-0.99)*	*(3.28)*
Liquidity Variable			
BANK: Continuous	-1.879***	0.033	0.483
	(-4.19)	*(0.10)*	*(1.37)*
BANK: Indicator	-0.287	1.390***	-0.78
	(-0.44)	*(2.18)*	*(-1.08)*
R^2 MAX	0.784	0.183	0.257

Panel C: Liquidity Variable is Amihud Liquidity Measure (STKLIQ)

	Stock Market: Russell 3000	**Bond Market: Lehman Brothers Bond Index**	**Currency Market: FRB Dollar-Weighted Index**
Hedge Fund Index Indicator Contagion Variable			
COUNT8	0.060	0.002	0.483***
	(0.32)	*(0.01)*	*(2.64)*
Liquidity Variable			
STKLIQ: Continuous	0.799***	0.156	-0.603*
	(2.56)	*(0.54)*	*(-1.88)*
STKLIQ: Indicator	-1.620**	-1.379*	1.326**
	(-2.19)	*(-1.80)*	*(1.99)*
R^2 MAX	0.676	0.166	0.232

Table VIII, continued: Channel Variables and Contagion of Extreme Events from Hedge Funds to Main Markets

The event of an extreme monthly negative return in a main market (stock, bond, and currency) is separately modeled as the outcome of a binary variable and estimated as a Logit regression. A monthly return is classified as extreme and the dependent variable is set to 1 if it belongs to the bottom 10% of all returns of that style. The independent variables are described in Section III. The *COUNT8* variable takes a value from 0 to 8 and measures the number of hedge fund indices that have bottom 10% tail returns for the month. In addition, the regressions also include the continuous and indicator values for the liquidity variables, Prime Broker Index (*PBI*), Bank Index (*BANK*), Amihud's (2002) Liquidity Measure (*STKLIQ*), BAA-AAA Credit Spread (*CRSPRD*), Changes in Repo Volume (*REPO*), and flows from other hedge funds, both contemporaneous and one month in the future ($FLOW_t$ and $FLOW_{t+1}$). The liquidity indicator variables are set to 1 when liquidity is in the lowest quartile. For brevity, only coefficients on the COUNT8 and liquidity variables are reported. t-values are shown below the coefficients in parentheses. R^2 MAX is a scaled coefficient of determination suggested by Nagelkerke (1991). Coefficients with ***, **, and * are statistically significant at the 1%, 5%, and 10% levels, respectively.

Panel D: Liquidity Variable is BAA-AAA Credit Spread (CRSPRD)

	Stock Market: Russell 3000	Bond Market: Lehman Brothers Bond Index	Currency Market: FRB Dollar-Weighted Index
Hedge Fund Index Indicator Contagion Variable			
COUNT8	-0.074	-0.287	0.535^{***}
	(-0.42)	*(-1.55)*	*(3.06)*
Liquidity Variable			
CRSPRD: Continuous	0.067	-1.921^{***}	-0.202
	(0.19)	*(-6.24)*	*(-0.65)*
CRSPRD: Indicator	0.806	-10.075	0.095
	(1.29)	*(-0.06)*	*(0.14)*
R^2 MAX	0.661	0.494	0.207

Panel E: Liquidity Variable is change in Repo Volume (REPO)

	Stock Market: Russell 3000	Bond Market: Lehman Brothers Bond Index	Currency Market: FRB Dollar-Weighted Index
Hedge Fund Index Indicator Contagion Variable			
COUNT8	-0.108	-0.339	0.567^{***}
	(-0.54)	*(-1.36)*	*(2.94)*
Liquidity Variable			
REPO: Continuous	-0.067	-0.269	-0.947^{***}
	(-0.17)	*(-0.77)*	*(-2.43)*
REPO: Indicator	-0.029	-0.035	-1.278^{*}
	(-0.04)	*(-0.05)*	*(-1.66)*
R^2 MAX	0.658	0.089	0.295

Panel F: Liquidity Variable is Fund Outflows ($FLOW_t$ and $FLOW_{t+1}$)

	Stock Market: Russell 3000	Bond Market: Lehman Brothers Bond Index	Currency Market: FRB Dollar-Weighted Index
Hedge Fund Index Indicator Contagion Variable			
COUNT8	0.152	-0.150	0.489^{***}
	(0.81)	*(-0.81)*	*(2.92)*
Liquidity Variable			
$FLOW_t$: Continuous	-0.063	0.191	0.952^{***}
	(-0.20)	*(0.71)*	*(3.18)*
$FLOW_t$: Indicator	-1.802^{***}	0.069	2.184^{***}
	(-2.31)	*(0.11)*	*(3.75)*
$FLOW_{t+1}$: Continuous	-0.494	0.201	0.038
	(-1.36)	*(0.75)*	*(0.15)*
$FLOW_{t+1}$: Indicator	-0.809	0.620	0.168
	(-1.19)	*(1.06)*	*(0.29)*
R^2 MAX	0.704	0.145	0.317

Figure 1
Daily Hedge Fund Returns: August 2007

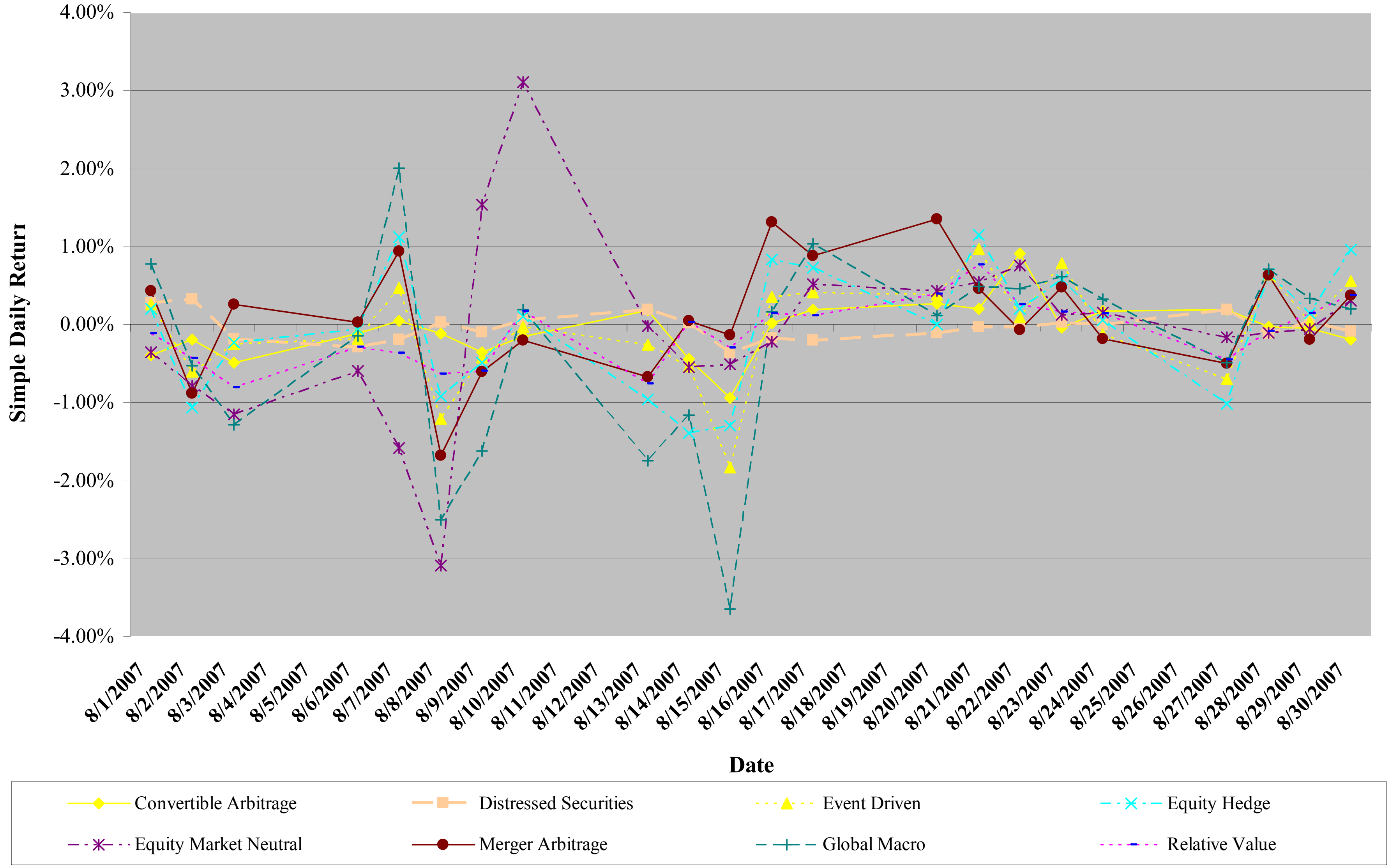


Figure 2:
Number of 10% Exceedances by Month

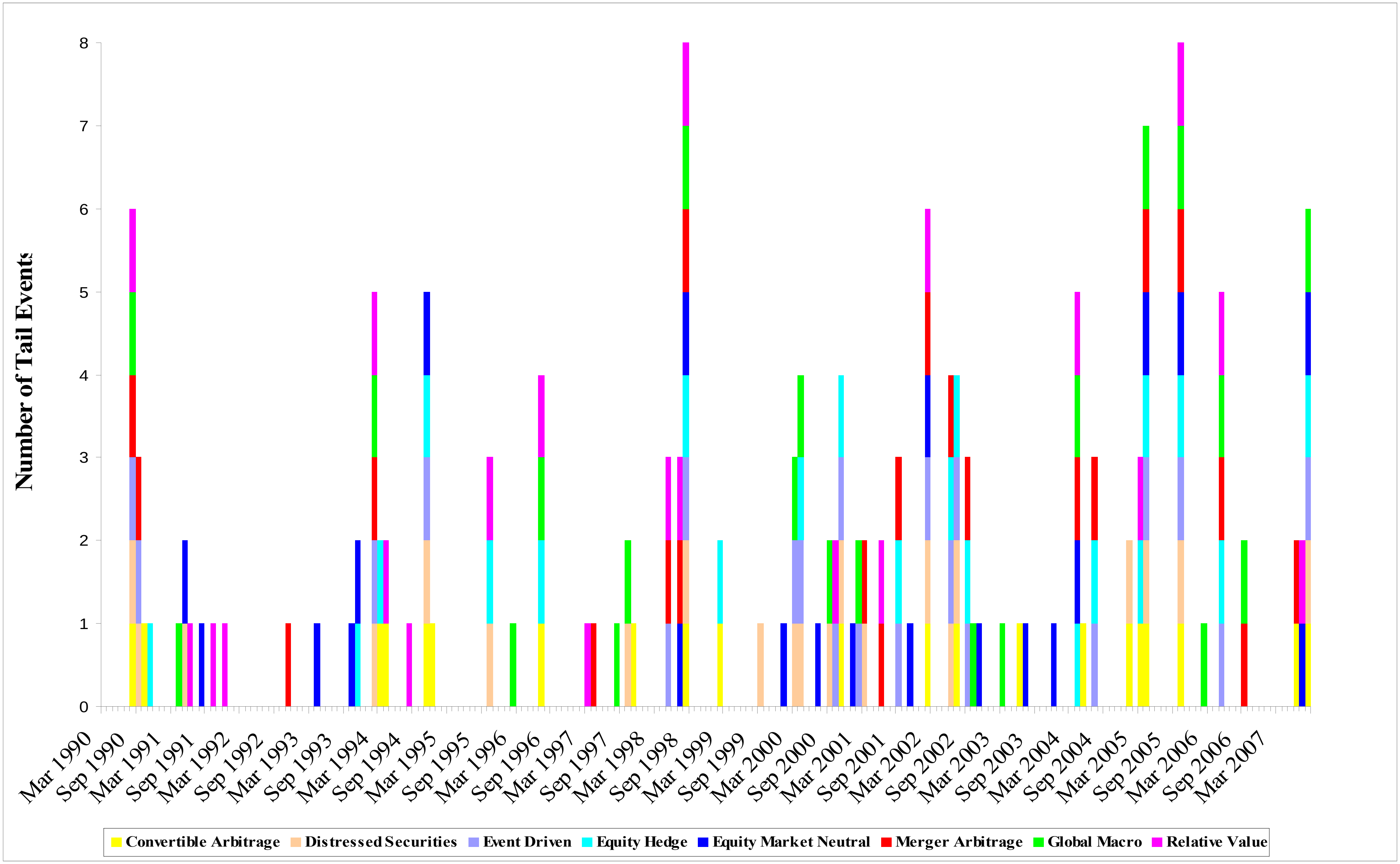
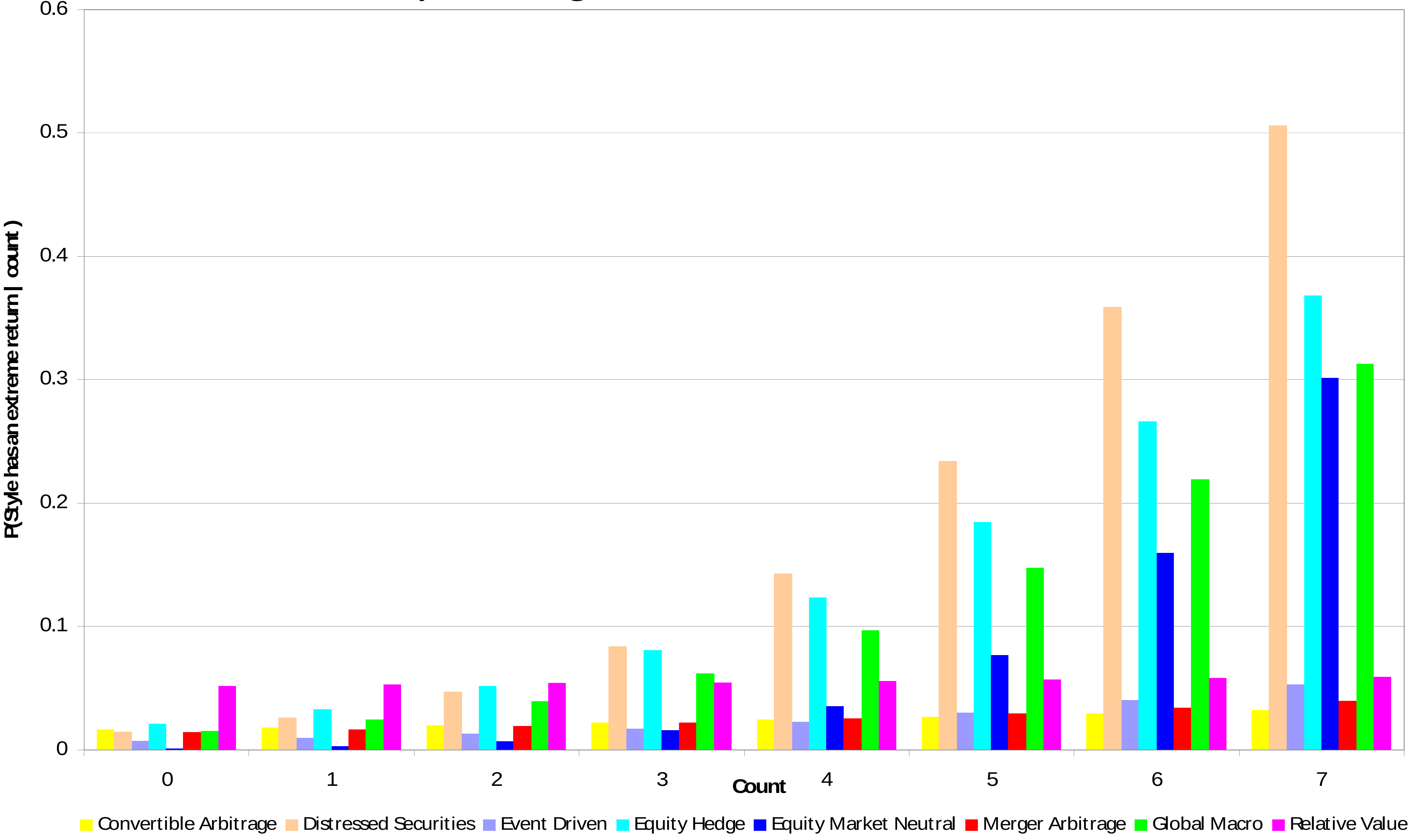


Figure 3:
Probability of Contagion Conditional on the Count Variable



Appendix A

This appendix contains descriptions of the eight hedge fund strategies included in the HFR hedge fund indices. The source of these descriptions is Hedge Fund Research.

Convertible Arbitrage

Convertible Arbitrage involves taking long positions in convertible securities and hedging those positions by selling short the underlying common stock. A manager will, in an effort to capitalize on relative pricing inefficiencies, purchase long positions in convertible securities, generally convertible bonds, convertible preferred stock or warrants, and hedge a portion of the equity risk by selling short the underlying common stock. Timing may be linked to a specific event relative to the underlying company, or a belief that a relative mispricing exists between the corresponding securities. Convertible securities and warrants are priced as a function of the price of the underlying stock, expected future volatility of returns, risk free interest rates, call provisions, supply and demand for specific issues and, in the case of convertible bonds, the issue-specific corporate/Treasury yield spread. Thus, there is ample room for relative misvaluations.

Distressed Securities

Distressed Securities managers invest in, and may sell short, the securities of companies where the security's price has been, or is expected to be, affected by a distressed situation. Distressed Securities managers invest primarily in securities and other obligations of companies that are encountering significant financial or business difficulties, including companies which (i) may be engaged in debt restructuring or other capital transactions of a similar nature while outside the jurisdiction of Federal bankruptcy law, (ii) are subject to the provisions of Federal bankruptcy law or (iii) are experiencing poor operating results as a result of unfavorable operating conditions, over-leveraged capital structure, catastrophic events, extraordinary write-offs or special competitive or product obsolescence problems. Managers will seek profit opportunities arising from inefficiencies in the market for such securities and other obligations.

Negative events, and the subsequent announcement of a proposed restructuring or reorganization to address the problem, may create a severe market imbalance as some holders attempt to sell their positions at a time when few investors are willing to purchase the securities or other obligations of the troubled company. If manager believes that a market imbalance exists and the securities and other obligations of the troubled company may be purchased at prices below the value of such securities or other obligations under a reorganization or liquidation analysis, the manager may purchase the securities or other obligations of the company. Profits in this sector result from the market's lack of understanding of the true value of the deeply discounted securities. Results are generally not dependent on the direction of the markets, and have a low to moderate expected volatility.

Equity Hedge

Equity Hedge, also known as long/short equity, combines core long holdings of equities with short sales of stock or stock index options. Equity hedge portfolios may be anywhere from net long to net short depending on market conditions. Equity hedge managers generally increase net long exposure in bull markets and decrease net long exposure or even are net short in a bear market. Generally, the short exposure is intended to generate an ongoing positive return in addition to acting as a hedge against a general stock market decline. Stock index put options are also often used as a hedge against market risk. Profits are made when long positions appreciate and stocks sold short depreciate. Conversely, losses are incurred when long positions depreciate and/or the value of stocks sold short appreciates. Equity hedge managers' source of return is similar to that of traditional stock pickers on the upside, but they use short selling and hedging to attempt to outperform the market on the downside.

Equity Market Neutral

"Equity market neutral" strategies strive to generate consistent returns in both up and down markets by selecting positions with a total net exposure of zero. Trading Managers will hold a large number of long equity positions and an equal, or close to equal, dollar amount of offsetting short positions for a total net exposure close to zero. A zero net exposure is referred to as "dollar neutrality" and is a common characteristic of all equity market neutral managers. By taking long and short positions in equal amounts, the equity market neutral manager seeks to neutralize the effect that a systematic change will have on values of the stock market as a whole.

Some, but not all, equity market neutral managers will extend the concept of neutrality to risk factors or characteristics such as beta, industry, sector, investment style and market capitalization. In all equity market neutral portfolios stocks expected to outperform the market are held long, and stocks expected to under perform the market are sold short. Returns are derived from the long/short spread, or the amount by which long positions outperform short positions.

Event Driven

Event Driven investment strategies or "corporate life cycle investing" involves investments in opportunities created by significant transactional events, such as spin-offs, mergers and acquisitions, industry consolidations, liquidations, reorganizations, bankruptcies, recapitalizations and share buybacks and other extraordinary corporate transactions. Event Driven trading involves attempting to predict the outcome of a particular transaction as well as the optimal time at which to commit capital to it. The uncertainty about the outcome of these events creates investment opportunities for managers who can correctly anticipate their outcomes. As such, Event Driven trading embraces merger arbitrage, distressed securities, value-with-a-catalyst, and special situations investing.

Some Event Driven Trading managers will utilize a core strategy and others will opportunistically make investments across the different types of events. Dedicated merger arbitrage and distressed securities managers are not included in the Event Driven index. Instruments include long and short common and preferred stocks, as well as debt securities, warrants, stubs, and options. Trading Managers may also utilize derivatives such as index put options or put option spreads, to leverage returns and to hedge out interest rate and/or market risk. The success or failure of this type of strategy usually depends on whether the Trading Manager accurately predicts the outcome and timing of the transactional event. Event Driven Trading Managers do not rely on market direction for results; however, major market declines, which would cause transactions to be repriced or break, may have a negative impact on the strategy.

Macro

Macro strategies attempt to identify extreme price valuations in stock markets, interest rates, foreign exchange rates and physical commodities, and make leveraged bets on the anticipated price movements in these markets. To identify extreme price valuations, Trading Managers generally employ a top-down global approach that concentrates on forecasting how global macroeconomic and political events affect the valuations of financial instruments. These approaches may be systematic trend following models, or discretionary. The strategy has a broad investment mandate, with the ability to hold positions in practically any market with any instrument. Profits are made by correctly anticipating price movements in global markets and having the flexibility to use any suitable investment approach to take advantage of extreme price valuations. Trading Managers may use a focused approach or diversify across approaches. Often, they will pursue a number of base strategies to augment their selective large directional bets.

Merger Arbitrage

Merger Arbitrage, also known as risk arbitrage, involves investing in securities of companies that are the subject of some form of extraordinary corporate transaction, including acquisition or merger proposals, exchange offers, cash tender offers and leveraged buy-outs. These transactions will generally involve the exchange of securities for cash, other securities or a combination of cash and other securities. Typically, a manager purchases the stock of a company being acquired or merging with another company, and sells short the stock of the acquiring company. A manager engaged in merger arbitrage transactions will derive profit (or loss) by realizing the price differential between the price of the securities purchased and the value ultimately realized when the deal is consummated. The success of this strategy usually is dependent upon the proposed merger, tender offer or exchange offer being consummated.

When a tender or exchange offer or a proposal for a merger is publicly announced, the offer price or the value of the securities of the acquiring company to be received is typically greater than the current market price of the securities of the target company. Normally, the stock of an acquisition target appreciates while the acquiring company's stock decreases in value. If a manager determines that it is probable that the transaction will be consummated, it may purchase shares of the target company and in most instances, sell short the stock of the acquiring company. Managers may employ the use of equity options as a low-risk alternative to the outright purchase or sale of common stock. Many managers will hedge against market risk by purchasing S&P put options or put option spreads.

Relative Value Arbitrage

"Relative value arbitrage" is a multiple investment strategy approach. The overall emphasis is on making "spread trades" which derive returns from the relationship between two related securities rather than from the direction of the market. Generally, Trading Managers will take offsetting long and short positions in similar or related securities when their values, which are mathematically or historically interrelated, are temporarily distorted. Profits are derived when the skewed relationship between the securities returns to normal. In addition, relative value managers will decide which relative value strategies offer the best opportunities at any given time and weight that strategy accordingly in their overall portfolio. Relative value strategies may include forms of fixed income arbitrage, including mortgage-backed arbitrage, merger arbitrage, convertible arbitrage, statistical arbitrage, pairs trading, options and warrants trading, capital structure arbitrage, index rebalancing arbitrage and structured discount convertibles (which are more commonly known as Regulation D securities) arbitrage.

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