Hedge fund contagion and liquidity

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Abstract

Calling contagion the dependence in the probability of occurrence of extreme returns across different hedge fund styles and asset classes that cannot be explained by correlation, we find no systematic evidence of contagion between monthly returns on eight hedge fund styles and equity, bond, and currency markets. In contrast, the average probability that a style index has a return in the lower 10% tail increases from 1.67% to 39.92% as the number of other styles indices with a return in the lower 10% tail increases from 0 to 7. To explain this strong evidence of contagion across hedge fund styles, we investigate how the intensity of contagion depends on various proxies for funding liquidity and asset liquidity. We find that hedge fund contagion is magnified when prime brokerage firms have poor performance (which we would expect to affect hedge fund funding liquidity adversely) and when asset market liquidity is low. Commodity Trading Advisors (CTAs) are not subject to hedge fund contagion.

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Figure 1 reports the returns of eight hedge fund style daily indices during August, 2007. The figure shows that, strikingly, most indices performed extremely poorly at the same times even though the indices correspond to very different hedge fund styles. Why would a hedge fund index of convertible arbitrage funds perform poorly when an index of macro funds has poor performance? It could be that such a 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, where poor performance spreads across countries, asset classes, or investment strategies for reasons not related to correlation in fundamentals. In this paper, we investigate whether the apparent contagion that took place in August 2007 is atypical within the hedge fund industry, or whether hedge fund contagion is a systematic phenomenon.

In epidemiology, the concept of contagion describes a situation where an individual with a disease transmits his sickness to a healthy individual. In this paper, we investigate whether hedge fund styles can suffer from contagion, in the sense that extremely poor returns on the main markets or on other hedge fund styles lead to extremely poor returns for a hedge fund style. Since many hedge fund style returns are positively correlated with each other and with the returns on main markets, it would not be unusual for a given hedge fund style to perform poorly when other hedge fund styles or the main markets perform poorly. However, to describe this relationship as contagious, the association between extremely poor performance in a hedge fund style and extremely poor performance in other hedge fund styles or the main markets must be stronger than that predicted by historical correlations alone. Given this distinction, we find no consistent evidence of contagion between the main markets and hedge fund indices, but we demonstrate strong evidence of contagion between hedge fund indices. The probability of one hedge fund having extremely poor performance increases significantly with the number of other hedge fund indices that also have extreme poor performance.

Whether hedge fund styles suffer from contagion is an important issue for investors, risk managers, and regulators. For investors, the diversification benefits obtained from investing in hedge funds are compromised if hedge fund contagion is economically significant. 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 are likely overstated when based on historical correlations.[1] 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 et al. (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 a problem, 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. However, if contagion is a serious issue, 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.

Our paper builds on a large economics and finance literature that investigates contagion. This literature has its origin in studies of contagion resulting from emerging market crises and currency crises. As shown by Dornbush, Park, and Claessens (2000), there are many definitions of contagion. Our definition is that used in Eichengreen, Rose, and Wyplosz (1996) and Bae, Karolyi, and Stulz (2003). These papers define contagion as the heightened likelihood of occurrence of extreme adverse events in a sector of the world economy when extreme adverse events have occurred elsewhere, after controlling for fundamental correlation effects. Eichengreen, Rose and Wyplosz (1996) examine devaluations and Bae, Karolyi, and Stulz (2003) investigate extremely poor stock index returns. These papers test for contagion using the logistic model, assuming an underlying binomial or multinomial distribution. However, for rare

[1] 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).

events such as the contagion events that we model, the Poisson regression framework has an advantage in that it explicitly assumes that the probability of observing an additional event of a count variable (as in 0 events versus 1 event, or 1 event versus 2 events) is "small."[2] We therefore report results using the Poisson regression framework, but discuss robustness tests that use the binomial and multinomial distribution models.[3]

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 that an explanation for this relation is 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 because of losses in unrelated strategies. Their paper therefore 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. Our paper significantly extends this research in several ways. First, we document contagion between hedge fund indices and show that there is no systematic contagion between hedge funds and the broad markets. Second, we investigate channels through which contagion is hypothesized to occur and find strong support for the role of some of these channels.

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[2] We thank Bill Greene for suggesting the use of the Poisson model.

[3] 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.

In our analysis, we use monthly hedge fund index return data from HFR (Hedge Fund Research) for eight different hedge fund styles. We focus on 10% tail events (i.e., the bottom 10% of the entire time series of returns). Using the Poisson regression methodology, 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 on the number of other hedge fund style indices that have a negative tail event (represented by the COUNT variable, which ranges in value from 0 to 7). We use as explanatory variables the returns of the main markets and of 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 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 the COUNT variable. Across the eight regressions (one for each hedge fund style), the coefficients on the indicator variables for the main market returns have inconsistent signs. Consistently positive signs on the main market indicator variables would indicate contagion – that a negative tail event in a main market makes it more likely that a negative tail event takes place in a hedge fund style. Specifically, of 24 coefficients on main market indicator variables (three main market indicator variables for eight separate hedge fund style regressions), 15 have a negative sign, which is inconsistent with the hypothesis of contagion from the main markets. In contrast, the coefficient on the COUNT variable is positive in all eight of the regressions, with seven coefficients significant at the 10% level or better, and the eighth coefficient significant at the 12% level, indicating a high level of contagion between hedge fund styles. The economic significance of the hedge fund contagion we measure is large. If all the explanatory variables are at their mean except for COUNT, the average probability that a style index has a return in the lower 10% tail increases from 1.67% to 39.92% as COUNT increases from 0 to 7.

After documenting the existence of contagion between hedge fund styles, we investigate its possible causes. An obvious concern is that there are problems with the indices we use, such as funds being misclassified in indices. Such misclassification would not, however, explain contagion – it would simply explain greater correlation. 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 due to their trading strategies. These unique trading strategies result in a nonlinear relationship between hedge fund returns and main market returns, similar to the payoff of an option contract. Thus, it is possible that our finding of contagion between hedge fund style returns is simply a proxy for these nonlinearities in hedge fund returns. We find that this is not the case: after allowing for these proxies, the COUNT variable is still positive for all styles and is still significant for six styles.

After rejecting statistical explanations for our findings, we turn to economic explanations for the contagion we document. We focus on the role of funding liquidity and asset liquidity as channels of contagion. Hedge fund losses in one or a few styles can lead lenders to hedge funds to reduce their lending across the board and make it more expensive, so that the funding liquidity of hedge funds falls. As a result, levered funds must reduce their leverage, typically by selling some of their holdings. These asset liquidations will put pressure on prices and reduce asset liquidity, leading to a trading liquidity spiral (Brunnermeier and Pedersen (2008). Also, as funds make mark-to-market losses, their access to credit falls, giving raise to a funding liquidity spiral (Brunnermeier and Pedersen (2008); see also Cifuentes, Ferrucci and Shin (2004) for contagion induced by mark-to-market losses).

As Chan, Getmansky, Haas, and Lo (2005) emphasize, lenders to hedge funds may also be pursuing similar strategies to hedge funds through their proprietary trading desks, which can worsen contagion because losses by these lenders reduces their capital and their ability to lend. Since prime brokers are direct lenders to hedge funds, we create a stock return index for the 11 most active prime brokers. We find that the number of hedge fund styles with extremely poor returns is significantly higher when our Prime Broker Index has an extremely poor return. Using our Poisson regression model, we show that, accounting for correlations and for various control variables, the increase in the probability of an extremely poor return when our Prime Broker Index has a poor return is statistically and economically significant. We find similar but slightly weaker results when we use a broader bank index. 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 across stocks of the daily ratio of absolute stock return to dollar volume. 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. Using this measure in our Poisson model, we show that the probability of an extremely poor return in a hedge fund style is higher when stock market liquidity is low. In some sense, our proxies for channels of contagion work too well because, when we use 10% tails for these proxies, we find it difficult to estimate the Poisson regression models because of multicollinearity. We therefore confine the analysis to 25% tails for the proxies. However, we also show that the COUNT variable is significantly higher when the channel proxies have 10% tail returns. Strikingly, when the proxies for funding liquidity (the prime broker index) and asset liquidity both have 10% tail returns, COUNT has a mean of 4.33; otherwise, the mean of COUNT is 0.54.

We also explore several additional factors that may affect hedge fund contagion. First, we use credit spreads for the cost of funding. We find that their effect is similar in direction but weaker than the effect of our prime broker index. Second, we use as proxies for funding liquidity measures of activity and cost in the repo market. These measures have little success. Third, hedge funds flows to other hedge fund styles do not seem to be associated with the intensity of contagion.

Finally, we examine the prevalence of contagion among Commodity Trading Advisors (CTAs) using an index from MAR/Hedge, since the HFR indices we use do not include a CTA index. These funds have been shown to have negative correlations with stock markets and other hedge funds during periods of extreme returns (Fung and Hsieh, 1999, Liang, 2004), have a primary trading venue consisting of highly liquid futures markets, and are specialized in the strategies they employ. We would therefore expect CTAs to be less affected, or not affected at all, by contagion propagated through funding and asset liquidity shocks. In our Poisson regressions for the CTA index, the coefficient on the COUNT variable is negative and highly significant, in contrast to the coefficients on the COUNT variable for the other hedge fund styles which is always positive. In addition, CTA funds also have no contagion with main market indices.

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 examines the relationship between the eight hedge fund indices and broad market returns, and the relationship across hedge fund returns. Section III examines possible economic explanations for contagion using proxies for funding illiquidity and asset illiquidity. Section IV performs an analysis of contagion for Commodity Trading Advisors (CTAs). We attempt to interpret our results and conclude in Section V.

I. Data

Our hedge fund style returns are the monthly style index returns provided by 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, Macro, Merger Arbitrage, and Relative Value Arbitrage.[4] The monthly indices are aggregates that include over 1,600 funds, with no required minimum track record or asset size. Additionally, the monthly indices are not investible; that is, they include funds that are closed to new investment dollars. In addition to the eight HFR indices, we also report data on a Commodity Trading Advisor Index, provided by MAR/Hedge. 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 unchanged.

In our study, we also investigate contagion between the main financial markets and hedge fund indices. 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 trade-weighted US dollar exchange index published by the Board of

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

Governors of the US Federal Reserve System (FRB dollar index in the following) to proxy for the return of the currency market.[5]

Table I provides summary statistics and correlations for the monthly hedge fund indices and the 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 other 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.[6] The approach to filter a time-series with a GARCH process and use the residuals 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 therefore be viewed in light of these EVT applications.

The relatively high correlations we observe between hedge fund indices and between hedge fund indices and market indices indicate how important it is for us to control for correlation in our contagion

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

[6] Ljung-Box tests on these residuals indicate that using AR(1)-GARCH(1,1) processes are sufficient to remove the autocorrelation except for the equity market neutral style where we employed a AR(2)-GARCH(1,1) model.

tests to make sure 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 linear relationship between hedge funds returns and market returns in our tests by including the returns on the market factors as well as the returns on the other hedge fund indices. 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 monthly HFR index data

The monthly data used in our analysis is from January 1990 to August 2007 for 212 monthly observations. This 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 observations for each style. Had we chosen a 5% cutoff instead, we would have only ten observations per index in our sample.

II.1. Existing approaches

There is a large literature on contagion in emerging markets.[7] 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), Forbes and Rigobon (2002), and others 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 investigating behavior during extreme market conditions, while the approach we use specifically focuses on nonlinearities in return distributions. Third, correlations are

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

particularly ill-suited for evaluating contagion for hedge funds because these funds often pursue strategies with non-linear payoffs.

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 resorting to using correlations, it 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.

A 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. 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 a few observations.

II.2. The Poisson regression approach

We use a Poisson regression model to examine contagion.[8] A Poisson regression model is a generalized linear model with a "log" link function and Poisson distributed errors. This model attributes to a count response variable Y a Poisson distribution whose expected value depends on predictor variables

[8] Much of the following discussion follows Hausman, Hall, and Griliches (1984).

x in the following way: $\log E[Y_{it} | x_{it}] = \beta_i x_{it}$ where x_{it} is a vector of regressors describing the characteristics of an observation unit i (a hedge fund index return in our study) during a given time period t, and Y_{it} is the observed event count (number of extreme returns) for unit i 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. As noted earlier, the Poisson regression is particularly appropriate when analyzing "count" data for rare events that occur during a period of time t. In the analysis of hedge fund returns, we set the dependent variable to 0 if the index does not have an extreme return in any given month, and to 1 if the index does have an extreme return, where an extreme return is defined as a standardized return that is in the lowest 10% of all returns for that index over the entire time period studied. Because the events or incidents of extreme returns during any given period we are modeling are rare events by construction, the Poisson approach is well-suited for our analysis. 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.

If there is no contagion, a regression model in which the values of risk factors that affect hedge fund index returns enter linearly should describe the likelihood that a hedge fund index will have an extreme return. By contrast, with contagion from a specific risk factor, the likelihood of an extreme hedge fund index return is greater when that risk factor has an extreme realization than would be predicted by a model in which the risk factors enter only linearly. To account for this nonlinear dependence, we add to the regression model in which risk factors also enter linearly, indicator variables that take the value 1 when certain of the risk factors have extreme realizations and 0 otherwise where the definition of an extreme realization in a risk factor is equivalent to the definition of an extreme hedge fund index return. The coefficients on these extreme return indicator variables measure contagion.

The basic Poisson probability specification is:

$$\Pr\left(Y_{it} = n_{it} \mid x_{it}\right) = \frac{e^{-\exp(\beta_i x_{it})} \exp(\beta_i x_{it})^{n_{it}}}{n_{it}!} \tag{1}$$

In our monthly analysis, i represents a hedge fund index, t the month, and $n_{it} \in \{0,1\}$ whether index i has an extreme outcome ($Y_{it} = 1$) during month t. The mean value of Y, $\exp(\beta_i x_{it})$, depends on a vector of explanatory variables x_{it}, where the exponential function guarantees non-negativity. Maximum likelihood with a log-likelihood function is used to estimate the model for a sample of T observations for each index as:

$$L(\beta_i) = \sum_{t=1}^{T} [n_{it}! - e^{\beta_i x_{it}} + n_{it}! \beta_i x_{it}] \tag{2}$$

Goodness-of-fit is measured using McFadden's (1974) pseudo-R^2 approach, where both unrestricted (full model) likelihood, L_ω, and restricted (constant-only model) likelihood, L_Ω, are compared:

$$\text{pseudo } R^2 = 1 - \frac{\log L_\omega}{\log L_\Omega} \tag{3}$$

As noted earlier, we use the Poisson regression approach for the majority of our analyses. In addition, we use the binomial and multinomial logit models for robustness tests.[9]

II.3. 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. Our basic regression specification has as the dependent variable an indicator set to 1 if the hedge fund index under study has a return in the bottom 10% of all returns for that index, and 0 otherwise. Independent variables include the three main market indices: the Russell 3000, the LB bond index, and the FRB dollar index. Also included are indicator variables for extreme returns in the main market indices (set to 1 if the return for that month is in the bottom 10% of all returns for the index). A positive and significant coefficient on an indicator variable is interpreted as contagion between that main market and the hedge fund index. Additionally included are returns on the other seven hedge fund indices, measured as an equally-weighted index of these indices. Our tests are robust to including each other hedge fund index return separately.

[9] For a detailed description of the logit models used, see Bae, Karolyi, and Stulz (2003).

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, 1 if one of the other indices has an extreme return for the month, and so on up to a maximum value of 7 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.

Results are presented in Table II. 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. As noted earlier, all variables except the indicator variables have been standardized using an AR-GARCH process to remove autocorrelation and volatility clustering.

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. For the hedge fund indices, the result is similar; of the 3 significant coefficients, 2 are positive and 1 is negative. The results are also similar for the indicator variables for the main markets. While there are some statistically significant results, the signs are not consistent. Of the 24 indicator variables, 15 are negative, of which 6 are statistically significant, and 9 are positive, of which 4 are statistically significant. These results provide no evidence of systematic contagion between main markets and hedge funds. However, it is noteworthy that for the Russell 3000 index, we find three significant positive indicator variables and no significant negative indicator variables, whereas for the other market indicator variables, almost all significant coefficients are negative. One might therefore conclude that there is a hint of contagion between hedge funds and equity markets.

The results for the COUNT variable provide strong evidence of contagion. All eight of the coefficients on the COUNT variable are positive and seven are statistically significant at least at the 10% probability level. The one coefficient that is not significant at the 10% level has a p-value of 12%. Importantly, this evidence is obtained when controlling for the equally-weighted returns of the other hedge fund styles indices, so that we fully allow for correlation to play its role. We also estimated these regressions replacing the average return of the hedge fund indices with the return of each individual index. Our conclusions are not affected using this approach.

Since Fung and Hsieh (1997), it is well-known that hedge funds pursue strategies with highly non-linear payoffs.[10] 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. Further, to address the concern that our evidence of contagion is due to omitted variables, we also add additional control variables to our regressions. Because it is likely that the 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. For the non-linear factors, 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.[11]

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 - Wilshire Large Cap 750 monthly return, a bond factor, calculated as the change in the 10-year treasury constant maturity yield from month-end to

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[10] 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).
[11] We thank David Hsieh for providing us these returns for the period January, 1990 to August, 2007.

month-end, and finally, 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.[12]

Table III adds these factors to the regressions from Table II. The addition of these factors adds significant explanatory power to the regressions. The average likelihood ratio (McFadden's pseudo R^2) increases from 0.254 to 0.400. Further, many of the additional variables are individually significant in the regressions. In particular, each of the additional variables has statistically significant coefficients in at least one of the regressions, and many are significant in several regressions (for example, volatility on the FRB dollar index and the size-spread variable are significant for 6 of the 8 regressions).

Despite the addition of many control variables to our regressions, the results for contagion between main markets and hedge fund styles do not change. In these results, 13 of the 24 coefficients on the main market indicator variables are negative, as compared to 15 of the 24 from the first set of regressions in Table II. Clearly, in both sets of regressions there is no systematic evidence of contagion between hedge funds styles and the main markets. However, the evidence of contagion between hedge fund styles documented in Table II continues to hold in these regressions. Here, even after controlling for a number of additional factors, all the coefficients on the *COUNT* variable are positive, and 6 of 8 are statistically significant.

We now evaluate the economic significance of the contagion we document. The average return of a particular style is strongly related to the number of other styles that experience an extremely poor return. The difference in average returns for style indices when all other styles experience an extreme negative return compared to the average return when none of the others 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 1.67% (1.50%) to 39.92% (21.00%) as COUNT increases from 0 to 7. Another way to evaluate the economic significance of contagion is as in Figure 2. This figure shows the

[12] 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.

probability of an extreme return for each hedge fund style index as the COUNT variable increases from 0 to 7. The probability of an extreme return increases for all style indices as the COUNT variable increases. The increase is especially dramatic for the Event Driven style and the Merger Arbitrage style. It is smallest by far for the Convertible Arbitrage style and for the Global Macro style.

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 event 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 the contagion that we observe. Hence, we reject this explanation as implausible.

The results of this section clearly document 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.

Section III: Contagion Channels

Why could the poor performance of a hedge fund style affect adversely the performance of another, different, hedge fund style? We discussed in the introduction the role of funding liquidity as a channel through which contagion can take place. 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 they do so, they reduce the prices of the assets they sell if these assets trade in imperfectly liquid markets. The sales consume liquidity when they take place. As prices fall because of price pressure, hedge funds have to liquidate more assets because of mark-to-market losses. Consequently, a reduction in asset liquidity leads to greater contagion and can be viewed as a contagion channel. This view of mechanisms of contagion is not original to this paper. It follows directly from the seminal paper of Brunnermeier and Pedersen (2008).

We now consider why hedge fund losses in one style could lead to a reduction in funding liquidity and hence lead to losses of hedge funds in other styles. For a reduction in funding liquidity to take place, it has to be that the hedge fund losses in one 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 that are 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 implement through proprietary trades the trades that led to hedge fund losses. Second, losses by hedge funds can become losses for prime brokers both because hedge funds are debtors of prime brokers (though 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 have to decrease their lending, which then 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 Lipper Hedge World.[13] 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.[14] We construct an

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

[14] 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-

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 http://finance.yahoo.com to gather the data for 2007. All returns are adjusted for splits and dividends.

Our second proxy is the Datastream bank stock index. This index is an equally weighted index of large banks provided by Datastream. It includes primarily national commercial and regional banks; the only company common to both the Datastream index and the Prime Broker Index is Bank of America. 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. 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, 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.

Third, we employ as a proxy for asset liquidity the liquidity measure of Amihud (2002).[15] This variable measures the daily price response associated with one dollar of trading volume, and serves as a rough measure of price impact. Though this measure is used for the stock market, the literature suggests that reduced liquidity on the stock market is associated with reduced liquidity in other markets.[16]

E39D693EE55D%7D&siteid=, and Moore, Heidi, "Lehman Takes Aim at Prime Brokerage," September 29, 2006. http://www.financialnews-us.com/?page=ushome&contentid=1045562640

[15] 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.

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

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 volume, and Adrian and Fleming (2005) argue that while not perfect, net repo volume reflects dealer leverage. Volume in the repo market is obtained from John Kambhu of the Federal Reserve Bank of New York and is the difference between overnight repo and reverse overnight repo volume. This variable is available only at the weekly frequency. Thus, 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 dependent variable.

The final proxy we use is cash flows for other hedge funds. If hedge funds are forced to sell assets in a liquidity crisis due to withdrawal requests by their investors, there would be an increase in hedge fund redemptions across styles. We calculate monthly flows for hedge fund styles from the Tremont/Lipper hedge fund database for the entire period. These cash flows are calculated for each hedge fund separately, and aggregated by fund style. Then the monthly percentage change in cash flows is calculated for the entire style index.[17]

Thus, we have six measures: 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 flows from other hedge funds (FLOW).[18] As in earlier regressions, we use the standardized residuals from GARCH(1,1) models for each variable to control for autocorrelation and volatility clustering. Each of the standardized measures enters the regression as a continuous variable. In addition, we create dummy variables for each of the variables to capture extreme realizations of these variables that can be interpreted as situations in which liquidity is poor. For the PBI and BANK indices, we create a

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[17] In the regressions, the flows for all other hedge fund style styles besides the style of interest are aggregated to form the "flow" variable. The matching process from the TASS 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 TASS and HFR and use judgment to match as closely as possible. This methodology might explain why our results for flows are generally weak.

[18] We also use first difference in the repo spread over the Tbill and find much weaker results.

dummy variable set to 1 if the returns for the index are in the bottom quartile of returns for the entire time series and 0 otherwise. For CRSPRD, we create a dummy variable set to 1 representing the quartile when the credit spread is the largest and 0 otherwise. For REPO, we create a dummy variable set to 1 if the decrease in repo volume is in the top quartile (largest absolute decreases in volume) and 0 otherwise. For STKLIQ we create a dummy variable that is set to 1 if the stock illiquidity is in the top quartile, and 0 otherwise, and finally for FLOW, we create a dummy variable set to 1 for the quartile with the highest fund outflows, and 0 otherwise. The variables are constructed so that when the dummy variable is equal to 1, liquidity is low. We also performed the analysis setting the dummy variables equal to 1 at the 10^{th} percentile for PBI, BANK, and REPO, and at the 90^{th} percentile for the other variables. A difficulty with this approach is multicollinearity becomes a concern, though this problem suggests that the variables we have chosen are important channels of contagion.

Table IV presents summary statistics for the channel variables. These are the raw measures of the 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 25^{th} and 75^{th} percentiles, and all variables have excess kurtosis. The correlations between the variables are generally not high or are 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 financial services industry. However, our results below show 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 0 to 8. It is set to 0 if no hedge fund index has a 10% tail return during a month, 1 if one hedge fund index has a 10% tail return during a month, and so on, up to a maximum value of 8 when all 8 hedge fund indices have an extreme negative return. We calculate the mean value of the COUNT8 variable conditional on the realization (0 or 1) 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 1 implies that more hedge funds styles perform poorly when liquidity is low, i.e., contagion is more important when that measure of liquidity is low.

The results in Table V indicate that 4 of the 6 liquidity variables proxy for contagion channels. These include the PBI, BANK, STKLIQ, and CRSPRD. The results are strongest for PBI and STKLIQ, 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 about 2 hedge funds have extreme poor realizations in returns, compared to 0.33 hedge funds when PBI returns are not in the bottom quartile. The results are similar for STKLIQ. These tests provide strong support that hedge fund contagion is affected by the liquidity proxies. The only liquidity proxies that are not helpful to predict COUNT8 are the hedge fund outflows and the repo volume. As further evidence of the importance of asset and funding liquidity, the COUNT8 variable has a mean of 3.71 in the joint presence of poor asset liquidity (in the form of a top quartile value of Amihud's measure) and of poor funding liquidity (in the form of a bottom quartile value of the prime broker index return) and 0.26 otherwise.

In the last part of Table V, we show results for the case where both PBI and STKLIQ have values in the 10% percentile of their distribution. This is the case for only six sample months. However, the mean count for these six sample months is extremely high at 4.33. This evidence shows that hedge fund styles perform poorly when both funding liquidity and asset liquidity are poor at the same time, confirming the importance of these contagion channels.

We also perform multivariate tests using the liquidity proxies in Table VI. Specifically, we repeat the regressions of Table III, adding separately each liquidity proxy, both the indicator variable and the continuous variable. Note that in these regressions, COUNT is defined as in Table III and ranges in value from 0 to 7, set equal to the number of other hedge fund indices that have returns in their 10% negative tail when the index being tested has a return in its 10% negative tail. Because the dummy variables are set to 1 when markets are illiquid, a positive and significant coefficient on the dummy variable indicates that this variable increases the probability that a hedge fund will have an extreme negative return. With the Poisson regressions, a positive and significant coefficient on the dummy variable also means that the relation between the probability of a tail return and COUNT is magnified. A difficulty with estimating the regressions is that, for some styles, multicollinearity is a serious problem when we define the indicator variables for the liquidity proxies at the 10% tail of the distribution of these proxies. This difficulty suggests that our channel variables do well in specifying states of the world when hedge fund styles in general perform poorly. To reduce the importance of this problem, we only consider regressions where the indicator variables for the liquidity proxies are defined at the 25% tail of the distribution of these proxies.

The regressions in Table VI include all the control variables from Table III, but for brevity, they are not reported. In Table V, each panel (A-F) reports regression results for a different liquidity proxy. Examining the results, the coefficients on the COUNT variable generally do not change in sign or significance from their values in Table III. Turning to the liquidity proxies, the proper interpretation is that a positive coefficient on a liquidity variable indicates that this variable intensifies contagion in hedge funds. Prior results of Table IV indicate that four liquidity proxies are significantly associated with increases in the COUNT variable. These are PBI, BANK, STKLIQ, and CRSPRD. Coefficients on each of the dummy variables using these proxies are estimated for the eight hedge fund indices. Of the 32 coefficients, 26 are positive, and of these, 17 are statistically significant. The results are strongest for PBI, followed by STKLIQ, BANK and CRSPRD. There is one exception to this general trend, the Global Macro index. While the coefficient on the PBI contagion variable is positive and statistically significant for Global Macro, the coefficients on STKLIQ, BANK, and CRSPRD are negative and statistically significant. Thus, it appears that Global Macro funds rely on their Prime Brokerage firms to provide liquidity, but are not affected through other liquidity channels. With this one exception, these regressions provide consistent evidence that contagion in hedge funds is strongly amplified when funding and asset are poorer.

Because the regressions use an indicator variable as the dependent variable, interpretation of the coefficients on the liquidity indicator variables is not straightforward. Hence, to help facilitate the interpretation of these coefficients, we perform the following analysis for the most significant liquidity proxies (PBI, STKLIQ, BANK, and CRSPRD). In each regression, we set all variables equal to their mean levels (with the exception of the COUNT variable and the dummy variable for liquidity) and evaluate the regression. We then calculate a conditional probability difference as follows: [P(COUNT = k|Liquidity dummy = 1) – P(COUNT = k|Liquidity dummy = 0)] for all possible realizations of the COUNT variable (k = 0 to 7). The difference in probability represents the magnitude of the impact that the liquidity variable has on hedge fund contagion.

Figure 3 graphs these probability difference results for each liquidity proxy (PBI, STKLIQ, BANK, and CRSPRD) by each hedge fund index and COUNT variable. The x-axis plots different realizations of the count variable, while the y-axis plots the probability difference. The results provide an assessment of the magnitude of the effect of the liquidity proxy dummy variable on contagion. For example, for the PBI illiquidity variable and the Distressed Securities hedge fund index, the probability of the count variable being equal to 7 increases by over 50% when the PBI has a return in the bottom quartile versus when it does not. For the same index, the probability of the count variable being equal to 7 increases by over 80% when the STKLIQ has a realization in the top quartile versus when it does not. A similar interpretation applies to the other illiquidity indicator and associated COUNT variables.

The STKLIQ and PBI variables provide the most explanatory power for hedge fund contagion, consistent with the "phase locking" behavior described by Chan, Getmansky, Haas, and Lo (2005) and the liquidity spirals modeled by Brunnermeier and Pedersen (2008). Taken together, these results indicate strong evidence that funding and asset liquidity are channels through which contagion takes place.

V. Contagion and Commodity Trading Advisers

As an additional test of contagion, we perform a contagion analysis of Commodity Trading Advisers (CTAs). CTAs (also known as Managed Futures funds) are investment vehicles that invest primarily in derivatives contracts, including highly liquid futures contracts. CTAs do not typically trade in the underlying equity, stock, or bond markets (see Liang, 2004). As opposed to hedge funds, which are unregulated, they operate in the regulated futures environment. Traders with large futures positions are required to file daily reports with the CFTC (Commodity Futures Trading Commission). In addition, the CFTC and the futures exchanges set futures margins and position limits on futures contracts. (see Fung and Hsieh, 1999).

Fung and Hsieh (1997, 2001) examine the performance features of CTA funds. They focus on one type of CTA fund, known as a trend following fund. In their sample, about 70% of the CTAs represented follow this investment style. Briefly stated, trend following funds attempt to profit from major trends in markets, either up or down, and their strategies may be described as long “gamma” or long volatility. Fung and Hsieh (1997, 2001) document that these funds perform extremely well when broad markets perform extremely well or extremely poorly, and perform the worst when broad markets have average performance. As a result, the returns of CTAs have extremely low correlations with broad markets and with most other types of investment categories.

Based on these patterns in performance, a number of research papers have suggested that CTAs make good hedging vehicles to protect against downside risk. Not only do CTAs have good performance when broad markets have poor performance, but because CTAs trade in the highly liquid futures market, they are unlikely to face the type of asset liquidity crisis described by Brunnermeier and Pedersen (2008). Further, CTAs are also positioned to withstand better decreases in funding liquidity because they are not holding illiquid positions, and hence would not have to liquidate such positions if funding availability decreases.

Thus, CTAs provide an interesting venue in which to study contagion. Table I presents means and correlations of CTAs. The CTA index we use is a monthly index provided by Barclay Hedge. As expected based on prior literature, CTAs have a very low correlation with the equity market, -0.07. Their correlations with the bond and dollar are slightly higher but still not large. In addition, they are generally uncorrelated with hedge fund returns as well.

To examine whether CTAs have contagion with broad markets or other hedge funds, we perform a regression analysis identical to that performed in Table III for hedge funds. We set the dependent variable to 1 if the CTA return is in the bottom 10% of all returns and 0 if not. Results are reported in

Table VII, column 1. For brevity, we only report the coefficients on the equally weighted index of the eight hedge fund indices, the COUNT8 variable, which takes a value of 0 to 8 corresponding to the number of hedge fund indices that experience extremely poor returns in a given month, and indicator variables for poor performance in stock, bond, and currency markets.

The results in Table VII are striking. In column 1, the coefficient on the COUNT8 variable is negative and statistically significant. This result provides strong evidence that CTAs do not experience contagion from hedge fund styles. Also notable in column 1 is that none of the coefficients on the broad market indicator variables are significant. Hence, there is no evidence of contagion between broad markets and CTAs. When the liquidity proxies are included in columns 2-7, with the exception of the prime broker variable, the liquidity indicator variables are all negative and highly statistically significant, implying that low levels of liquidity generally decrease the probability that a CTA will have an extreme negative return.

The results on CTAs provide a consistent picture: they exhibit no contagion with hedge funds or broad markets, and further, funding or asset liquidity measured by our proxies do not appear to affect CTAs.

VI. Implications and Conclusions

In this paper, we use a new approach to study contagion in hedge funds. Our approach, which uses a Poisson regression model, avoids many of the issues inherent in tests of correlations. By using the Poisson model, we focus on co-incidences of extreme poor returns in the broad markets and hedge fund indices. 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 properties and determinants of hedge fund returns.

Further, we investigate a number of possible channels through which this contagion might take place. Specifically, we use proxies for asset liquidity and funding liquidity, based on theoretical work by Brunnermeier and Pedersen (2008). These channels include a prime broker index, a bank index, Amihud's (2002) illiquidity measure, change in credit spreads, change in repo volume, and flows from other hedge funds.

We find no systematic evidence of contagion between broad markets and hedge funds 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 typically 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 also find that CTAs are not exposed to contagion from hedge fund style index 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 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. 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.

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 I.1. and Appendix A. In addition, summary statistics are reported for the Commodity Trading Advisor Index (CTA) which is provided by MAR/Hedge. 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								Mar/Hedge CTA Index	Main Market Factors		
	Convertible Arbitrage	**Distressed Securities**	**Event Driven**	**Equity Hedge**	**Equity Market Neutral**	**Merger Arbitrage**	**Global Macro**	**Relative Value**	**CTA Index**	**Russell 3000 return**	**Return on LB bond Index**	**Δ in FRB Dollar Index**
Number of observations	212	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%	0.79%	0.94%	0.58%	0.07%
Median	0.99%	1.14%	1.34%	1.35%	0.65%	1.04%	0.84%	0.92%	0.99%	1.39%	0.66%	0.00%
Standard deviation	1.00%	1.68%	1.83%	2.46%	0.88%	1.20%	2.31%	1.01%	1.00%	4.01%	1.09%	1.81%
Skewness	-1.082	-0.631	-1.272	0.209	0.186	-2.504	0.405	-0.813	-1.082	-0.585	-0.398	-0.190
Excess kurtosis	2.028	6.018	4.818	1.599	0.566	11.282	0.796	10.630	2.028	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**	0.01	**0.30**	0.18	**-0.03**
Distressed Securities		1.00	**0.79**	**0.59**	**0.20**	**0.52**	**0.47**	**0.68**	-0.09	**0.44**	0.03	-0.06
Event Driven			1.00	**0.78**	**0.24**	**0.73**	**0.56**	**0.64**	-0.05	**0.69**	0.06	-0.02
Equity Hedge				1.00	**0.38**	**0.50**	**0.60**	**0.54**	0.03	**0.72**	0.07	0.04
Equity Market Neutral					1.00	**0.25**	**0.28**	**0.28**	**0.20**	**0.16**	**0.19**	0.04
Merger Arbitrage						1.00	**0.32**	**0.47**	-0.04	**0.50**	0.08	-0.02
Global Macro							1.00	**0.40**	**0.40**	**0.41**	**0.33**	-0.02
Relative Value								1.00	-0.12	**0.39**	0.06	-0.06
CTA Index									1.00	-0.07	**0.22**	**0.14**
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**	**CTA Index**
Ljung-Box test (1-6)	**80.41**	**57.68**	**19.57**	11.08	**34.76**	12.03	**14.15**	**27.41**	**13.09**
p-value	<.0001	<.0001	0.00	0.09	<.0001	0.06	0.03	0.00	0.04

Panel 3: Normality test

	Convertible Arbitrage	**Distressed Securities**	**Event Driven**	**Equity Hedge**	**Equity Market Neutral**	**Merger Arbitrage**	**Global Macro**	**Relative Value**	**CTA Index**
Jarque-Bera Test	**74.42**	**316.00**	**249.58**	**22.29**	3.64	**1285.21**	**10.68**	**969.71**	**57.26**
***p*-value**	<.0001	<.0001	<.0001	<.0001	0.16	<.0001	0.00	<.0001	<.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 Poisson 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.3. 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 p-values in parentheses. The pseudo R^2 is McFadden's likelihood ratio index. Coefficients with ***, **, and * are statistically significant at the 10%, 5%, and 1% levels, respectively.

	Conv. Arbitrage	**Distressed Securities**	**Event Driven**	**Equity Hedge**	**Equity Market Neutral**	**Merger Arbitrage**	**Global Macro**	**Relative Value**
Constant	-2.877***	-3.556***	-4.144***	-3.467***	-2.777***	-3.210***	-2.969***	-2.793***
	(0.00)	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*
Continuous Variables								
Russell 3000	-0.360	-0.321	0.271	-0.437**	0.129	-0.119	-0.256	-0.045
	(0.15)	*(0.14)*	*(0.16)*	*(0.05)*	*(0.60)*	*(0.62)*	*(0.30)*	*(0.85)*
Change in FRB dollar index	-0.050	0.006	-0.604***	-0.833***	-0.172	-0.634***	0.139	-0.370*
	(0.81)	*(0.98)*	*(0.00)*	*(0.00)*	*(0.42)*	*(0.00)*	*(0.50)*	*(0.07)*
Return on LB bond index	-0.615***	0.325*	0.269*	-0.378**	-0.309	-0.094	-0.497***	-0.598***
	(0.00)	*(0.06)*	*(0.08)*	*(0.05)*	*(0.13)*	*(0.63)*	*(0.01)*	*(0.00)*
Equally Weighted Return on other hedge fund indices	-0.331	0.468*	0.500**	0.269	-0.477	0.005	-0.166	-0.498*
	(0.25)	*(0.07)*	*(0.02)*	*(0.24)*	*(0.11)*	*(0.99)*	*(0.52)*	*(0.09)*
Contagion Variables								
Market Indicator Variables								
Bottom 10% return in Russell 3000	-0.063	0.044	2.362***	1.075***	-0.176	0.846**	-0.456	0.463
	(0.90)	*(0.92)*	*(0.00)*	*(0.01)*	*(0.74)*	*(0.05)*	*(0.36)*	*(0.34)*
Bottom 10% return in Bond index	-1.260**	0.199	-0.271	-1.062**	-0.676	-0.149	-0.085	-0.694
	(0.03)	*(0.73)*	*(0.57)*	*(0.04)*	*(0.27)*	*(0.79)*	*(0.87)*	*(0.21)*
Bottom 10% return in FRB index	0.060	0.995**	-1.410***	-1.383***	0.646	-0.939*	-0.294	-1.870***
	(0.91)	*(0.05)*	*(0.00)*	*(0.00)*	*(0.22)*	*(0.07)*	*(0.62)*	*(0.01)*
Other Hedge Fund Index Indicator Variable								
COUNT	0.181*	0.657***	0.814***	0.402***	0.213**	0.379***	0.331***	0.158
	(0.08)	*(0.00)*	*(0.00)*	*(0.00)*	*(0.05)*	*(0.00)*	*(0.00)*	*(0.12)*
McFadden's Pseudo R^2	0.212	0.284	0.420	0.341	0.127	0.252	0.199	0.200

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 Poisson 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.3. 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 p-values in parentheses. The pseudo R^2 is McFadden's likelihood ratio index. Coefficients with ***, **, and * are statistically significant at the 10%, 5%, and 1% levels, respectively.

	Conv. Arbitrage	**Distressed Securities**	**Event Driven**	**Equity Hedge**	**Equity Market Neutral**	**Merger Arbitrage**	**Global Macro**	**Relative Value**
Constant	-3.609***	-4.887***	-6.096***	-4.400***	-3.631***	-4.135***	-4.488***	-3.105***
	(0.00)	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*
Russell 3000 return	-1.859***	0.194	-0.559*	-1.180***	-0.131	0.033	-0.297	-0.208
	(0.00)	*(0.53)*	*(0.06)*	*(0.00)*	*(0.72)*	*(0.92)*	*(0.37)*	*(0.56)*
Change in FRB dollar index	0.068	0.291	-0.980***	-0.889***	0.037	-0.836***	0.458**	-0.347
	(0.78)	*(0.19)*	*(0.00)*	*(0.00)*	*(0.89)*	*(0.00)*	*(0.05)*	*(0.14)*
Return on LB bond index	-1.346**	-0.035	-0.858**	-1.008*	2.762***	-0.476	-3.354***	-1.023
	(0.03)	*(0.95)*	*(0.05)*	*(0.06)*	*(0.00)*	*(0.38)*	*(0.00)*	*(0.12)*
Eq. wtd. ret. on other H.F. indices	-0.262	0.672**	1.325***	0.531*	-1.005***	-0.082	-0.075	-0.440
	(0.48)	*(0.02)*	*(0.00)*	*(0.06)*	*(0.01)*	*(0.79)*	*(0.82)*	*(0.30)*
Return on 3 month T-bill	-5.523*	-2.565	-5.977***	-0.960	4.113	5.173*	4.356	-2.440
	(0.10)	*(0.37)*	*(0.01)*	*(0.72)*	*(0.13)*	*(0.08)*	*(0.20)*	*(0.49)*
S&P volatility	-0.044***	0.006	-0.038***	-0.021	0.001	-0.008	0.046***	0.016
	(0.00)	*(0.65)*	*(0.01)*	*(0.14)*	*(0.93)*	*(0.54)*	*(0.00)*	*(0.19)*
FRB dollar index volatility	-0.063*	0.234***	-0.122***	-0.025	0.180***	-0.071*	-0.094***	0.039
	(0.07)	*(0.00)*	*(0.00)*	*(0.55)*	*(0.00)*	*(0.07)*	*(0.00)*	*(0.47)*
LB bond index volatility	-0.223***	0.042	0.049	0.077	0.115	-0.111*	0.088	0.022
	(0.00)	*(0.70)*	*(0.67)*	*(0.45)*	*(0.25)*	*(0.09)*	*(0.32)*	*(0.79)*
Return on negative portion of S&P	0.069	-0.524***	-0.221**	0.001	0.102	0.145	-0.184	0.170
	(0.62)	*(0.00)*	*(0.03)*	*(0.99)*	*(0.46)*	*(0.26)*	*(0.13)*	*(0.20)*
Size spread	-0.292***	-0.237***	-0.357***	-0.241***	0.164***	-0.019	-0.229***	-0.077
	(0.00)	*(0.00)*	*(0.00)*	*(0.00)*	*(0.01)*	*(0.70)*	*(0.00)*	*(0.15)*
Δ in 10-year constant maturity YTM	-0.050**	-0.017	-0.020	-0.020	0.118***	-0.004	-0.095***	-0.022
	(0.03)	*(0.40)*	*(0.30)*	*(0.30)*	*(0.00)*	*(0.85)*	*(0.00)*	*(0.37)*
BAA-AAA spread	-0.583***	-0.552**	0.758***	0.149	0.098	0.660***	-0.532**	0.128
	(0.02)	*(0.03)*	*(0.00)*	*(0.52)*	*(0.68)*	*(0.01)*	*(0.02)*	*(0.64)*
Lookback Straddle factors								
Lookback on bonds	-0.549	-4.324***	-3.808***	-0.941	-0.074	-2.858**	-2.866***	-1.337
	(0.64)	*(0.00)*	*(0.00)*	*(0.35)*	*(0.95)*	*(0.02)*	*(0.01)*	*(0.24)*
Lookback on currencies	-1.372	0.687	2.971***	1.594*	-4.813***	1.294	-2.511***	-0.537
	(0.22)	*(0.43)*	*(0.00)*	*(0.07)*	*(0.00)*	*(0.16)*	*(0.01)*	*(0.61)*
Lookback on commodities	-2.319*	-0.481	0.080	-1.882*	-0.509	3.783***	-5.818***	2.368**
	(0.07)	*(0.66)*	*(0.94)*	*(0.09)*	*(0.68)*	*(0.00)*	*(0.00)*	*(0.04)*
Lookback on short term interest rates	1.586**	-0.857	-2.046***	0.025	0.289	-2.696***	-0.781	-0.617
	(0.04)	*(0.26)*	*(0.00)*	*(0.97)*	*(0.76)*	*(0.00)*	*(0.34)*	*(0.48)*
Lookback on equities	1.674**	1.123	-2.456***	-2.201***	0.936	-1.924***	2.128**	-1.307
	(0.04)	*(0.13)*	*(0.00)*	*(0.01)*	*(0.30)*	*(0.01)*	*(0.02)*	*(0.13)*
Contagion Variables								
Market Indicator Variables								
Bottom 10% return in Russell 3000	-1.298**	-0.738	2.010***	1.051**	-0.262	2.141***	-1.797***	0.625
	(0.03)	*(0.13)*	*(0.00)*	*(0.02)*	*(0.66)*	*(0.00)*	*(0.00)*	*(0.24)*
Bottom 10% return in Bond index	-0.260	0.377	1.104	-0.165	-0.128	0.581	-0.430	0.135
	(0.68)	*(0.62)*	*(0.11)*	*(0.80)*	*(0.85)*	*(0.40)*	*(0.44)*	*(0.83)*
Bottom 10% return in FRB index	-0.360	0.997*	-2.738***	-2.088***	1.731***	-1.433**	0.140	-2.053***
	(0.50)	*(0.06)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.02)*	*(0.84)*	*(0.01)*
Other Hedge Fund Index Indicator Contagion Variable								
COUNT	0.042	0.676***	0.977***	0.411***	0.349***	0.673***	0.121	0.196*
	(0.69)	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.30)*	*(0.10)*
McFadden's Pseudo R^2	0.394	0.398	0.565	0.458	0.324	0.366	0.415	0.282

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, the monthly returns from the Datastream bank index, and the monthly returns from the prime broker index. Further description of these variables is in Sections I.1. and 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	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%
25th percentile cutoff	-8.00	-13.747%	-0.198%	0.016%	-0.185%	-0.219%
75th 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 Hedge Fund Flows as a % of Assets				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 (FLOW)), 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 10%, 5%, and 1% levels, respectively.

	Number	Mean of *COUNT8*
Indicator Variable = Bottom Quartile Returns for Prime Broker Index (PBI)		
PBI = 0	157	0.331
PBI = 1	53	2.188
Difference in *COUNT8* Means: (PBI=1 less PBI=0)		1.857***
		(6.03)
Indicator Variable = Bottom Quartile Returns for Bank Index (BANK)		
BANK = 0	157	0.541
BANK = 1	53	1.566
Difference in *COUNT8* Means: (BANK=1 less BANK=0)		1.025***
		(3.53)
Indicator Variable = Quartile with Largest Amihud Liquidity Measure (STKLIQ)		
STKLIQ = 0	157	0.452
STKLIQ = 1	53	1.83
Difference in *COUNT8* Means: (STKLIQ=1 less STKLIQ=0)		1.378***
		(4.23)
Indicator Variable = Top Quartile BAA-AAA Credit Spread (CRSPRD)		
CRSPRD= 0	157	0.675
CRSPRD= 1	53	1.17
Difference in *COUNT8* Means: (CRSPRD=1 less CRSPRD=0)		0.495*
		(1.68)
Indicator Variable =Quartile with Largest Decreases in Repo Volume (REPO)		
REPO = 0	117	0.795
REPO = 1	40	1.075
Difference in *COUNT8* Means: (REPO=1 less REPO=0)		*(0.28)*
Indicator Variable = Top Quartile Fund Outflows (FLOW)		
FLOW = 0	157	0.815
FLOW = 1	53	0.755
Difference in *COUNT8* Means: (FLOW=1 less FLOW=0)		-0.06
		(0.23)
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 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 Poisson 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.3, and include all the variables in Table III 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 (FLOW). The liquidity indicator variables are set to 1 when liquidity is low. For brevity, only the coefficients on the *COUNT* variable, and the continuous and indicator liquidity variables are reported. Below the coefficients are the p-values in parentheses. The pseudo R^2 is McFadden's likelihood ratio index. Coefficients with ***, **, and * are statistically significant at the 10%, 5%, and 1% levels, respectively.

Panel A: The Prime Broker Index (PBI) is the Liquidity Proxy

	Conv. Arbitrage	Distressed Securities	Event Driven	Equity Hedge	Equity Market Neutral	Merger Arbitrage	Global Macro	Relative Value
Hedge Fund Contagion Indicator								
COUNT	-0.055	0.583***	1.097***	0.303***	0.299**	0.567***	0.048	0.137
	(0.61)	*(0.00)*	*(0.00)*	*(0.00)*	*(0.02)*	*(0.00)*	*(0.68)*	*(0.26)*
Liquidity Proxies								
PBI Continuous Variable	0.162	0.323	-0.847***	1.977***	0.047	0.654**	0.958***	0.104
	(0.63)	*(0.29)*	*(0.00)*	*(0.00)*	*(0.87)*	*(0.02)*	*(0.00)*	*(0.75)*
PBI Indicator Variable	1.227***	1.952***	-0.772	2.998***	0.588	1.695***	0.895*	0.930**
	(0.01)	*(0.00)*	*(0.13)*	*(0.00)*	*(0.25)*	*(0.00)*	*(0.06)*	*(0.04)*
McFadden's Pseudo R^2	0.407	0.419	0.571	0.516	0.328	0.388	0.429	0.294

Panel B: The Bank Index (BANK) is the Liquidity Proxy

	Conv. Arbitrage	Distressed Securities	Event Driven	Equity Hedge	Equity Market Neutral	Merger Arbitrage	Global Macro	Relative Value
Hedge Fund Contagion Indicator								
COUNT	0.072	0.658***	1.099***	0.302***	0.365***	0.680***	-0.104	0.203
	(0.51)	*(0.00)*	*(0.00)*	*(0.01)*	*(0.00)*	*(0.00)*	*(0.34)*	*(0.13)*
Liquidity Proxies								
BANK Continuous Variable	-0.132	0.469**	0.305	0.839***	-0.429	0.208	1.041***	0.101
	(0.59)	*(0.05)*	*(0.20)*	*(0.00)*	*(0.13)*	*(0.42)*	*(0.00)*	*(0.73)*
BANK Indicator Variable	0.208	1.085***	1.452***	1.763***	-0.781	0.661	-1.561***	0.498
	(0.61)	*(0.01)*	*(0.00)*	*(0.00)*	*(0.14)*	*(0.13)*	*(0.00)*	*(0.26)*
McFadden's Pseudo R^2	0.396	0.410	0.580	0.483	0.330	0.371	0.478	0.286

Panel C: Amihud's lliquidity Measure (STKLIQ) is the Liquidity Proxy

	Conv. Arbitrage	Distressed Securities	Event Driven	Equity Hedge	Equity Market Neutral	Merger Arbitrage	Global Macro	Relative Value
Hedge Fund Contagion Indicator								
COUNT	-0.013	0.469***	0.815***	0.273***	0.320***	0.477***	0.435***	0.087
	(0.91)	*(0.00)*	*(0.00)*	*(0.02)*	*(0.01)*	*(0.00)*	*(0.00)*	*(0.50)*
Liquidity Proxies								
STKLIQ Continuous Variable	-0.729***	-1.642***	-0.210	-0.164	0.603***	-0.251	0.258	0.265
	(0.00)	*(0.00)*	*(0.22)*	*(0.41)*	*(0.01)*	*(0.13)*	*(0.24)*	*(0.24)*
STKLIQ Indicator Variable	0.845*	3.486***	1.373***	1.032**	-0.103	2.027***	-2.121***	0.670
	(0.10)	*(0.00)*	*(0.00)*	*(0.04)*	*(0.83)*	*(0.00)*	*(0.00)*	*(0.20)*
McFadden's Pseudo R^2	0.412	0.474	0.573	0.464	0.349	0.397	0.438	0.306

Table VI, Continued: Contagion Regressions Including Liquidity Proxies

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 Poisson 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.3, and include all the variables in Table III In addition, the regressions also include the continuous and indicator values for the illiquidity variables, Prime Broker Index (PBI), Bank Index (BANK), Amihud's Illiquidity Measure (STKLIQ), BAA-AAA Credit Spread (CRSPRD), Changes in Repo Volume (REPO), and flows from other hedge funds (FLOW). The liquidity indicator variables are set to 1 when illiquidity is high. For brevity, only the coefficients on the *COUNT* variable, and the continuous and indicator liquidity variables are reported. Below the coefficients are the p-values in parentheses. The pseudo R^2 is McFadden's likelihood ratio index. Coefficients with ***, **, and * are statistically significant at the 10%, 5%, and 1% levels, respectively.

Panel D: The Credit Spread (CRSPRD) is the Liquidity Proxy

	Conv. Arbitrage	Distressed Securities	Event Driven	Equity Hedge	Equity Market Neutral	Merger Arbitrage	Global Macro	Relative Value
Hedge Fund Contagion Indicator								
COUNT	0.035	0.671***	0.978***	0.410***	0.302***	0.665***	0.144	0.195
	(0.73)	*(0.00)*	*(0.00)*	*(0.00)*	*(0.01)*	*(0.00)*	*(0.22)*	*(0.11)*
Liquidity Proxies								
CRSPRD Continuous Variable	-0.801***	-0.635**	0.757***	-0.008	-0.126	0.621**	-0.367	0.117
	(0.00)	*(0.02)*	*(0.00)*	*(0.97)*	*(0.64)*	*(0.03)*	*(0.15)*	*(0.69)*
CRSPRD Indicator Variable	0.831*	0.379	0.075	1.456***	0.865*	0.145	-1.005*	0.051
	(0.07)	*(0.42)*	*(0.83)*	*(0.00)*	*(0.10)*	*(0.74)*	*(0.06)*	*(0.92)*
McFadden's Pseudo R^2	0.400	0.399	0.565	0.473	0.330	0.367	0.420	0.282

Panel E: Changes in Repo Volume (REPO) is the Liquidity Proxy

	Conv. Arbitrage	Distressed Securities[19]	Event Driven[19]	Equity Hedge	Equity Market Neutral	Merger Arbitrage	Global Macro	Relative Value
Hedge Fund Contagion Indicator								
COUNT	0.026	1.150***	1.545***	1.324***	0.824***	0.616***	0.030	-0.161
	(0.83)	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.80)*	*(0.26)*
Liquidity Proxies								
REPO Continuous Variable	-0.405	-1.986***	-0.232	0.171	0.207	-0.030	-1.132***	0.806**
	(0.25)	*(0.00)*	*(0.58)*	*(0.67)*	*(0.50)*	*(0.92)*	*(0.00)*	*(0.02)*
REPO Indicator Variable	0.764	-4.008***	1.261**	1.361***	2.163***	0.335	-3.784***	1.723**
	(0.22)	*(0.00)*	*(0.03)*	*(0.05)*	*(0.00)*	*(0.56)*	*(0.00)*	*(0.01)*
McFadden's Pseudo R^2	0.559	0.634	0.702	0.679	0.617	0.542	0.583	0.637

Panel F: Flows from Other Hedge Funds (FLOW) is the Liquidity Proxy

	Conv. Arbitrage	Distressed Securities	Event Driven	Equity Hedge	Equity Market Neutral	Merger Arbitrage	Global Macro	Relative Value
Hedge Fund Contagion Indicator								
COUNT	0.084	0.666***	0.995***	0.447***	0.403***	0.659***	0.115	0.231***
	(0.43)	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.33)*	*(0.05)*
Liquidity Proxies								
FLOW Continuous Variable	-0.247	0.338**	0.033	-0.723***	0.180	0.117	0.290	0.343
	(0.32)	*(0.03)*	*(0.86)*	*(0.00)*	*(0.31)*	*(0.61)*	*(0.12)*	*(0.09)*
FLOW Indicator Variable	-0.848	0.478	1.628***	-0.668	-0.259	0.244	0.413	-0.224
	(0.12)	*(0.28)*	*(0.00)*	*(0.14)*	*(0.59)*	*(0.59)*	*(0.35)*	*(0.70)*
McFadden's Pseudo R^2	0.399	0.404	0.582	0.480	0.331	0.367	0.418	0.299

[19] The regressions for Distressed Securities and Event Driven exhibit quasi-separation with all explanatory variables. The results reported here were established by deleting some statistically insignificant variables. To the extent that this ad-hoc omission of these variables is affecting the estimation of the probability that a hedge fund index will have an extreme return, these results should be interpreted with caution.

Table VII: Contagion of extreme events in the CTA (Commodity Trading Adviser) Index

The event of an extreme monthly negative return in the CTA index is separately modeled as the outcome of a binary variable and estimated as a Poisson 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.3 and include all control variables as in Table III. Some of the control variables are not reported for brevity. 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 8 and measures the number of hedge fund indices that have bottom 10% tail returns for the month. The regression in Column 1 includes all the control variables, and the contagion indicator variables, but none of the liquidity variables. The regressions in Columns 2-7 include the liquidity variables PBI, BANK, CRSPRD, REPO, STKLIQ, and FLOW, where FLOW represents the flows for the 8 hedge fund indices. Both continuous and indicator illiquidity variables are included. The liquidity indicator variables are constructed so that a positive coefficient on the variable indicates that contagion is exacerbated when poor liquidity is present. Below the coefficients are the p-values in parentheses. The pseudo R^2 is McFadden's likelihood ratio index. Coefficients with ***, **, and * are statistically significant at the 10%, 5%, and 1% levels, respectively.

	No Liquidity Proxies	PBI included	BANK included	CRSPRD included	REPO included	STKLIQ included	FLOW included
<u>Contagion Variables</u>							
Market Indicator Variables							
Bottom 10% return in Russell 3000	-0.189	-1.503*	-0.392	-0.721	-1.028	-1.897***	-0.491
	(0.88)	*(0.06)*	*(0.79)*	*(0.56)*	*(0.29)*	*(<.0001)*	*(0.67)*
Bottom 10% return in Bond index	-0.028	1.243**	-0.014	0.113	0.172	1.310***	0.178
	(0.96)	*(0.02)*	*(0.98)*	*(0.84)*	*(0.80)*	*(0.01)*	*(0.76)*
Bottom 10% return in FRB index	-1.153	1.842***	-0.987	-1.002	0.816	2.515***	-1.072
	(0.15)	*(0.01)*	*(0.21)*	*(0.20)*	*(0.42)*	*(<.0001)*	*(0.16)*
Other Hedge Fund Index Indicator Variable							
COUNT	-0.562***	0.160	-0.383*	-0.421***	-0.095	-0.839***	-0.503***
	(0.01)	*(0.25)*	*(0.06)*	*(0.03)*	*(0.53)*	*(<.0001)*	*(0.01)*
Liquidity Proxies							
Continuous Liquidity Proxy	NA	-0.084	-0.533**	0.471*	-0.242	-0.213	-0.241
		(0.81)	*(0.04)*	*(0.08)*	*(0.42)*	*(0.43)*	*(0.27)*
Indicator Liquidity Proxy	NA	0.711	-2.357***	-2.107***	-0.998*	-3.742***	-2.319***
		(0.27)	*(0.00)*	*(0.00)*	*(0.09)*	*(<.0001)*	*(0.00)*
McFadden's Pseudo R^2	0.269	0.274	0.273	0.269	0.509	0.359	0.279

Figure 1
Daily Hedge Fund Returns: August 2007

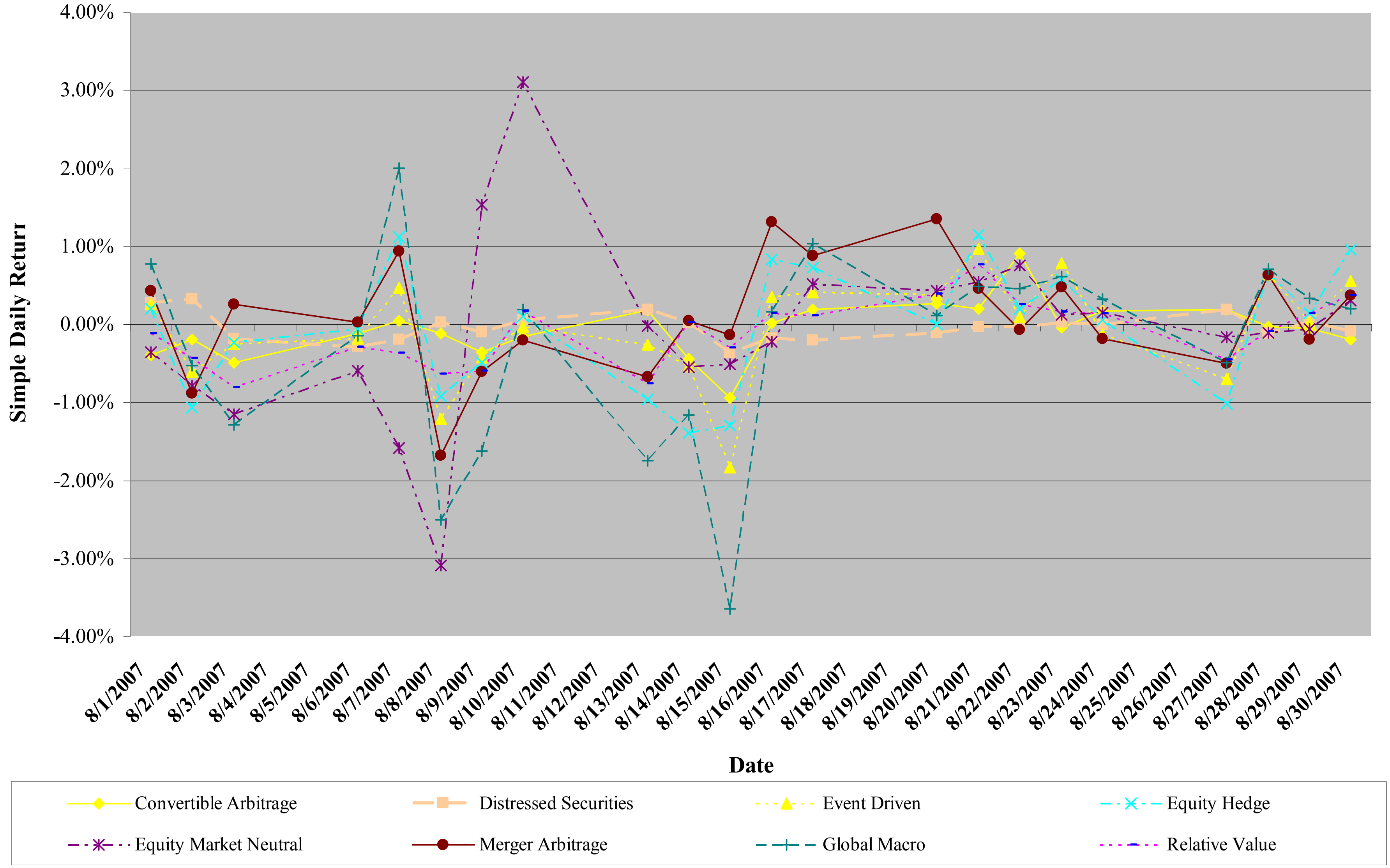


Figure 2
Probability of Contagion Conditional on the Count Variable

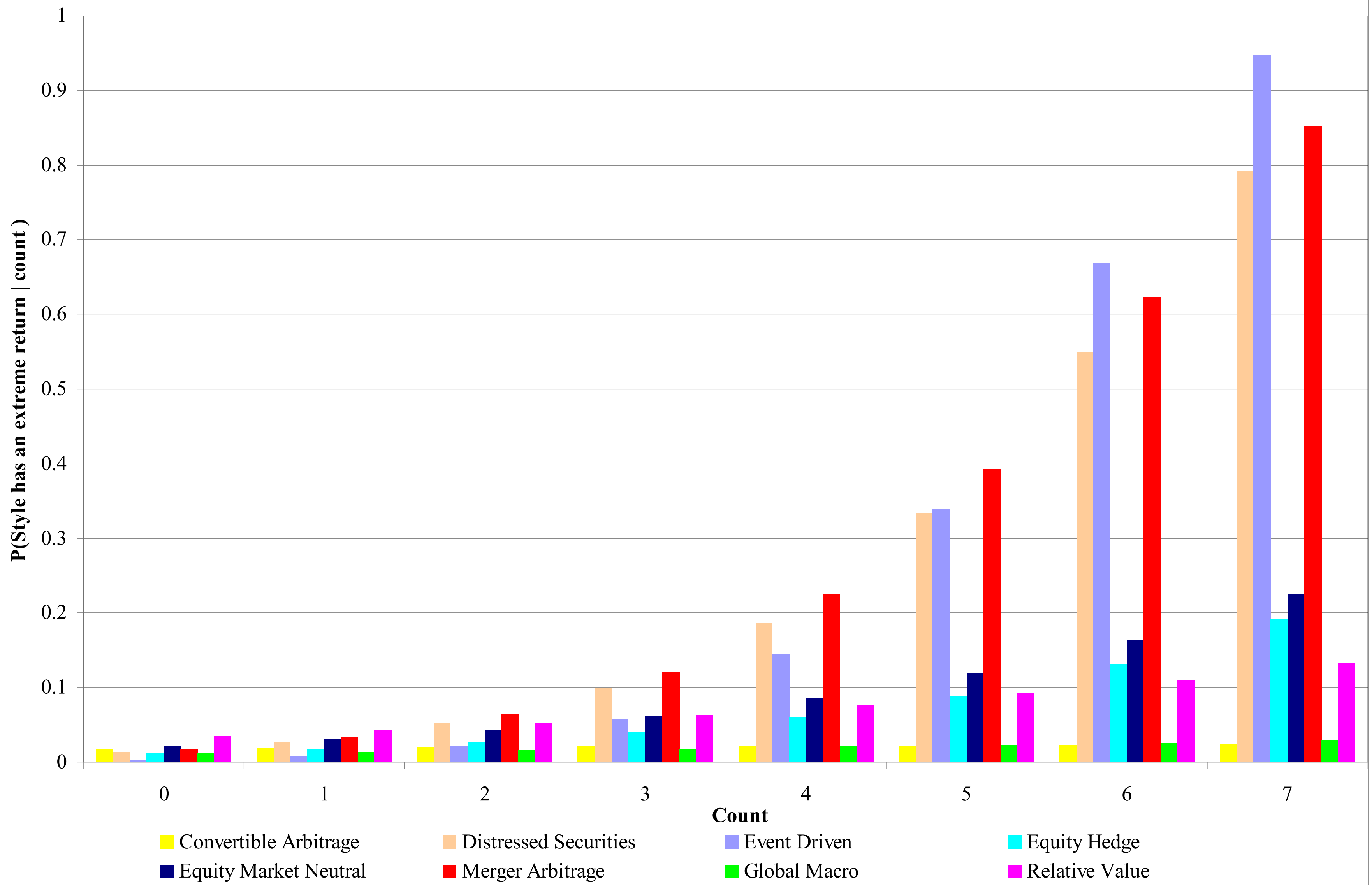


Figure 3: Probability Changes by *COUNT* Variable when Low Liquidity is Present

To facilitate the interpretation of the coefficients on the liquidity indicator variables from Table V, we perform the following analysis. We set all variables in each regression (with the exception of the *COUNT* variable and the dummy variable for poor liquidity) to their mean levels and evaluate the regression. We then calculate a conditional probability difference as follows: [P(*COUNT* = k|Liquidity dummy = 1) – P(count = k|Liquidity dummy = 0)] for all possible realizations of the *COUNT* variable (k=0 to 7) for each hedge fund index. The difference in probability represents the magnitude of the effect that the liquidity proxy has on hedge fund contagion. This analysis is performed for the PBI, BANK, STKLIQ, and CRSPRD liquidity proxies.

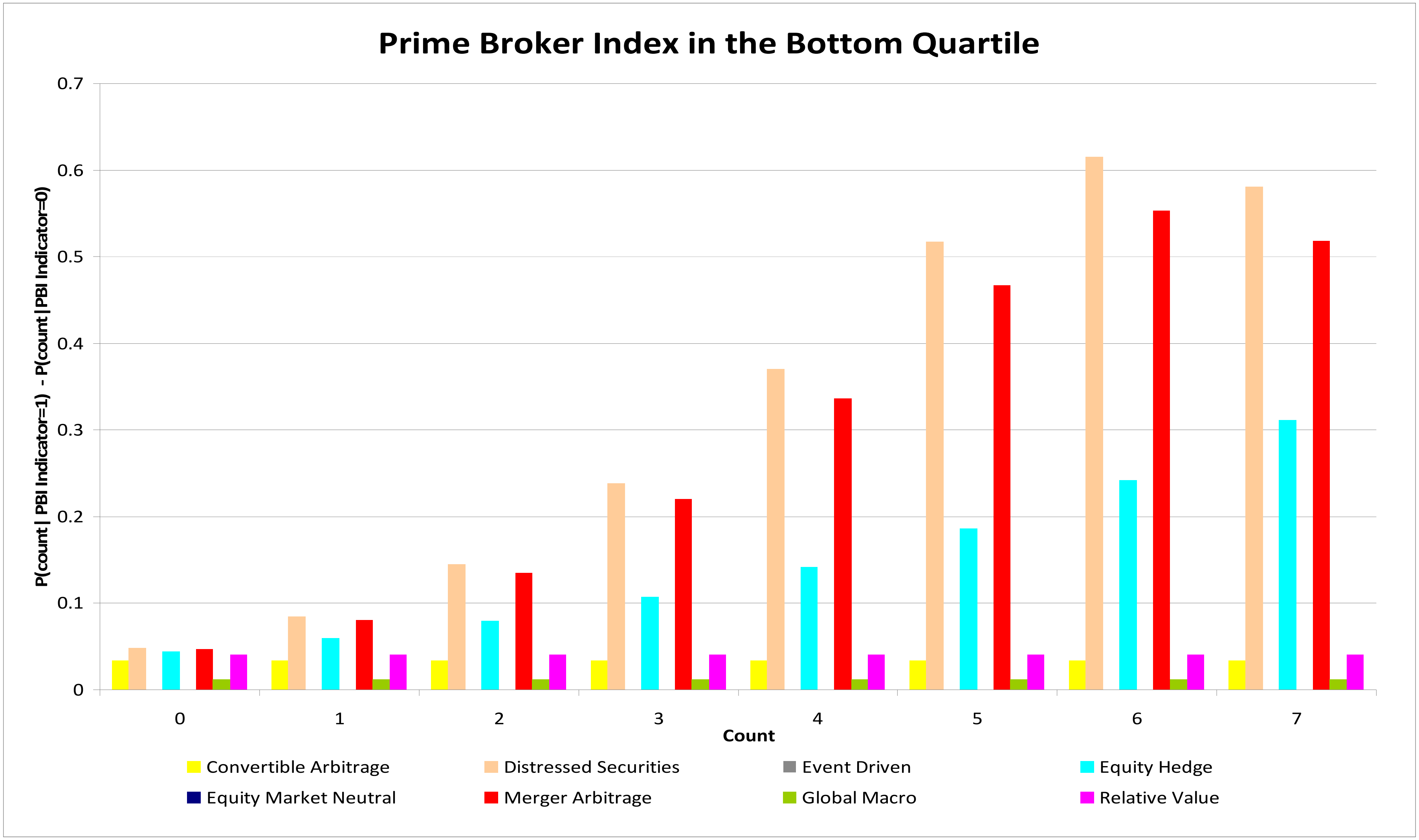


Figure 3, Continued

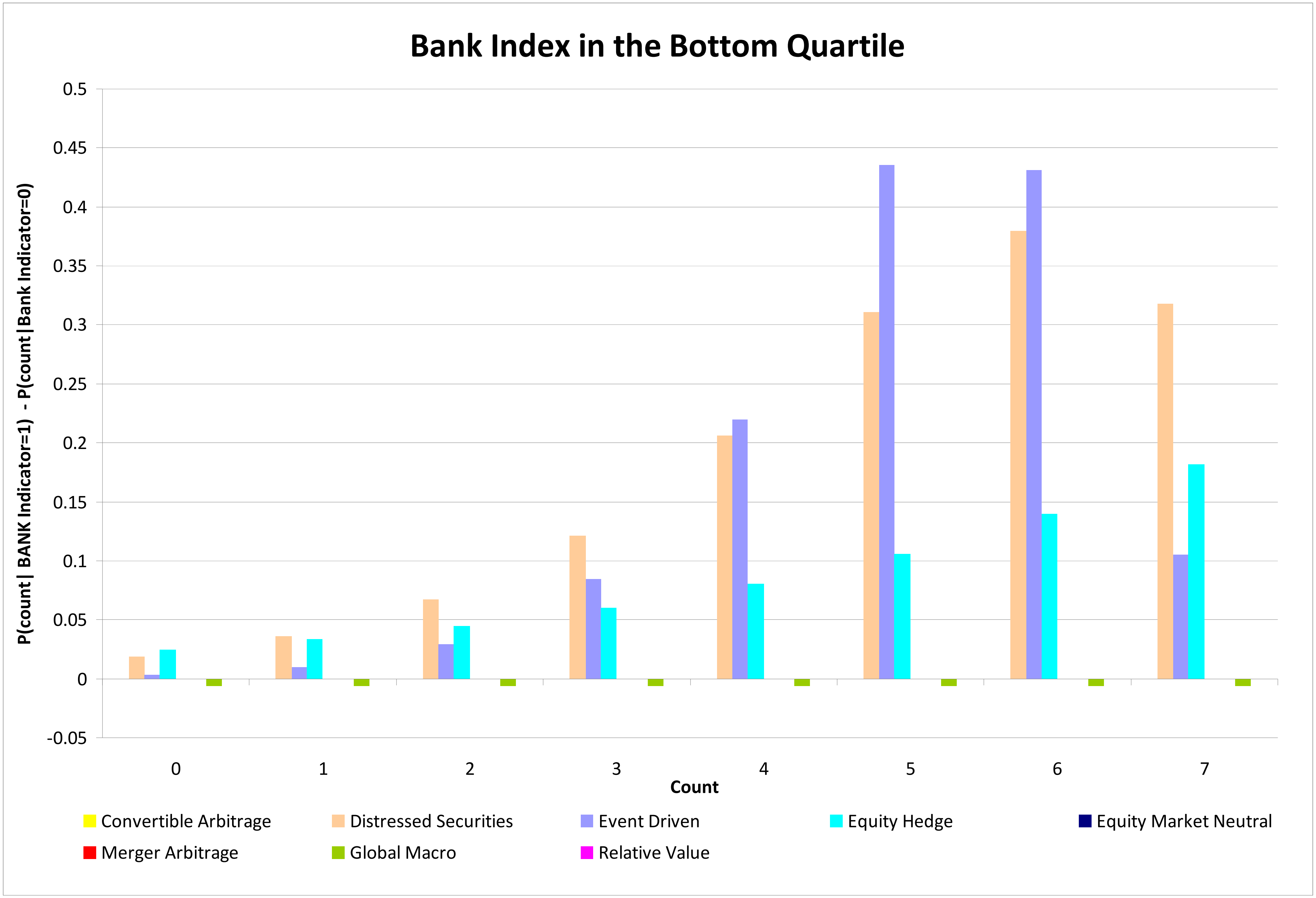


Figure 3, Continued

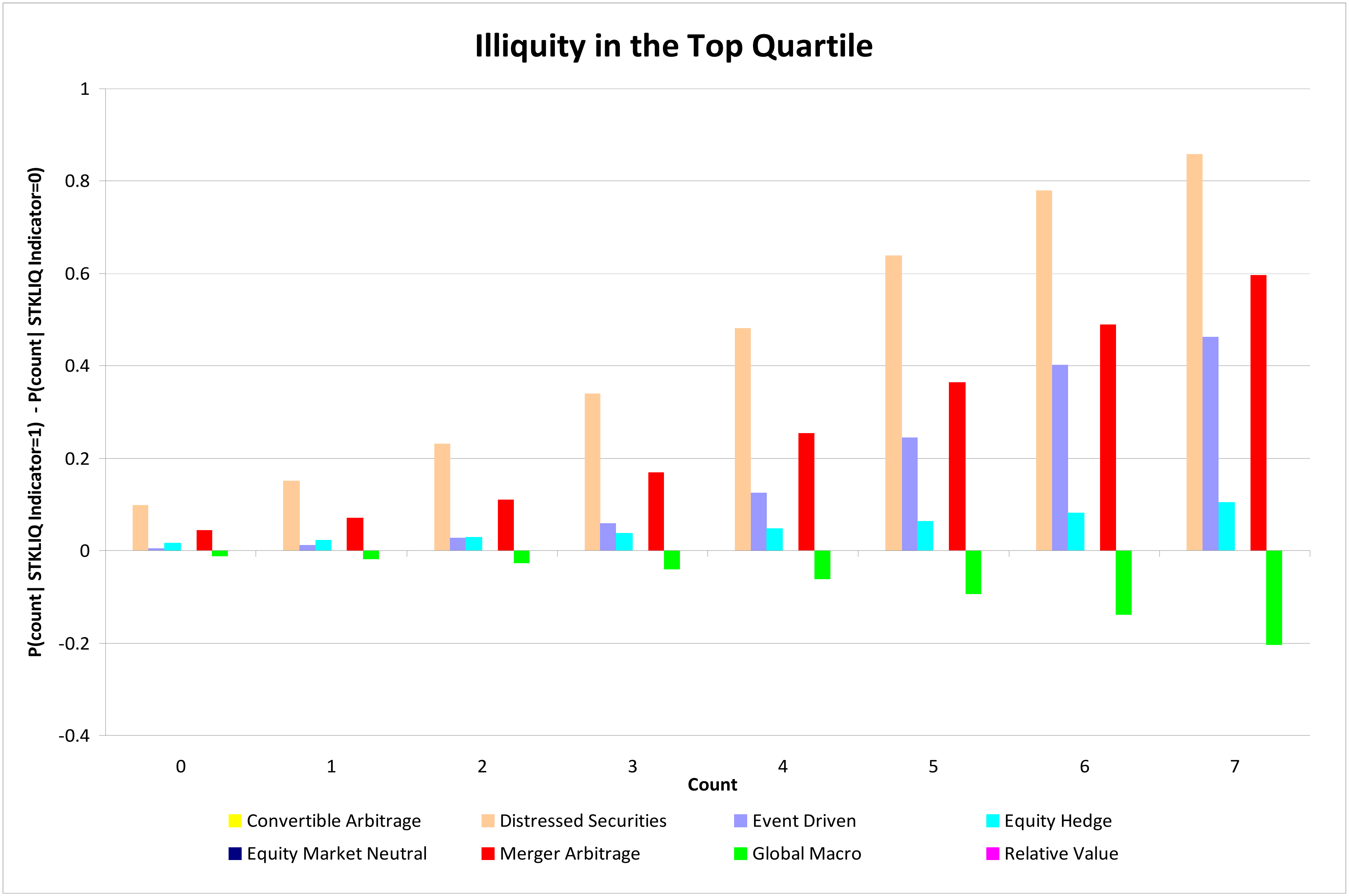
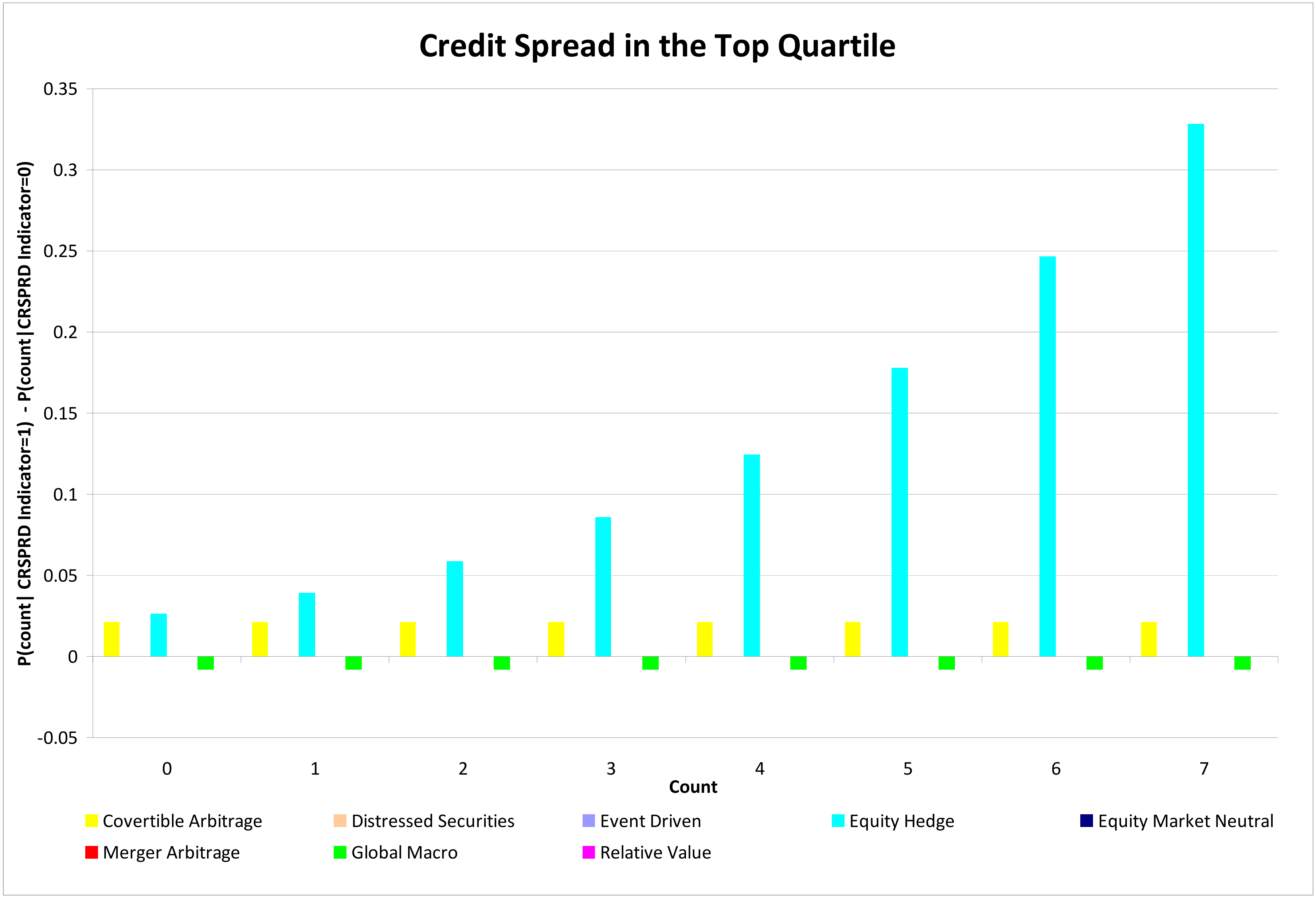


Figure 3, Concluded



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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