THE UNIVERSITY OF CHICAGO

# THE LIMITS OF ARBITRAGE: AN EMPIRICAL ANALYSIS OF EVIDENCE FROM HEDGE FUND PERFORMANCE

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## ABSTRACT

Shleifer and Vishny (1997) state that capital constraints impair the arbitrage activity of hedge funds. Their model demonstrates that, although expected returns to arbitrage are high when there are shocks to asset prices, investment risks also increase, giving hedge fund managers the incentive to reduce rather than increase investment exposure. Consistent with anecdotal evidence, their model introduced the notion of the *limits of arbitrage* as a theory, but has remained untested, primarily due to data limitations and problems with heteroskedasticity and multicollinearity. This paper develops and applies an empirical methodology to test the hypothesis that hedge funds reduce their exposure to investment risk in response to shocks. To test the hypothesis, the paper employs a sample of contemporaneous returns to fixed income hedge funds and various proxies for spread relationships underlying fixed income trading strategies. Since changes in notional investment can be inferred from changes in the cross-sectional variation between returns and these underlying spreads, the observed pattern of change in cross-sectional variation provides evidence that fixed income hedge funds substantially reduce their investment exposure when a shock occurs. The sensitivity of hedge fund returns to changes in the volatility of asset returns is also found to be a determinant in the manner in which hedge funds respond to shocks. In addition to comparing the more constrained to the less constrained surviving fixed income hedge funds within the sample, this paper also compares surviving funds with those hedge funds that fail during the period. Furthermore, the paper documents a similar more general delevering effect within a much broader sample of hedge funds, which are engaged in more diverse strategies.

# CHAPTER 1

# INTRODUCTION

As arbitrageurs, hedge funds are believed to play an important role in aligning market prices with fundamental asset values.[1] To the extent that shocks to asset prices temporarily drive market prices away from fundamental value, the classical view of arbitrage (*CA*) holds that hedge fund managers should increase investment exposure when shocks occur, since expected returns are greater when volatility increases (Grossman and Miller, 1988; DeLong *et al*, 1990; Campbell and Kyle, 1993).

Shleifer and Vishny (1997) (SV1997) present a different view. According to SV1997, arbitrageurs, such as hedge funds, may be ineffective at aligning market prices with fundamental asset values because arbitrageurs might actually *reduce* rather than increase their investment exposure in response to asset price shocks. The reason is that capital constraints (e.g., margin requirements, costly asset liquidation, etc.) may lead the

[1] The presence and importance of hedge funds in the financial markets have been increasing rapidly. The current figure of $817 billion of equity capital under management by hedge funds is expected to exceed $1 trillion under management within the next few years. Given the degree of leverage employed by hedge funds, the aggregate asset exposures of hedge funds are several multiples of the capital under management.

arbitrageur to “insure” against future states where capital is unavailable by not betting fully against potential asset mispricing. SV1997 label this effect the “limits of arbitrage” (*LoA*). Recent theoretical research has explored *LoA* in the context of various capital constraints. Liu and Longstaff (2001), Vayanos and Gromb (2000), and Xiong (1999), all show that constraints, such as margin requirements and bankruptcy costs, limit the trading activity (i.e. investment exposure) of hedge funds. Anecdotal evidence during extreme market events affirm this proposed relationship between market conditions and investments by hedge funds, since severe volatility shocks seem to trigger the simultaneous unwinding of their positions (Dunbar, 1999; Lowenstein, 2000; Getmansky, Lo and Makarov, 2003; Goldman, 2003).

This paper develops and applies an econometric methodology to document empirically whether hedge funds increase their exposure to risky investments in response to shocks, as predicted by *CA*, or reduce it, as predicted by *LoA*. The most obvious and direct test of *CA* versus *LoA* would involve examining the notional investment exposures of hedge funds in response to shocks. Unfortunately data on notional investment is unavailable; publicly available data on hedge funds is primarily limited to monthly returns, i.e. the changes in *net asset value* (*NAV*).

Given that the most reliable publicly available data on hedge funds is limited to their reported monthly returns, how can changes in their investment exposure be documented? One approach that may be feasible would be to approximate changes in *risk-based leverage* from changes in the volatility of hedge fund returns.

Risk-based leverage (*RBL*) is the ratio of the riskiness of the investment exposure to the equity capital of a fund. According to *Sound Practices for Hedge Fund Managers* (February 2000), a policy study prepared for regulators by five of the largest hedge funds, *RBL* is accepted in practice as an accurate approximation of the effective, aggregate investment exposure of a fund, since it reflects the relationship between the risk of the fund's total investments and the fund's capacity to absorb that risk. The use of leverage increases the expected return, and the risk, for a given investment.

> "Hedge Fund Managers must recognize that leverage is important…i.e., leverage influences the [magnitude and rate] of changes in the value of the portfolio due to changes in market risk, credit risk, or liquidity risk factors. Consequently, the most relevant measures of leverage are "risk-based" measures… Hedge Fund Managers should assess the degree to which a Hedge Fund is able to modify its risk-based leverage in periods of stress or increased market risk."

Citing the systemic accumulation of investment leverage as one of the key contributors to the financial crisis that resulted from the 1998 Russian debt moratorium (Schinasi and Smith, 1999), subsequent to the extensive investigations that followed the collapse of Long Term Capital Management (LTCM), the International Monetary Fund, as well as other multilateral institutions, and regulatory agencies (for example, The President's Working Group on Financial Markets, 1999) also proposed various measures similar to *RBL* (Breuer, 2000). All of these measures relate the elasticity of the change in the value of the equity (i.e., the hedge fund return) to changes in the value of the (hedge fund's) investment portfolio.

In the absence of data on the actual ratio of the notional investment risk to the capital of hedge funds, *RBL* may be approximated by using regression to estimate the covariation between hedge fund returns and the factors underlying those returns. Changes in investment exposure by hedge funds in response to changes in volatility may be documented by measuring changes in estimates of risk-based leverage when shocks occur.

The aforementioned data limitation problem was overcome by developing a regression methodology to infer approximate *RBL* from the returns of those hedge funds engaged in fixed income strategies. These funds provide a homogeneous data sample for testing the empirical implications of *LoA*. In order to exploit temporary price discrepancies between correlated assets, fixed income hedge funds employ considerable leverage, especially relative to traditional managers. This leads these hedge fund managers to trade much more actively than traditional (long-only) investment managers, more frequently rebalancing portfolios to mitigate their magnified sensitivity to volatility changes when shocks to underlying factors occur.

Since returns to fixed income instruments (e.g. bonds) are highly correlated with identifiable common factors, e.g., term structure changes (Litterman and Scheinkman, 1991), proxies for common factors in returns to relative-value investment strategies, based on broadly-quoted benchmarks for interest rates or bond yields, should be readily observable. Assuming that expected returns increase with risk (i.e. risk premia are on average positively-sloped), despite the fact that notional investments themselves are unobservable, the covariation between hedge fund returns and changing risk conditions can serve as evidence for documenting changes in investment exposure conditioned on changes in market conditions.

Using the regression methodology to measure changes in *RBL* proportional to changes in the covariation between returns and risk, provides evidence that fixed income hedge funds substantially reduce their exposure to investment risk when a shock occurs. The paper also finds evidence that changes in volatility may constrain a hedge fund from rebalancing its portfolio when a shock occurs. Comparable tests on a broader sample of hedge funds find similar patterns for strategies invested in more diverse asset classes.

The remainder of the paper is comprised of two parts: the first part consists of empirical tests of predictions derived from the model, employing data on fixed income hedge fund returns and yield spread relationships underlying fixed income relative-value strategies. In the second part, further tests generalize the results to a more diverse sample of hedge fund strategies, invested in fixed income instruments, as well as other assets, for example, equities.

The paper proceeds as follows: Chapter 2 develops the hypothesis, its empirical implications, and outlines predictions based on these implications. Chapter 3 describes the specification of the regression model, the characteristics of the data, and variables selected as factors. Chapter 4 presents the test of the one-factor regression model, in which monthly fixed income hedge fund returns are regressed against the average monthly change in the spread between 2-year versus 30-year swaps (a proxy for market risk). Chapter 5 presents the test of the three-factor regression model, which includes proxies for market risk, liquidity risk, and credit risk. An out-of-sample test also compares the surviving funds to those hedge funds that fail during the period. Chapter 6 compares changes in leverage and returns of funds with higher-variance (more constrained) strategies versus lower-variance (less constrained) strategies. Chapter 7 tests the empirical implications of the model more generally, by specifying the multi-factor regression for a sample of hedge funds engaged in strategies more diverse than fixed income arbitrage. Chapter 8 discusses the regression results as evidence for the limits of arbitrage within the context of the theoretical predictions of the model and current theories.

# CHAPTER 2

# TESTABLE IMPLICATIONS OF THE LIMITS OF ARBITRAGE

This section discusses how testable predictions based on the limits of arbitrage (*LoA*) might manifest in data comprised of hedge fund returns, when regressed against variables that serve as proxies for the risks underlying the investments common to those hedge funds within the sample. As suggested by Shleifer and Vishny (1997) (SV1997), the fact that hedge fund managers actually reduce investment when shocks occur may imply that during periods of increased mispricing, limitations such as capital constraints or increased risk may dominate the prospect of the higher expected returns.

Since SV1997 first introduced the notion of *LoA*, there has subsequently followed considerable theoretical research on this topic (Kyle and Xiong, 2001; Liu and Longstaff, 2000; Liu, Longstaff, and Pan, 2001; Vayanos and Gromb, 2000; Xiong, 1999; Xiong, 2001; Yuan, 1999). However, although hedge funds best fit the description of the *professional arbitrageurs* described by SV1997, due to the limited availability of data, there exists no research that systematically documents empirical evidence for *LoA*, based on the investment activity of hedge funds.[1] The primary contribution of this paper is to use the available data on hedge fund returns to empirically document evidence for *LoA*.

Although the empirical implications of SV1997 have yet to be systematically tested, Fung and Hsieh (1997) (FH1997) find that the covariation between hedge fund returns and common factors in those returns does tend to decrease during market rallies and declines. FH1997 employ multi-factor regression to compare, across market rallies and declines, changes in the investment leverage (relative to long-run averages) for hedge funds engaged in diverse strategies relative to buy-and-hold investors (e.g. mutual funds). They find investment leverage, on average, to be considerably higher and far more variable for hedge funds relative to mutual funds.

By adopting a somewhat similar approach to FH1997, Brown, Goetzmann, and Park (2001) (BGP2001) document a reduction in the volatility of returns for a sample of hedge funds that underperform relative to their peers. In order to examine incentives related to survival and competition among hedge funds, BGP2001 measure the cross-sectional and time-varying changes in the risk preferences of hedge fund managers in general, by comparing changes in excess returns and the standard deviations of returns comprising their funds' Sharpe ratios. They find that managers with mediocre or worse performance exhibit increased variance of returns, relative to those managers with the best performance who

[1] However, Gabaix, Krishnamurthy and Vigneron (2004) do find evidence for *LoA* by examining the pricing of mortgage-backed securities (MBS). The authors find that option-adjusted spread (OAS), analogous to the implied volatility of the prepayment option embedded within MBS exhibit the systematic pricing of residual risk correlated with the aggregate consumption or aggregate wealth of arbitrageurs as the marginal investor in this asset class.

exhibit lower variance. They suggest that the reduction in the volatility of returns for underperfoming hedge funds corresponds to reduced risk-taking during periods when better performing peers increase risk-taking, which may be due to capital constraints consistent with the *LoA* hypothesis as posed by SV1997.

Although both FH1997 and BGP2001 explore related problems employing somewhat similar data, neither paper discusses changes in hedge fund investment (i.e. risk-based leverage) as evidence for *LoA*.[2] Furthermore, neither paper focuses specifically on changes in risk-based leverage conditioned on changes in underlying spread volatility, nor do either employ options-based factors to measure the sensitivity of the hedge fund returns within the sample to increased volatility. For example, neither FH1997 nor BGP2001 distinguish between periods that exhibit higher and lower volatility, nor do they classify groups of funds according to their relative sensitivity to increases in volatility. BGP2001 also do not account for differences between the variance of returns across diverse hedge fund strategies, or the sensitivity of different strategies to volatile market conditions.

In order to document evidence regarding the empirical implications of *LoA*, by developing and applying similar methods for measuring the changes in the investment leverage of hedge funds (a) across higher volatility periods versus lower volatility periods, and (b) between groups of funds that exhibit greater or lesser sensitivity to increased

[2] BGP2001 alludes to evidence of increases in [risk-based] leverage due to incurred losses (i.e., passive leverage hypothesis) being offset by decreases in [risk-based] leverage due to externally-imposed capital constraints (i.e., active leverage hypothesis), but not specifically within the context of *LoA*.

volatility, this paper extends the body of empirical research related to FH1997 and BGP2001, as follows:

(1) By constructing three proprietary data sets comprised of one-month hedge fund returns and the corresponding underlying fixed income spreads, as proxies for the common factors underlying those returns. The returns and contemporaneous spreads are sorted into preshock, shock, and postshock periods, based upon the "volatility" (i.e. standard deviation) exhibited by those spreads over the corresponding month.
(2) By specifying a regression model that employs a homogeneous sample of returns exhibited by hedge funds engaged in fixed income investment strategies; and, by identifying factors underlying returns to fixed income hedge fund returns, based on common factors underlying bond returns (Litterman and Scheinkman, 1991; Litterman, Scheinkman and Weiss, 1991), as well as anecdotal evidence (Berens and Friend, 1997; Dunbar, 1999; Lowenstein, 2000) on the predominant fixed income hedge fund trading exposures during the sample period.
(3) By developing and applying options-based proxies for the sensitivity of hedge fund returns to volatility changes, in order to measure this sensitivity as a limiting factor for hedge fund investment activity (Merton, Scholes, and Gladstein, 1982; Fung and Hsieh, 1998b; Agarwal and Naik, 2000).
(4) By modifying the Fung and Hsieh (1997) model with the addition of the three options-based proxies to measure the sensitivity of hedge fund returns to volatility changes, in order to conduct a more general test of the *LoA* hypothesis, on a broader sample of hedge funds. These more general results are consistent with the results exhibited by the fixed income hedge fund sample, and show that:

    (a) hedge funds in general reduce investment leverage during periods of extreme volatility, and
    (b) the sensitivity of hedge fund returns to volatility in general tends to increase during shocks.

In the case of fixed income relative value investing by hedge funds, shocks to asset prices correspond to spread changes that are extreme in magnitude or in frequency. Since the classical view of arbitrage (*CA)* implies that the covariance between returns and spread changes should increase as managers maintain or increase investment given the occurrence of a shock, observing a substantial decline in hedge fund risk exposure conditioned on large changes in spreads (in either magnitude or increased variability) serves as evidence for *LoA*. In summary, during a period of shocks, observing a reduction in investment risk implies that hedge fund managers actually reduce their investment in response to shocks.

When sorted into preshock, shock, and postshock periods, the returns of hedge funds engaged in fixed income strategies regressed against the contemporaneous volatility of spread changes, should approximate, on average, the relative change in *RBL* during and after shocks. First, fixed income hedge funds should, in general exhibit negative returns during periods of severe spread widening. Second, for the overall sample, *RBL* should decrease during and after severe spread widening occurs. Third, less constrained funds should be more levered preshock and should exhibit less volatile returns (conditioned on the magnitude of spread changes) than less levered funds. Fourth, during shocks, less constrained funds should delever more (or exhibit lower *RBL*), and the returns of the funds with higher *RBL* during shocks should be more negative than the returns of less levered funds. Finally, during shocks, the preshock returns of funds that are negatively correlated with volatility should be more negative than the preshock returns of those funds that are not negatively correlated.

## 2.1. Defining the Role of Risk Based Leverage

In the context of comparing useful measures for the inherent leverage implied by the mean and variance of investment returns, Breuer (2000) discusses the interaction between leverage and risk, motivated by the commonly held concern that the simultaneous unwinding of leveraged investments by market participants amplifies market turmoil.

Breuer describes leverage as the *elasticity* of the equity return, i.e. "the change in the net asset value (*NAV*) of the investment portfolio [of a hedge fund], given a specified change in the asset value of its investment portfolio". Accordingly, Breuer articulates the following fundamental relationships between the risk and return of an investment portfolio:

(1) $$return_{fund} = return_{Investment} * Leverage \text{ and}$$

(2) $$\sigma(return_{fund}) = \sigma(return_{Investment}) * Leverage$$

where σ, the notation for standard deviation, describes the risk, and

(3) $$Leverage = Assets/Equity$$

is the "leverage ratio".[3] Breuer states, "increasing *either* the risk of the assets or the leverage ratio increases the riskiness of the equity base," and notes that a highly

[3] The President's Working Group on Financial Markets (1999) proposed as a measure of [risk-based] leverage, the ratio of the portfolio *value-at-risk* (or "*VaR*, i.e. the 99th percentile loss of capital over a pre-specified time horizon) to the equity capital of the portfolio, which is essentially a risk coverage ratio, similar to *RBL* as presented by the document *Sound Practices for Hedge Fund Managers* (2000).

leveraged portfolio of low-risk investments can imply less risk to equity capital than an unleveraged portfolio of high-risk investments.

If $Assets = (m * I)/E$ , where *m* represents the units of investment *I*, expressed in notional amounts equal to or greater than $1, and *E* is the endowment of equity capital equal to $1, then the return of the fund (and the risk of the fund's return) will increase or decrease, with either an increase or decrease in the investment return (and the risk of the investment return), or with the notional amount of investment supported by the equity capital of the fund. Hence, the change in *RBL* measures the change in the risk of the equity capital of the fund resulting either from changes in the riskiness of the investment or from changes in the actual leverage assumed by the fund.

Assume that hedge fund managers each choose some target *RBL*, given a specified "*risk of ruin*", i.e., a threshold *RBL* based on a level of expected loss that, if breached, results in the complete (and costly) liquidation of the equity capital of the fund (Perold, 1999; Krishnamurthy, 2003). In a particularly volatile market environment, as hedge funds approach their *RBL* thresholds, then the managers may have an incentive, or be forced by creditors, to partially liquidate their investments to maintain their target *RBL*. Although this partial liquiditation may still be costly, it avoids complete liquidation, and the complete failure of the fund. Those managers whose portfolios are less constrained by the increased volatility, may be able to voluntarily and selectively liquidate less costly investments, and therefore incur less severe losses during shocks, and thus preserve more capital, relative to managers who are more constrained.

### 2.2. Spread Relationships Underlying Fixed Income Arbitrage Strategies

Hedge funds that engage in fixed income strategies trade in order to exploit differences in the relative value of comparable interest rate-related instruments. The differences in relative value of fixed income instruments are a function of the spreads between their effective yields, i.e. the rates at which one can borrow or invest in those instruments. For example, if mean reversion holds, and the spread in the yield between 2-year riskless debt and 30-year riskless debt is wider than the historical average,[4] then one should sell (short) the 2-year debt security and buy the 30-year debt security. As the spread between “2s versus 30s” narrows, the 2-year (30-year) security should depreciate (appreciate) in value relative to the 30-year (2-year) security, resulting in a gain to the net investment position.

A fixed income spread can be defined as the difference between two interest rates or yields, corresponding to a difference in value between two (or more) fixed income investments. Expected returns increase when the volatility of spreads increase, which provides an incentive to increase investment exposure. However, the increased volatility of spreads also results in an increased risk of decline in the value of the fund investments.

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[4] Assuming that the yield curve is positively sloped.

Hence, fixed income spreads can be selected in order to serve as proxies for market risk, liquidity risk, or credit risk. These underlying spread proxies do not represent specific trades, but rather, generic relationships between risks and the underlying factors in return considered common to the fixed income-based investment strategies of hedge funds.

Hedge fund strategies vary according to differences in the specific assets selected, as well as the financing and hedging approach in which the manager engages. Distinct strategies will covary differently with common factors underlying the returns to those respective strategies. For example, according to Litterman and Scheinkman (1991), 98% of the variation in bond values is explained by factors related to the term structure of interest rates. The liquidity premium implicit in the yield of a bond is well established as the factor underlying the relative value of comparable fixed income instruments (Buraschi and Menini, 2001; Krishnamurthy, 2001).

Furthermore, it is well documented that fixed income hedge funds typically engage in arbitrage strategies based on the liquidity premium implicit in bond yields (Dunbar, 1999; Lowenstein, 2000). Volatility changes are also well documented as determinants in fixed income returns (Litterman, Scheinkman and Weiss, 1991). Both academic and industry research suggest the existence of relative value trading opportunities that hedge funds attempt to exploit (Longstaff, Santa Clara and Schwartz, 2000a,b; Kocic, 2000, 2001; Berens and Friend, 1997). The sensitivity of hedge fund returns to volatility changes may be attributed to attempts to exploit (a) time-varying risk premia by trading options, or (b) the inherent optionality implicit to instruments traded, and the financing and/or hedging of those instruments by managers.

Following the events surrounding the collapse of LTCM and similar funds during the Fall of 1998, numerous sources have documented the dominant trading strategies and exposures of fixed income arbitrage hedge funds. In addition to anecdotal evidence compiled by Dunbar (1999) and Lowenstein (2000), more formal studies have been published by regulatory groups, including the President's Working Group on Financial Markets (1999) and the Bank for International Settlements (1999a, b & c).

Several papers by Fung and Hsieh perform extensive multi-factor regression analysis on the returns of LTCM and other fixed income arbitrage hedge funds during the 1998 period. It has been well-established that LTCM and other fixed income arbitrage hedge funds engaged in substantial bets on the implicit market risk in the volatility of the slope of the term structure, the volatility of the liquidity premium (as implied by the yields of US government bonds), and the credit risk inherent in the volatility of swap spreads, relative to Treasury instruments.

Based on the empirical implications of SV1997, fixed income hedge funds will on average also exhibit higher *RBL* prior to the occurrence of severe shocks to spread volatility, than either during or after these shocks occur. In addition, their *RBL* should be inversely proportional to the volatility of returns. Therefore, fixed income hedge funds with returns that are highly negatively correlated with volatility increases will exhibit lower *RBL* pre- and postshock, and higher *RBL* during shocks, than fixed income hedge funds with preshock returns that are positively correlated with volatility increases.

It is generally accepted that, on average, hedge funds engaged in relative value fixed income trading strategies exhibit returns adversely affected by spread widening. As spreads widen significantly, returns will on average become negative. Therefore, the signs of the regression coefficients of fixed income hedge fund returns on the standard deviation of spreads between benchmark interest rates (or bond yields) are expected to be negative. Negative regression coefficients imply that the returns of fixed income arbitrage funds, (being negatively correlated with spread widening), are consistent with spread positions which, by definition, are highly (and adversely) sensitive to the increased magnitude, or frequency, of spread changes (Fung and Hsieh, 2002).

Spread widening tends to be associated with increased volatility. Fung and Hsieh (1995) demonstrate that the correlation between interest rate and yield spread shocks is positive and statistically significant. Consistent with anecdotal evidence, hedge funds can be even more constrained by negative correlation to volatility increases, such that their returns will become even more negative, as spreads widen. Christiansen (2002) shows that the correlation between interest rate volatility and changes in the shape of the term structure is positive. Hedge funds with investments that are adversely affected by increased interest rate volatility, and more volatile term structure or liquidity spreads, are likely to incur higher losses and be more constrained during periods where shocks to both volatility and term structure spreads occur.

As spreads converge (postshock), fixed income hedge funds that are more constrained from portfolio rebalancing, and thus, remain more highly levered than their peers during shocks, may actually exhibit lower returns with a higher return volatility than fixed income hedge funds that delever more during shocks. During shocks, the least constrained funds (alternatively, those funds less impaired by the sensitivity of their preshock returns to future volatility increases) may be positioned to more easily modify *RBL* when spreads widen, might better preserve investment capital during shocks, and therefore, should profit more from postshock spread convergence than more constrained funds.

The performance history of hedge funds engaged in fixed income relative value trading (a relatively new strategy with fewer participants compared with equity-based strategies) is limited to only a few years. Nonetheless, although fixed income securities often have complex payoff distributions, the underlying yields that determine the prices of fixed income instruments are well defined, making relative value calculations tractable and the common factors to returns readily observable.

However, properties inherent in the return sample (e.g., survivor bias, multicollinearity, and heteroskedasticity), might result in estimates that may understate actual leverage (Kennedy, 1993).[5] For example, the change in the volatility of interest

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[5] The resulting effect reduces the statistical significance of the OLS estimator, which remains unbiased.

rates, swap spreads, and the spread between long-dated versus short-dated (e.g., 30-year versus 2-year) fixed income securities tend to be highly correlated. This high degree of correlation (i.e. low cross-sectional variation) between the common factors that explain returns to fixed income arbitrage hedge funds may result in regression coefficients that systematically underestimate actual leverage.

# CHAPTER 3

## A REGRESSION MODEL FOR DOCUMENTING CHANGES IN RISK-BASED LEVERAGE

To test the stated predictions regarding the relationship between hedge fund investment and market shocks, the monthly returns for twenty-four hedge funds engaged in fixed income arbitrage are regressed against monthly changes in fixed income spreads, as follows:

(4) $$return_{n,t} = \alpha + \Sigma_i \left[ b_i X_{i,t} \right] + u_t$$

where,

$\alpha = 0$

$n$ = the $n^{th}$ fund in the sample of 24 hedge funds

$b$ = the factor coefficient where $\Sigma|b|$ is a proxy for an estimate of *RBL*

$X$ = a proxy for factors based on monthly changes in specified fixed income spreads

$i$ = where $i = 1,2,3$ each represent a spread proxy related to market, liquidity or credit risk

$t$ = month in the sample from February 1997 to March 2000

Since changes in *RBL* can be estimated from the cross-sectional variation between hedge fund returns and the standard deviation of spreads related to term structure risk, liquidity risk and credit risk, evidence for *LoA* can be empirically documented, should the hedge funds in the sample reduce their *RBL* when the standard deviation of spreads increase. It seems reasonable to expect higher *RBL* to correspond to greater cross-sectional variation between hedge fund returns and underlying spread changes.

However, due to the high variance (heteroskedasticity) and cross-sectional correlation (multi-collinearity) of hedge fund returns for fixed income strategies, these regressions may understate estimates of actual *RBL* (in absolute terms). Nonetheless, although these estimates may be somewhat biased approximations of the degree of volatility exposure in any given period, comparing the relative change in the cross-sectional variation observed across preshock, shock and postshock periods should provide a suitable proxy for changes in exposure between periods, conditioned on the change in the sensitivity of hedge fund returns to the magnitude of changes in a specified set of factors.

### 3.1. Empirical Design: the Motivation for Sorting the Data

In order to test the hypothesized inverse relationship between increased risk and the *RBL* of fixed income arbitrage hedge funds (as well as their corresponding returns), the returns to fixed income arbitrage hedge funds are sorted into preshock, shock and postshock periods as defined below.

A preshock month *immediately precedes* a month in which the standard deviation of spread is highest. Shock months have the highest standard deviation of spread. Postshock months are those which follow a shock month, excluding the next preshock month in the sample period.

If spreads are most volatile in those months when fixed income arbitrage hedge funds report losses, then it is likely that both expected returns and risks to hedge fund portfolios increase. As exhibited below (see *Description of the Data*), the standard deviations of spreads are highest when the mean returns to fixed income arbitrage funds in general are negative.

## 3.2. Description of the Data

These regressions employ as dependent variables, one-month hedge fund returns during the period February 1997 through March 2000 for the twenty-four fixed income arbitrage hedge funds. Since these fixed income hedge funds survived the LTCM crisis in 1998, one might hypothesize that they (a) were invested in strategies uncorrelated with LTCM, (b) had sources of capital unavailable to many other fixed income hedge funds, (c) liquidated positions that did not incur losses during those periods, or (d) were less levered than LTCM and the other fixed income arbitrage funds that were forced to close during the Fall of 1998. Since all fixed income hedge funds invest in similar instruments and employ similar financing, (a), (b), or (c) are unlikely reasons that the funds in the sample survived.

Therefore, due to survivor bias, it should be no surprise if these funds were to exhibit lower *RBL* than would be expected for fixed income hedge funds in general. Furthermore, a relatively limited sample of returns with very high variance and high cross-sectional correlation will tend to exhibit lower coefficients.

**Table 1. Return for the Sample Compared to Index Return and Average Change in the Term Structure of Swaps**

| Sample Period Jan 97- Mar 00 | Mean One-Month Return Fixed Income Arb Sample | Mean One-Month Return Fixed Income Arb Index | Mean One-Month Std Dev 10-Year vs. 2-year Swaps |
|---|---|---|---|
| Preshock | 0.950 | 0.913 | 0.054 |
| Shock | -0.792 | -0.391 | 0.076 |
| Postshock | 0.563 | 0.597 | 0.044 |

SOURCE: TASS Hedge Fund Index, Reuters

### 3.3. Comparing Mean Returns between the Fixed Income Hedge Fund Sample and the Fixed Income Hedge Fund Sector

During preshock and postshock months, the funds in the sample exhibit positive mean returns that are approximately 4% higher than the positive mean returns exhibited by the TASS index of returns for fixed income arbitrage hedge funds. However, during shock months, the magnitude of the negative returns exhibited by those funds represented within the sample are 100% greater in magnitude than those exhibited by the TASS index. Since the funds in the sample survive the entire sample period, this is consistent with the hypothesis that the funds in the sample employ lower *RBL* than funds in the index, also comprised of funds that do not survive to the end of the sample period, and funds that begin investing postshock as newly formed funds.

A comparison of one-month returns for the twenty-four fixed income hedge funds in the sample, relative to the index of corresponding one-month returns for the fixed income hedge fund sector in general, shows that returns to fixed income hedge funds in both the sample and the TASS index are negative when the standard deviation of the spread between the 30-year swaps versus 2-year swaps is greatest (40% greater than preshock months and 73% greater than postshock months). However, it also shows that although the average change in spread is greater (by 23%) in preshock months than in postshock months, preshock returns are higher than postshock returns (70% higher for the sample and 53% higher for the index). This implies that on average the fixed income hedge fund positions profit less from post-shock spread convergence than would be expected. In other words, postshock returns do not converge to preshock levels. This may be evidence of the hypothesized adverse effects of (involuntary) liquidation in spread positions positions prior to convergence of spreads. Given that postshock spreads are tighter than preshock spreads, lower returns postshock are suggestive of liquidation of positions and a loss of investment capital during the shock.

### 3.4. Variables Selected as Common Determinants Underlying Fixed Income Hedge Fund Returns

The three exogenous variables in these regressions are derived from changes in spreads between market yields or rates. Since the differences in relative value of fixed income instruments are a function of their respective spreads, as previously discussed, it is reasonable for spread changes to be common factors in fixed income hedge fund returns. As previously mentioned, these are test of general effects rather than specific investments or trading strategies. Therefore, documenting the absolute value of regression coefficients on the standard deviation of spread changes, applies to changes in investment leverage for the funds in the sample, regardless of whether any fund's portfolio is negatively or positively correlated with the widening or tightening of the spread in that month.

As discussed previously, although spread changes explain fixed income hedge fund returns, returns regressed on spread changes may exhibit coefficients that differ from the actual leverage of the funds. Spread changes are proportional, but not equivalent to changes in value (i.e., returns) of fixed income investments. However, assuming that the correlation between spread changes and returns are constant, the difference in the absolute values of these coefficients across preshock, shock and postshock periods should correspond to the relative percent change in *RBL*, which is more relevant to the hypothesis than actual *RBL* in the absolute sense.

**Table 2. Common Determinants Underlying Risk-Based Leverage for Fixed Income Hedge Funds**

| Factor in Return | Underlying Spread | Risk Factor | Spread Risk |
|---|---|---|---|
| Term premium | $Swaps_{30yr} - Swaps_{2yr}$ | Interest rate risk | $SD\left(Swaps_{30yr} - Swaps_{2yr}\right)$ |
| Liquidity premium | $30USGov_{On} - 30USGov_{Off}$ | Liquidity risk | $SD\left(30USGov_{On} - 30USGov_{Off}\right)$ |
| Credit risk premium | $Swaps_{10yr} - TBills_{3Mo}$ | Financing/hedging risk | $C^{S=Swaps-Tbill}_{K=S_t,T} = \max\left[0, S_T - K\right]$ |

As illustrated in Table 2, the common proxies for those risk factors underlying return that comprise the three right-hand side variables are as follows: (1) the mean one-month standard deviation of the difference between the 30-year swap rate and the 2-year swap rate ("*SWAPS30_2*"), a proxy for "market" risk, i.e. the volatility of slope changes in the term structure of interest rates, (2) the mean one-month standard deviation in the difference in the yield between On-the-run and Off-the-run 30-Year Treasury bond ("*ON/OFF_30"),* a proxy for changes in the liquidity risk, and (3) the average monthly change in daily value of a one-month straddle written on the spread between 3-month Treasury bills versus 10-year swaps *("STRADDLE3M_10Y*"), a proxy for the volatility changes of short- to intermediate- term credit spreads or financing/hedging risk.

*SWAPS30_2*, i.e. monthly changes in the swap spread, represents changes in the difference between the 30-year swap rate and the 2-year swap rate. These changes reflect changes in the slope of the interest rate curve. Lending at the 2-year swap rate (a long position), financed by borrowing at the 30-year swap rate (a short position) is effectively a bet that the spread will narrow as the curve flattens, and hence is commonly referred to in the industry as a "flattener" or curve-flattening trade. *Flatteners* and *steepeners* (e.g. borrowing at the 2-year rate and lending at the 30-year rate) are among the most common trades engaged in by fixed income arbitrage funds and are commonly discussed by fixed income analysts in published securities industry research.

*ON/OFF_30*, the monthly changes in the spread (i.e. the difference in yield) between *On-the-run* and *Off-the-run* 30-year Treasury bonds represents changes in the spread between the more liquid benchmark Treasury bond yield and the less liquid Treasury bond yield, respectively, which represents a liquidity premium. Buying the off-the-run bond (to receive the off-the-run yield) and selling the on-the-run (to pay the on-the-run yield) is effectively a bet that the yield difference between the on-the-run versus the off-the-run will converge. This trade is widely documented as a substantial exposure of LTCM (Lowenstein, 2000; Dunbar, 1999) in the Summer and Fall of 1998.

*STRADDLE3M_10Y* reports monthly changes in the value of a straddle (long a 30-day ATM European call and long a 30-day ATM European put) for which the underlying basis of each option is the difference in yield between receiving the 3-month Treasury bill rate versus paying the 10-year swap rate. Buying a call (put) to receive the 3-month T-bill rate and pay the 10-year swap rate is effectively a bet that short-term rates will increase (decrease) relative to long-term rates. The value of the combination of puts and calls (and hence the value of the straddle) increases with the increase in *implied* volatility, commonly described as the "market price of risk" (a function of hedging demand, often employed as the market estimate of future volatility). The spread of the swap rate relative to the treasury rate is the benchmark for the credit risk premium for banks of investment grade credit quality (average "A" rating). Hence, the volatility of swap spreads can be interpreted as a proxy for financing risk.

Fixed income hedge fund strategies often involve hedging and financing by referencing swap rates. Receiving the swap rate (lending) and paying the Treasury rate (borrowing) is analogous to being positively correlated with an increase in the swap spread. Paying the swap rate (borrowing) and receiving the Treasury rate (lending) is analogous to being negatively correlated with an increase in the swap spread.[1]

Collin-Dufresne and Goldstein (2002) employ at-the-money straddles (sensitive to changes in volatility but not in rate levels), to show the sensitivity of fixed income portfolios to volatility changes, as evidence that derivatives are needed to hedge the volatility risk of fixed income portfolios. Therefore, being *long a straddle*, which is equivalent to purchasing a matched combination of calls and puts with the same exercise price in equal proportions, is a bet that the volatility of the spread between the underlying short-term and long-term rates will increase. Volatility bets are also commonly cited as

[1] Among the most common instruments employed by fixed income hedge funds are Treasury bills, pledged as margin, and swaps (and swaptions, i.e., options on swaps), as hedging and financing instruments. Hedge funds generally finance and hedge by lending (borrowing) at the swap rate and borrowing (lending) at the Treasury bill rate. It has been documented that in 1998 LTCM and similar funds assumed substantial exposure to such at bet of swaps versus treasuries.

trades that are engaged in by fixed income arbitrage funds. Being negatively correlated with the volatility of the spread between short-term and long-term rates is evidence of being *net short volatility*, i.e. a bet that the volatility of the spread will not increase.

**Table 3. Three "Factors" Selected as Proxies for Generic Fixed Income Hedge Fund Trading Exposures**

| RHS Variables 'Factors' | Mean 1-Mth Std Deviation *'SWAPS30_2'* | Mean 1-Mth Std Deviation *'ON/OFF_30'* | Mean Monthly Return *'STRADDLE3M_10Y'* |
|---|---|---|---|
| Preshock | 0.054 | 0.010 | 0.015 |
| Shock | 0.076 | 0.018 | 0.055 |
| Postshock | 0.044 | 0.016 | 0.283 |

SOURCE: TASS Hedge Fund Index

The following observations support the empirical validity of the choice of variables:

(A) A comparison of the average monthly spread changes for *SWAPS30_2* and *ON/OFF_30* shows that, as predicted, spreads for both factors are wider during shock months than during preshock and postshock months. However, in contrast to *SWAPS30_2*, although the *ON/OFF_30* spread narrows somewhat during postshock months, it remains persistently wider on average relative to preshock months. This is consistent with documented anecdotal evidence that LTCM accumulated a massive exposure to on-the-run versus off-the-run Treasuries prior to its collapse, and that for several months during the collapse and subsequent bailout, the spread between the on-the-run versus off-the-run 30-year Treasury did not converge, but remained at historically wide levels.

(B) As expected, the value of the long volatility position *STRADDLE3M_10Y* increases during the shock month, suggesting that on average the increase in the implied volatility (the price of risk based on the market expectation of future volatility between short-term and long-term rates) corresponds with the increase in the magnitude of *SWAPS30_2* and *ON/OFF_30*. This suggests that the implied volatility of the spread between the 3-month T-bill versus 10-year swaps is positively correlated with the widening of the other two observed spreads.

(C) During post-shock months, the value of *STRADDLE3M_10Y* remains higher than the preshock value, due to increased implied volatility (from prolonged hedging demand, as described by Scholes, 2000). This is also consistent with documented anecdotal evidence (Dunbar, 1999; Lowenstein, 2000), that the perverse practice of selling options to meet margin calls with harvested premiums may have contributed to LTCM's ultimate collapse as implied volatility continued to increase.

These three exogenous variables selected as factors to test the predictions of the model are employed as follows. First, the one-month returns of the sample of twenty-four fixed income arbitrage hedge funds will be regressed against monthly spread changes of *SWAPS30_2* in a one-factor regression model, in order to test whether the predicted change in *RBL* occurs, conditioned on the increased magnitude of spread changes during shock months. Second, the one-month returns of the sample of fixed income arbitrage hedge funds will be regressed against monthly spread changes of *SWAPS30_2* and *ON/OFF_30*, and the returns of *STRADDLE3M_10Y* in a three-factor regression model to test whether the results of the one-factor model persists in a model with multiple factors.

Third, the sample of fixed income arbitrage funds are sorted into two subgroups based on the standard deviation of their preshock returns. The three-factor model regression model is then employed to compare *RBL* estimates across preshock, shock and postshock return for these two cohorts.

# CHAPTER 4

## ONE FACTOR MODEL FOR FIXED INCOME ARBITRAGE HEDGE FUNDS

As described in Section 3.2. (*Description of the Data*), the one-month returns of those hedge funds identified in the sample as being engaged in fixed income arbitrage and the corresponding monthly spread changes in *SWAPS30_2* are sorted into preshock, shock and postshock cohorts. The fixed income arbitrage hedge fund returns are regressed against the one-month changes in *SWAPS30_2*, according to the one-factor regression model (where each one-month return of each fund *n* is interpreted as a position in a single representative fund at time *t*), specified as follows:

(5) $$return_{n,t} = \alpha + b_{1,t}\left[SWAPS30\_2_t\right] + \xi_t \text{, where } \alpha = 0$$

A comparison of the results of the one-factor regression performed for each cohort of returns shows the change in $|b_1|$, the estimated *RBL* of the hedge fund (the cross-sectional variation in return) conditioned on the average monthly change in the spread between the 30-year swap rate versus the 2-year swap rate, i.e., the difference in spread based on the slope of the term structure of the interest rate swap curve.

**Table 4: One-Factor Model Results for the Fixed Income Hedge Fund Return Sample**[a]

| **One-Factor Regression *SWAP30_2*** | $b_1$ | **t-statistic** | **N** | $R^2$ | **F-Statistic** | **SE of Equation** |
|---|---|---|---|---|---|---|
| Preshock | -0.20 (0.069) | -2.90** | 201 | 0.040 | 8.397 | 0.033 |
| Shock | -0.24 (0.065) | -3.77** | 224 | 0.059 | 14.226 | 0.050 |
| Postshock | -0.04 (0.058) | -0.65 | 296 | 0.000 | 0.072 | 0. 028 |

[a] Standard error of coefficients in parentheses

The univariate regression of fixed income arbitrage hedge fund returns against *SWAPS30_2* shows postshock *RBL* ($|b_1| = 0.04$) to be 80% less than preshock *RBL* ($|b_1| = 0.2$), consistent with the prediction that the occurrence of shocks (the 40% increase in the average change for *SWAPS30_2*) will result in delevering by hedge funds. The sign of the coefficient $b_1$ implies that on average hedge fund returns in the sample are inversely correlated with the change in the spread between 30-year swaps versus 2-year swaps, as predicted by current theory (Vayanos and Gromb, 2000; Liu and Longstaff, 2000), and reported by Fung and Hsieh (2002) in the results of their regressions of fixed income arbitrage hedge fund returns on various spreads.

During shock months, the average 0.2% marginal increase in estimated *RBL* (relative to the estimate for preshock months) might be evidence of mark-to-market losses (and/or the inability to reduce *RBL*). Alternatively, it may simply be an artifact in the data (due to the increased cross-sectional variation in hedge fund returns during shock months).[1] In either case, this minor increase is statistically indistinguishable from zero.

As shown by the standard error ("SE") of the coefficient reported in Table 4, the sampling variability remains 25-30% of the magnitude of the preshock and shock estimates. However, the magnitude of the postshock estimate is dwarfed by the sampling variability. Although the SE of the shock period regression is larger than the preshock period and postshock period regressions by 52% and 78%, respectively, the statistical significance of the shock period regressions appear to be higher, as demonstrated by the $R^2$ and F-statistics.

[1] In order to further determine whether the increase in *RBL* is due to mark-to-market losses (gains) requires a more direct observation of actual leverage (e.g., leverage based on margins or trading positions), currently not available and beyond the scope of this paper.

# CHAPTER 5

## THREE FACTOR MODEL FOR FIXED INCOME ARBITRAGE HEDGE FUNDS

The fixed income arbitrage hedge fund returns (sorted into preshock, shock and postshock months) are regressed against the one-month changes in *SWAPS30_2* and *ON/OFF_30*, and the monthly returns of *STRADDLE3M_10Y*, according to the three-factor regression model (where the return of each fund *n* is interpreted as a position in a single representative fund at *t*), specified as follows:

(6)

$$return_{n,t} = \alpha + b_{1,t}\left[SWAPS30\_2_t\right] + b_{2,t}\left[ON/OFF\_30_t\right] + b_{3,t}\left[STRADDLE3M\_10Y_t\right] + \eta_t$$

where $\alpha = 0$

The results of the three-factor multivariate regression for the full sample of fixed income arbitrage funds are reported in Table 12. As explained in a previous section, the three factors selected represent the following trading exposures: the difference in yield based on the slope of the term structure of interest rates, the difference in yield between more versus less liquid government bonds with identical underlying cashflows (perfect substitutes with fundamentals that ultimately must converge), and the implied volatility of the term structure of interest rates. A comparison of the results of the three-factor regression performed for each cohort of returns shows a change in $\Sigma|b_i|$ (where $i = 1,2$), the estimated *RBL* of the hedge fund. The *RBL* estimate is the cross-sectional variation in return, conditioned on the average monthly change in the linear combination of two spreads, which serve as proxies for common factors in fixed income arbitrage returns.

The three-factor multivariate regression of fixed income hedge fund returns (as reported in Table 12) shows postshock RBL to be statistically indistinguishable from zero, relative to preshock RBL ($\sum|b|$=0.70), consistent with the prediction that hedge funds drastically reduce investment exposure subsequent to the occurrence of shocks. The signs of the coefficients $b_1$ and $b_2$ imply that on average, hedge fund returns in the sample (both preshock and shock) are inversely correlated with the change in the spread between 30-year swaps versus 2-year swaps, and on-the-run versus off-the-run 30-year Treasuries, as predicted by the current theory (Vayanos and Gromb, 2000; Liu and Longstaff, 2000), and reported by Fung and Hsieh (2002) in the results of their regressions of fixed income arbitrage hedge fund returns on various spreads. Postshock, the sensitivity of hedge fund returns to changes in volatility becomes statistically significant (and positive). The $R^2$, F-statistic and SE of the equation are highest during the shock than for either pre- or postshock.

Although the SEs of the three coefficients reported in Table 12 seem to imply higher sampling variability (in the absolute sense) for the preshock coefficients than for the shock or postshock coefficients of *SWAP30_2* and *ON_OFF30*, the coefficients for *SWAP30_2* is statistically significant only in the preshock period. Furthermore, the coefficient for *ON_OFF30* is more statistically significant in the preshock period than in the shock period. In other words, sampling variability has actually declined relative to the change in the slope coefficients for *SWAP30_2* and *ON_OFF30*. The differences in the SE of the shock period regression relative to the preshock period and postshock period regressions is comparable to those exhibited by the one-factor regression.

### 5.1. Survivor Bias: Out-of-Sample Test of Failed Fixed Income Arbitrage Funds

In order to estimate the change in *RBL* across preshock, shock and postshock periods from the returns of a sample of fixed income hedge funds, the sample is comprised of those funds that report returns every month of the sample period. The objective is to observe changes in *RBL* made by the same funds reporting returns across all three periods. Hence, the funds in the sample are limited strictly to those funds that survive periods of severe shocks. It may be worth exploring whether this approach introduces a sample selection bias in the regression results regarding the change in *RBL* in response to the occurrence of shocks.

In order to evaluate the bias in the results, an out-of-sample test employs the returns of fourteen (14) funds that, according to the TASS "graveyard" file liquidated during the sample period. Table 5 compares the monthly returns for the sample of 24 surviving funds ("Survivors") to the 14 funds that liquidated ("Failures"), and to the TASS index of all fixed income arbitrage funds. Although the monthly returns for Failures are marginally more positive for preshock months, during shocks, the losses incurred by Failures are 296% and 700% greater than for Survivors and for the Fixed Income Arbitrage Index, respectively! It should be noted that the remaining returns reported in the index represent fixed income hedge funds that only report intermittently during the period or stop reporting for reasons other than liquidation.

**Table 5. Mean Monthly Returns for Survivors, Failures and TASS Fixed Income Arbitrage Return**

| | Mean Return: Survivors | Mean Return: Fixed Income Arb Index | Mean Return: Failures |
|---|---|---|---|
| Preshock | 0.950 | 0.913 | 1.020 |
| Shock | -0.792 | -0.391 | -3.131 |
| Postshock | 0.563 | 0.597 | 0. 288 |

SOURCE: TASS

As exhibited by Tables 5A and 5B below, the *RBL* for Failures actually increases from the preshock to the shock period, which is consistent with the greater losses (relative to Survivors), incurred by Failures during the shock period. What is surprising, but nonetheless compelling, is the positive correlation with increased volatility exhibited by Failures during the shock period (and during the preshock period, although without statistical significance).

**Table 5A. The Change in Risk Based Leverage for Funds That Failed During the Sample Period**[a]

| | Survivors | | Failures | |
|---|---|---|---|---|
| | ***RBL*** | ***Vol Exposure*** | ***RBL*** | ***Vol Exposure*** |
| **Preshock** | 0.7 | -- | 0.3 | -- |
| **Shock** | 0.2 | -- | 0.8 | +0.3 |
| **Postshock** | -- | +0.2 | -- | -- |

[a] {--} indicates that the coefficients were not statistically significant

Although the interpretation of the results is limited by the availability of monthly returns only (versus more frequent returns), which prohibits any observation of intramonth changes in investment exposure, the funds that eventually fail do not appear to be volatility constrained. This pattern is surprising, but nonetheless consistent with the primary *LoA* hypothesis, and appears to make it that much more compelling. In fact, the story would seem that the funds that fail, being somewhat unconstrained by volatility, attempt to *increase* investment to exploit greater mispricing, during those months when markets are the most volatile, incurring even greater losses, preserving less investment capital, and recovering much less, hence showing much lower postshock gains.

**Table 5B. Funds That Failed During the Sample Period**[ab]

| **Three-Factor Regression** | $b_1$ *SWAPS30_2* | t-stat | $b_2$ *ON/OFF_30* | t-stat | $b_3$ *STRADDLE 3M_10Y* | t-stat | N | $R^2$ | F-Stat | SE of Eqn |
|---|---|---|---|---|---|---|---|---|---|---|
| **Preshock** | -0.12 (0.083) | -1.48 | -0.26 (0.086) | -3.06** | 0.08 (0.086) | 0.93 | 141 | 0.08 | 4.19 | 0.021 |
| **Shock** | -0.26 (0.114) | -2.26** | -0.50 (0.116) | -4.27** | 0.27 (0.095) | 2.87** | 95 | 0.38 | 18.4 | 0.056 |
| **Postshock** | 0.08 (0.131) | 0.64 | 0.18 (0.138) | 1.33 | 0.21 (0.156) | 1.33 | 84 | 0.03 | 0.79 | 0.048 |

[a] This table reports the variables and coefficients for regressions of monthly returns for fourteen (14) fixed income hedge funds that liquidated during the sample period (sorted according to preshock, shock and postshock months) versus contemporaneous mean standard deviations of spreads (*SWAPS30_2*; *ON/OFF_30*) and the one-month mean daily returns of straddles (*STRADDLE3M_10Y*).

[b] Standard errors of coefficients are noted in parentheses.

The sampling variability of the regressions, as exhibited by the SE of the regression, more than doubles for the shock regression relative to the preshock regression, however, due to the increase in the slope estimate, the shock regression is the more significant of the two. The postshock coefficients decline far more than the SEs with the result being that all estimates are insignificant. Although the SE of the coefficients increases for all three coefficients, the slope estimates increase even more, resulting in all three coefficients, *SWAPS30_2* ($t$=-2.26), *ON/OFF_30* ($t$=-4.27), and *STRADDLE3M_10Y* ($t$=-2.87), being statistically significant.

# CHAPTER 6

## HIGHER VERSUS LOWER VARIANCE FIXED INCOME ARBITRAGE HEDGE FUNDS

In order to examine the relative change in *RBL* and in returns by differentiating between more versus less constrained fixed income hedge funds, the funds are grouped according to their standard deviation of preshock returns, i.e. funds with a higher standard deviation of returns (.041%) versus a lower standard deviation of returns (.010%). As discussed in previous sections, *ceteris paribus*, lower *RBL* tends to be inversely proportional to higher standard deviation of returns.

**Table 6. Mean and Standard Deviation of Preshock Return for Groups of Funds by Cohort**

| Groups | Preshock Returns | | Shock Returns | | Postshock Returns | |
|---|---|---|---|---|---|---|
| | Mean | Std. Dev. | Mean | Std. Dev. | Mean | Std. Dev. |
| Higher St Dev | 0.9 | 0.41 | -1.2 | 0.68 | 0.3 | 0.35 |
| Lower St Dev | 0.1 | 0.10 | -0.7 | 0.31 | 1.0 | 0.12 |

The mean and standard deviation of returns for the two groups are exhibited in Table 6. The group with higher standard deviation (SD) of preshock returns exhibit slightly lower preshock mean returns, greater losses during shock months, and significantly lower postshock mean returns than the group with lower standard deviation of preshock returns. In addition, the group with higher SD of preshock returns, exhibit higher SDs of returns during shock and postshock periods. As with the full sample, the observation that the postshock mean return for the higher SD fund does not revert to the preshock level is consistent with liquidation of a losing position (and the corresponding realized capital loss) during the shock.

The fund returns within each of the two groups, sorted into preshock, shock and postshock months, are regressed against the corresponding monthly changes in *SWAPS30_2* and *ON/OFF_30*, and the one-month returns of *STRADDLE3M_10Y*, according to the three-factor regression model. The regression estimates for preshock, shock and postshock *RBL* ($\Sigma|b_i|$ for each group of funds, where $i = 1,2$), and volatility exposure ($b_3$ for each of cohort of each fund group), are exhibited in Table 7 below. The higher SD group exhibits lower preshock *RBL* and volatility exposure than the lower SD group of funds. However, during shocks, this group exhibits a *RBL* estimate that is *twice* as high (as well as higher volatility exposure as well), as the lower SD group.

*Vol Exposure,* i.e. “volatility exposure” (the sensitivity of the returns to increases in the volatility of an underlying spread), is expressed as the rolling one-month cumulative daily change in the value of a long position in a 30-day European straddle (i.e., the one-month return in *STRADDLE3M_10Y*, for which the underlying volatility parameter is the historical one-month standard deviation of the spread between the yield of 3-month T-bills and the yield of 10-year swaps). The value of a straddle covaries primarily with changes in the volatility of the underlying spread, such that an increase in the implied volatility of the spread results in an increase in the value of the straddle.

Fund returns that are positively correlated with the gains of a straddle are positively correlated with a future increase in volatility, i.e. gains or losses related to changes in implied volatility. As explained in the description of the data, the return, (the change in the value of *STRADDLE3M_10Y*), which serves as the proxy for the underlying factor *Vol Exposure*, increases from preshock through postshock. The sign of $b_3$, the coefficient for *STRADDLE3M_10Y*, shows the correlation between the fund returns with gains (losses) related to increases in implied volatility for each group of funds.

**Table 7. Estimates of Risk-Based Leverage and Volatility Exposure by Cohort and Fund Group**[a]

| | Higher Preshock SD Group | | Lower Preshock SD Group | |
|---|---|---|---|---|
| **Cohort** | **RBL** | **Vol Exposure** | **RBL** | **Vol Exposure** |
| Preshock | 0.63 | -0.03 | 1.31 | 0.23 |
| Shock | 0.31 | -0.10 | 0.29 | -0.07 |
| Postshock | 0.15 | 0.17 | 0.36 | 0.33 |

[a] Coefficients used to calculate *RBL* and *Vol Exposure* are reported in Table 13.

Examining the estimates of *RBL* and *Vol Exposure* exhibited above in Table 7 reveals that the preshock returns of the group with lower (higher) SD returns are positively (negatively) correlated with the preshock one-month return of

*STRADDLE3M_10Y*. The higher preshock SD group exhibits negative correlation with gains related to volatility increases, both prior to, as well as during, shocks.

In computing *RBL* by summing the regression coefficients, very low t-statistics ($t < 1.25$) were disregarded, although the small sample size combined with the multicollinearity of fixed income hedge fund factors can be expected to reduce statistical significance. However, when only statistically significant coefficients are summed to compute *RBL*, the pattern of delevering across cohorts, from preshock to postshock, is even more pronounced.

The pattern of *RBL* for both groups of funds is consistent with the empirical implications of *LoA*. The SD of returns for both groups increases substantially during shocks, and then postshock, converges to preshock levels. This is to be expected, since higher *RBL* tends to generate higher volatility of returns, as returns exhibit greater sensitivity to underlying factors (Breuer, 2000). In addition, both groups exhibit negative correlation with gains related to volatility increases during shocks, and both groups "delever" (i.e., reduce investment exposure) during shocks.

The higher preshock SD group, which is also the group with returns that are negatively correlated with future volatility increases preshock (and is more levered during shocks), delevers less during the shock, but continues to delever postshock. The group with lower preshock SD returns delevers *more* during the shock than the higher preshock SD group, and remains less levered postshock than preshock. However, the lower preshock SD group is less levered during the shock and *more* levered postshock than during the shock. This result is consistent with the proposition that hedge funds that are positively correlated with gains related to volatility increases tend to be less constrained than hedge funds that are negatively correlated with volatility-related gains (Shleifer, 2000).

The returns of the lower preshock SD group are positively correlated preshock and postshock with gains related to increased volatility. During shocks, when the lower preshock SD group delevers, its returns are negatively correlated with gains related to increased volatility. The fact that this lower preshock SD group also exhibits higher preshock and postshock *RBL* than the higher preshock SD group, but delevers more during shocks, is consistent with a fund manager facing a less constrained portfolio of investments, who delevers during a shock to avoid forced liquidation, and hence, retains more unencumbered investment capital to employ postshock. This is further supported by the fact that the postshock returns of the lower preshock SD group converge to the preshock level.

In contrast, the preshock returns of the higher preshock SD group covary negatively with gains related to increased volatility. During shocks, the negative covariation between the returns of the higher preshock SD group and volatility-related gains are three times greater than in the preshock months. However, although the higher preshock SD group appears to be less levered preshock, this group delevers less than the lower preshock SD group, and appears more levered during shocks.

This is consistent with a fund manager who faces a more constrained portfolio of investments, and is less able to modify *RBL* by rebalancing the portfolio in response to shocks, and whose investment capital may be even more severely encumbered postshock than preshock, due to forced liquidation of investments (and any corresponding capital losses). Although fixed income hedge funds may either be long or short spreads, even if spreads are historically wide or narrow, the degree to which a fixed income arbitrage fund is *net long* or *net short* volatility is a function of how investment positions are financed and/or hedged. The volatility of the credit spread (e.g. swap spread relative to treasuries) is also related to financing and hedging risk.

The observation that both groups delever during shocks, and the group that exhibits higher preshock leverage delevers more, is consistent with the hypothesis that barring other constraints, hedge funds have an incentive to delever when shocks occur. The observation that the lower preshock SD group exhibits higher *RBL* preshock and postshock than the higher preshock SD group, is consistent with the literature that states that firms with more volatile earnings have lower borrowing capacity on average. The observation that the higher preshock SD group, which during preshock, exhibits negative correlation with swap spread volatility, continues to delever postshock, may be evidence of the possible effects of forced liquidation due to a "short squeeze" when a severe shock occurs.

The results of the three-factor regressions for the two subgroups of fixed income arbitrage funds are reported in Appendix Table 13. The regression coefficients related to preshock *RBL* are statistically significant for both high and low preshock SD groups. The returns for both groups covary negatively with spread changes in both preshock and shock months (as predicted). However, postshock returns covary negatively only with *SWAPS30_2*, and only for the lower SD group.

The preshock and shock returns of both the higher preshock SD and lower preshock SD groups are negatively correlated with the spread changes corresponding with slope changes in the term structure of interest rates (*SWAPS30_2*) and in the liquidity premia of government bonds (*ON/OFF_30*). During shocks, the higher preshock SD group is most correlated with *ON/OFF_30* ($t = -1.89$), the widening of the liquidity spread, and the lower preshock SD group is most correlated with *SWAPS30_2* ($t = -2.14$), the widening of the term structure spread.

The statistical significance of the covariation of the preshock returns for the lower preshock SD group with both *SWAPS30_2* ($t = -4.95$) and *ON/OFF_30* ($t = -3.83$) is higher than for the higher preshock SD group ($t = -3.06$ and $t = -2.10$, respectively). Postshock, only the lower preshock SD group exhibits statistically significant covariation with any of the factors, being both positively correlated with both *ON/OFF_30* ($t = -2.22$) and the volatility-related factor, *STRADDLE3M_10Y* ($t = 2.75$).

The negative covariation with gains from increasing volatility for the higher preshock SD group's returns during preshock ($t = -0.28$) and shock ($t = -0.95$) months are not statistically significant, which is most likely due to the multicollinearity. This multicollinearity effect can be expected due to very high correlation between options-based volatility strategies and a volatility-related shock.

The positive covariation of the preshock returns with volatility shock-related gains are statistically significant ($t = 2.16$) for the lower preshock SD group. In contrast to the positive covariation of the lower preshock SD group with increasing postshock volatility-related gains, the positive covariation of the higher SD group with increasing postshock volatility-related gains is not statistically significant ($t = 1.62$), which may be due to any *long volatility* investments that remain after delevering during shocks.

The reduced statistical significance for the shock regression relative to the preshock regression is the result of the decline in the slope coefficients of the regressions with the SEs remaining approximately comparable between the two regressions. Although the SEs decline more for the postshock regressions relative to the shock regressions, the slope coefficients decline much more. Consistent with the prior tests, this result implies that the change in the slope rather than the change in sampling variability accounts for the change in *RBL*.

# CHAPTER 7

## A MORE GENERAL TEST USING A MORE DIVERSE SAMPLE OF HEDGE FUNDS

This section more generally tests the main hypothesis of the paper with a sample of hedge funds that are engaged in a broader set of strategies than exclusively fixed income arbitrage. When shocks occur (and expected returns to arbitrage increase), observing whether a more diverse sample of hedge funds reduces investment on average, can provide further evidence on whether capital constraints impair the trading activity of hedge funds in general.

The hypothesis that is tested is whether, in the aggregate, hedge fund *RBL* decreases substantially after severe price shocks. For a broader sample of hedge fund strategies, this more general analysis directly applies the regression specification employed by FH1997. However, it also further extends their regression model to include mimicking portfolios based on returns to static option positions as proxies for the sensitivity of hedge fund returns to changing market volatility, as do the regressions in the previous sections. Finally, the tests of the broader sample of hedge funds also sort returns into preshock, shock and postshock months, based on the idiosyncratic (asset-specific) residual variance exhibited within daily stock returns, as opposed to increased volatility of fixed income spreads employed in the regressions performed in the previous sections.

In contrast to the sample comprised exclusively of fixed income hedge funds, the determinants of expected returns to investment strategies cannot be based solely on common factors in bond returns, but upon a broader set of underlying return drivers. Also, given the diversity of strategies within the sample, the proxy for periods of mispricing (i.e. shocks) is based on residual idiosyncratic risk exhibited within a given month as described by Richards (1999). According to Asness, Krail and Liew (2000), hedge fund returns in general seem to exhibit significant *beta* exposure to stock market returns, and therefore, periods of extreme stock market volatility should influence hedge fund returns.

To infer leverage changes from a diverse sample of hedge funds, FH1997 makes two modifications to the specification and interpretation of the Sharpe (1992) regression model for explaining mutual fund performance. First, FH1997 allows coefficients to be either positive or negative with absolute values greater than one. This is contrary to the Sharpe model, which constrains the factor coefficients in the regressions to be positive and less than one (since mutual funds are unlevered, long-only, buy-and-hold investors). Second, FH1997 uses *principal components analysis* to summarize the sample variation of standardized returns of hedge funds in the sample. This simplifies the otherwise complicated task of variable selection, by identifying proxies for the most common hedge fund trading strategies represented in the sample.[1]

As defined in FH1997, a common trading strategy can be interpreted as the shared factor in the correlated returns of a sample of hedge funds. The extreme heterogeneity of trading strategies available to hedge funds requires a method for identifying (from the data) dominant trading strategies as common factors underlying the returns of the sample. However, the high correlation typically exhibited across a sample of hedge fund returns further complicates the identification of common trading strategies.

Principal components analysis simplifies this estimation problem by summarizing the sample variation of the hedge fund returns into the smallest number of orthogonal linear combinations possible.[2] According to FH1997, the coefficients of these proxies correspond to leverage estimated from the covariation between hedge fund returns and strategy-specific exposures (versus the covariation of exposures to buy-and-hold asset returns).[3]

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[1] See Appendix C. *The Fung and Hsieh 1997 Asset- and Returns-Based Multiple-Factor Model.*

[2] See Appendix D. *Principal Components Analysis.*

[3] The FH1997 notion of leverage estimates based on regression coefficients is quite similar to *RBL* as defined earlier.

The resulting FH1997 regression model specifies hedge fund returns as a linear combination of asset returns and correlated returns to the active trading strategies that are most common for the funds in the sample:

$$(7) \qquad return_{n,t} = \alpha + \Sigma_i \left[ b_i Assets_{i,t} \right] + \Sigma_f \left[ b_f Strategies_{f,t} \right] + u_t$$

where,

$n$ = the $n^{th}$ fund in the sample of 251 hedge funds

$i$ = proxies for one-month "buy-and-hold" asset returns ("*ASSETS*")

$f$ = proxies for one-month returns to hedge fund trading strategies ("*STRATEGIES*")

$t$ = months in the sample from January 1997 to March 2000

Although FH1997 documents the sensitivity of hedge fund returns to market rallies and declines, the authors also acknowledge that their model specification does not fully explain the sensitivity of hedge fund returns to changes in volatility. Past research has employed options as proxies to explain the (mutual) fund returns (Dybvig and Ross, 1985; Merton, 1981).

Including options-based returns as proxies for sensitivity to shifts in volatility may more effectively account for volatility-related variation in hedge fund returns (Glosten and Jagannathan, 1994; Grinblatt and Titman, 1989). Also, the use of leverage by most hedge funds tends to disproportionately magnify the variance of hedge fund returns relative to asset returns, which reduces the statistical significance of *OLS* regression coefficients. [4]

Hence, adding returns from passive option portfolios extends the FH1997 model, as follows:

$$(8) \qquad return_{n,t} = \alpha + \Sigma_i \left[ b_i Assets_{i,t} \right] + \Sigma_j \left[ b_j Strategies_{j,t} \right] + \Sigma_k \left[ b_k VolFactors_{k,t} \right] + \varepsilon_t$$

where,

$n$ = the $n^{th}$ fund in the sample of 251 hedge funds

$i$ = seven proxies for one-month "buy-and-hold" asset returns ("*ASSETS*")

$j$ = three proxies for one-month returns to proxies for hedge fund trading strategies ("*STRATEGIES*")

$k$ = three vectors of one-month returns for volatility sensitive option portfolios ("*VOLFACTORS*")

$t$ = preshock, shock or postshock months in the sample January 1997 to March 2000

Equation (8) specifies the regression of hedge fund returns on the returns to three broad categories of trading exposures: *ASSETS*, *STRATEGIES*, and *VOLFACTORS*. As in

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[4] Asset returns alone are insufficient to explain the state dependency of hedge fund returns. Bansal and Viswanathan (1993) demonstrate that the pricing kernel of a linear factor model comprised exclusively of asset returns is inadequate for pricing investments with nonlinear payoffs. Bansal, Hsieh and Viswanathan (1993) use a nonparametric statistical approach to derive a pricing kernel appropriate for instruments with nonlinear return distributions. These regressions account for nonlinearity by including factors with nonlinear returns.

the previous equation (7), leverage is the sum of both "buy-and-hold" asset exposures ("*ASSETS*") and strategy exposures ("*STRATEGIES*").

To account for the sensitivity of hedge fund returns to increased volatility, additional regressors have been added to the model. As in the regressions for fixed income hedge fund strategies, volatility-related exposures ("*VOLFACTORS*") measure the covariation of hedge fund returns with the volatility increases that result from the leveraged bets engaged in by hedge funds. Summing the coefficients for *VOLFACTORS* measures the sensitivity of hedge fund returns to volatility changes.

## 7.1. Description of the Data

The regressions employ the following contemporaneous one-month returns: (i) returns for a sample of 251 hedge funds, (ii) returns for seven asset indices, (iii) returns to three common trading strategies (summarized from the sample of hedge fund returns using principal components analysis), and (iv) returns to three passive options portfolios constructed to be sensitive to changes in volatility.

### *7.1.1. Hedge fund returns*

TASS tracks monthly returns for over 2,500 hedge funds and managed futures funds. The TASS database is comprised of hedge funds which engage in the following strategies: convertible arbitrage, equity market neutral, emerging markets, equity market neutral, event-driven, fixed income arbitrage, global macro, long/short equity, managed futures, and dedicated shortsellers. The sample runs from January 1997 through March 2000, the longest period in which the greatest number of funds report a one-month return for every month in the sample period. After eliminating all funds that do not report returns in each month over the entire period, the resulting sample consists of 251 hedge funds.

A comparison of the average preshock, shock, and postshock returns (defined in the subsequent section) for the entire sample of 2,500 hedge funds comprising the TASS database is exhibited below, disaggregated by strategy. The comparison shows that, on average, hedge fund returns tend to be lowest during shocks (with the exception of equity market neutral and shortsellers). Also, postshock returns are lower than preshock returns. The pattern of returns suggest that, in the aggregate, hedge funds experience weaker interim performance when shocks occur.

**Table 8. Average Returns of Hedge Funds by Strategy for the Sample Period**

| | Average Returns | | |
|---|---|---|---|
| **Strategy** | **Preshock** | **Shock** | **Postshock** |
| All Strategies | 2.20 | 0.06 | 1.49 |
| Convertible Arbitrage | 1.27 | 0.49 | 1.05 |
| Equity Market Neutral | 1.18 | 1.23 | 0.89 |
| Long Short Equity | 3.23 | 2.88 | 2.63 |
| Event Driven | 1.76 | 0.18 | 1.11 |
| Managed Futures | 1.33 | 0.60 | 0.26 |
| Global Macro | 1.69 | -1.24 | 1.57 |
| Fixed Income Arbitrage | 0.91 | -0.39 | 0.60 |
| Shortsellers | -0.91 | -0.70 | -0.57 |

SOURCE: TASS

*7.1.2. "Buy-and-Hold" Asset Returns*

In accordance with Sharpe's style-based regressions as also employed in FH1997, the asset returns ("*ASSETS*") included in the sample are as follows: the US Dollar trade-weighted index ("*US$INDEX*"), reflects the monthly returns to currency exposure. The Goldman Sachs Commodity Index ("*GSCI*") represents monthly returns for a diversified basket of commodities. The Lehman Composite Bond Index ("*LEHCOMP*") exhibits returns for a cross-section of US fixed income (corporate and government) markets. Four stock indices are represented in the model: the S&P500 index ("*S&P500*") comprised of the 500 largest US stocks weighted by their market capitalization, the Russell 2000 small-cap stock index ("*RUSSELL*"), the MSCI World Index ("*MSCIWRLD*"), and the MSCI index of European, Australasia, and Far East stocks ("*MSCIEAFE*"). These seven indices represent a comprehensive cross-section of all of the asset classes in which hedge funds might invest.

*7.1.3. Principal Components-Based Proxies for Common Trading Strategies*

As explained previously, the principal components analysis employed in FH1997 is used to identify proxies for the most common strategies. Principal components can be interpreted to represent common factors in returns between funds with "similar" (i.e. correlated) trading activities. The most common factors will explain the highest proportion of the sample variance.

Three proxies are constructed from the mean returns of the hedge funds in the sample, which are most highly correlated with a particular principal component. These proxies, referred to as *STRATEGIES*, summarize the most common trading hedge fund trading strategies pursued by funds within the sample. The most common trading strategies, namely convertible and equity arbitrage, merger arbitrage, and managed futures, exhibit hedge fund returns that explain the greatest proportion of variance in sample hedge fund returns during the period.

Each of the three *STRATEGIES* is equivalent to the equal-weighted average of the mean returns for those funds that are highly correlated with a given principal component. Two criteria determine whether an identified principal component is a suitable for constructing a proxy of a common trading strategy from mean hedge fund returns. First, at least one fund in the sample must be highly correlated (80%) with that particular component. Second, the factor loading of the funds used to construct each of the *STRATEGIES* must be positive.[5]

The three *STRATEGIES* explain 44.6% of the total variation of the 28-month subsample. The first proxy (*STRATEGY1*) explains 23.8% of total subsample variation and is highly (positively) correlated with certain market-neutral, convertible arbitrage and US equity hedge strategies, e.g. Gatev, Goetzmann and Rouwenhorst (1999). The second proxy (*STRATEGY2*) explains 14.4% of total subsample variation and is positively correlated with event-driven (merger and risk arbitrage) funds and European equity hedge

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[5] At present there is no feasible market to shortsell hedge fund equity, and so it is most reasonable to construct proxies based on an investable portfolio.

strategies. The third proxy (*STRATEGY3*) explains 7.9% of total subsample variation and is only (positively) correlated with managed futures funds.

For the sample of 251 hedge funds, the principal components are estimated using twenty-eight months of monthly returns (from November 1997 to March 2000).[6] The procedure used to identify the common trading strategies underlying the hedge fund returns in the sample employs similar methodology and data to FH1997, but uses a different sample period.[7]

As in FH1997, a total of five principal components are identified from the sample of standardized hedge fund returns over the twenty-eight month period. These five principal components explain 57.3% of the total variance of the subsample over the period. However, out of the five principal components identified, only three are suitable for constructing proxies for common trading strategies. *STRATEGIES*, the actual proxies used in the regressions, are then constructed from the mean returns of those hedge funds in the sample that are most highly correlated with each particular principal component that has been identified.

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[6] The sample of 251 funds exhibits sufficient sample variation to conduct principal components analysis. To isolate correlation, these returns are standardized by dividing each mean return by the sample standard deviation of the returns.

[7] FH1997 perform factor analysis of hedge funds as a single group (36 months of standardized returns from 1994 to 1997) to identify five mutually orthogonal principal components with high explanatory power ($R^2$=43% of the cross-sectional return variance). Fung and Hsieh then use the mean returns of hedge funds most highly correlated with those principal components to construct five factors whose returns are highly correlated (93%) with the principal components.

*7.1.4. Option-Based Proxies for Sensitivity to Increasing Volatility*

One-month returns for passive portfolios of *European* options on the S&P 500 account for common volatility-based factors underlying returns. Glosten and Jagannathan (1994) justify the use of passive option-index portfolios as proxies for the trading strategies employed by hedge funds.

Furthermore, Fung and Hsieh (2001) find that the returns to the majority of *managed futures* strategies are highly correlated with returns to long US equity *straddles* (long a call and a put with the same exercise price i.e. "strike"), despite having very little direct exposure to either equities or equity futures contracts. *Global macro* strategies, which primarily involve trading in government bonds, currencies and commodities, nonetheless exhibit returns correlated with *collars* (short calls and long puts with out-of-the-money "strike", i.e. exercise, prices) on US equities. Schneeweis and Spurgin (2000) use S&P500 options to evaluate mutual fund managers with dedicated *US equity hedge* portfolios.[8]

*7.1.5. Daily Stock Returns as a Proxy for Asset Mispricing*

As explained in previous sections, according to SV1997, during periods of increased mispricing, hedge funds have the incentive to increase trading exposure, and hence, become more susceptible to shocks to asset prices. As Ross (1976, 1977) suggests, increased residual returns imply increased asset pricing errors. Therefore, the occurrence

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[8] The Appendix E. *Passive Option Portfolio Strategies* explains in further detail how the three *VOLFACTORS* are constructed from these one-month returns.

of shocks represents even greater potential for asset mispricing, and therefore increased returns to arbitrage.

However, as also previously explained, *LoA* implies that shocks may also constrain investing by hedge funds, in particular for those hedge funds that are more sensitive to volatility increases, and hence more constrained when the shock occurs. Across the overall sample period (January 1997 to March 2000), the average monthly residual variance of daily stock returns for the Dow Jones Industrial Average (DJIA) is 33% higher than for the previous two years.

Since shocks as defined for fixed income arbitrage strategies in the previous regressions may not be a sufficiently broad definition for a sample of hedge funds engaging in more diverse strategies, contemporaneous monthly returns are sorted into preshock, shock and postshock months based on the degree of average daily residual variance exhibited by the stocks of large global corporations. As suggested by Richards (1999), months of high average daily residual variance exhibited by specific stocks in the DJIA, relative to the residual variance of the overall DJIA, may serve as a proxy for shock months, defined as months of high idiosyncratic risk.

This is a reasonable proposition, since the stocks which comprise the DJIA represent a sample of the largest US-based multinational companies. These firms are global concerns with economic interests across most, if not, all markets. Therefore, it is not surprising that during these periods of high residual variance for the DJIA, volatility is also extremely high for the S&P500, as well as for other asset classes (e.g. fixed income, currencies, commodities).

Erb, Campbell, and Viskanta (1995) examine correlation across global equity and fixed income markets during extreme declines over a twenty-year period. They find compelling evidence that the effectiveness of hedging by diversifying across world markets depends considerably on market conditions (e.g. variances, correlations) of the US equity market. Therefore, periods in which asset-specific residual variance is highest in a diversified sample of the largest U.S. equities may be indicative of similar conditions in other markets. This may be especially valid, given that cross-sectional dispersion in asset returns tends to be correlated across markets (Richards, 1999).[9]

Computing two different estimates of the residual variance of individual stock returns in the DJIA, $\hat{r}^1_{g,t}$ and $\hat{r}^2_{g,t}$ [10] for each month over the sample period January 1997 to March 2000, and comparing each estimate across each month in the sample, identifies ten months (approximately one-third of the sample) in which the DJIA stocks exhibit the most extreme residual variance. Based on both estimates $\hat{r}^1_{g,t}$ and $\hat{r}^2_{g,t}$, the months exhibiting the highest residual variance in individual stock returns include September

[9] As previously noted, Richards (1999) examines the characteristics of the idiosyncratic risk underlying certain arbitrage strategies, e.g. relative value trades as described by Gatev, Goetzmann and Rouwenhorst (1999).

[10] See Appendix F. *Estimates of Asset Mispricing using Stock Returns.*

1997, October 1997, August 1998, September 1998, October 1998, December 1998, April 1999, May 1999, July 1999, October 1999, and January 2000. These months correspond closely with the shock months identified for the smaller sample limited to fixed income hedge funds.

As in the previous tests, these months are classified as *extreme shock months*, and represent the first month of every shock period. In several cases, shocks extend beyond the initial month of increased residual variance. The timing of these shock periods coincide with the following events:

**Table 9. Shock Periods for the Broader Sample of Funds**

| Event | Dates |
|---|---|
| Asia Crisis | 8/97, 9/97, 10/97 |
| Russia Default, LTCM Crisis | 8/98, 9/98, 10/98, 12/98 |
| Brazil Crisis | 1/99 |
| Swap curve “events” (the repurchase of 30-Year US Treasuries) | 5/99, 7/99, 10/99 |
| NASDAQ (Internet Stock) Bubble | 1/00 |

The cohorts are defined as follows: (1) a *preshock month* is the month that immediately precedes the occurrence of a shock to the residual variance of the returns for the individual stocks in the DJIA, and (2) *shock months* are the months in the sample that exhibit the highest residual variance in individual stock returns, and (3) *post-shock months* are months with lower residual variance that follow a shock month (excluding the subsequent preshock month). Although preshock and postshock periods may extend beyond three months, there is only one preshock month for each shock period in the sample. By only classifying the month that immediately precedes an extreme shock period as a "preshock" month, the degree to which funds are levered prior to a shock (relative to during or after the shock) can be more easily identified.

For example, if the residual variance for two consecutive months classifies both months as shock months, both of these months are shock months. The month immediately preceding the first shock month is a *preshock* month (provided the residual variance for that month is too low to be classified as a price shock). Preshock months exhibit residual variance in DJIA individual stock returns that is almost one standard deviation greater than the average over the longer sixty-four month period from January 1995 through April 2000, which includes the sample period, in addition to the prior two years.

In other words, shock months are those that provide evidence of an idiosyncratic price shock, i.e. all months that exhibit extreme residual variance, substantially greater than one standard deviation higher than the previous two years (at least 30% higher than the residual variance of stock returns over the period from January 1995 through April 2000) as discussed above. Depending on the estimation method employed, shock months exhibit asset-specific residual variance as much as 4.5 standard deviations (between 83% and 169%) higher than the average for the period from January 1995 through April 2000.

Asset-specific residual variance tends to be persistent (Campbell, Lettau, Malkiel, Xu, 1999; Richards, 1999), i.e. shocks exhibit serial autocorrelation, and tend to decay slowly over time. Throughout the sample period, months of high residual variance are often followed by months of comparable or even greater residual variance. Therefore, consecutive months that exhibit extreme residual variance (of three standard deviations or more) are all classified as shock months.

Postshock months are those that follow a shock, excluding the next preshock month, i.e. the month immediately preceding the next shock. The residual variance of stock returns exhibited by postshock months is comparable to that of preshock months, contrary to *CA*, in which estimated *RBL* of hedge funds within the sample should return to preshock levels, but not decline further. It is reasonable to expect that, with regard to the observed *RBL* of a more diverse sample of hedge funds, any after-effects of a price shock, e.g. portfolio liquidation, may occur gradually over several months. Hence, the possibility of gradual or lingering after-effects on leverage requires extending the postshock period beyond the first month following a shock.

In addition, postshock returns exhibit lower standard deviations than preshock or shock returns. If postshock months are limited to only one month following a shock, the cross-sectional variation of hedge fund and factor returns may not adequately capture these after-effects.

The results of the full sample regressions show that when shocks occur, leverage declines substantially, by 52%, from preshock levels, and again by 100%. Also, during shocks, the sensitivity of hedge fund returns to changes in volatility increase significantly.

Summing the absolute values of the statistically significant regression coefficients for *ASSETS* and *STRATEGIES* provides an estimate of *RBL* in terms of hedge fund trading exposures. Changes in the magnitude of these coefficients between the preshock, shock, and postshock months illustrate the degree to which aggregate hedge fund activity may be impaired by severe or prolonged price shocks.

The aggregate *RBL* of the sample declines both during and following shocks. This is consistent with SV1997 which states that: (a) despite the incentive hedge fund managers have to increase trading exposure when volatility is high relative to previous periods; and (b) on average they are then forced to delever when shocks occur. During the sample period, the average residual variance of daily stock returns is 33% higher than for the previous twenty-four month period. In order to exploit expected opportunities from asset mispricing, preshock leverage for hedge funds is high, since fund managers have an incentive to be more rather than less invested.

The results of the full sample regressions provide clear evidence that, on average, hedge funds behave in a manner consistent with the existence of leverage constraints that are sensitive to idiosyncratic shocks. Hedge fund managers appear to attempt to mitigate the effects of idiosyncratic shocks on their performance by reducing *RBL* during and subsequent to a shock, and by reallocating their exposures to less volatile assets with lower returns.

The sensitivity of hedge fund returns to increases in volatility can be estimated as the sum of the absolute values of the statistically significant regression coefficients for the returns related to the three *VOLFACTORS* (*STRADDLE*, *STRANGLE*, and *COLLAR*). Summing the absolute values of the regression coefficients for *VOLFACTORS* shows the increase in the sensitivity of the hedge fund returns to increases in volatility during shock periods.

Table 10 below shows the decline in the aggregate *RBL* of hedge funds during and after shocks. *RBL* decreases by 52% from preshock (34.02) to shock (16.24). In the postshock months (those subsequent to the shock), aggregate *RBL* for the full sample of hedge funds declines even further, until the estimated leverage ratio approaches zero. If the *LoA* did not hold, when asset-specific shocks occur, hedge fund managers would maintain (or even) increase their exposure to investment risk, in order to capture higher returns in those periods when mispricing (and hence expected returns to arbitrage) are highest.

**Table 10. The Change in *RBL* for the Full Sample of Hedge Funds Engaged in Diverse Strategies**[a]

| | ***RBL*** | **Net Volatility Exposure** |
|---|---|---|
| **Preshock** | 34.02 | 0.00 |
| **Shock** | 16.24 | 13.28 |
| **Postshock** | 0.00 | 0.00 |

[a] Coefficients used to calculate *RBL* and *Vol Exposure* are significant at the 10% level and are reported in Appendix Table 12.

For the full sample, preshock and postshock hedge fund returns exhibit no sensitivity to volatility changes (at the 10% significance level). During shocks, volatility sensitivity (exposure of fund investments to increases in volatility) jumps to 161.5, which is the sum of the absolute values of the coefficients for the three *VOLFACTORS*, *STRADDLE* (-74.13), *STRANGLE* (77.25), and *COLLAR* (10.16). During preshock and postshock months, none of the coefficients for any of these three *VOLFACTORS* are statistically significant.

**Table 11. The Change in Strategy Exposure for the Full Sample of Hedge Funds**[a]

| | ***STRATEGY1*** | ***STRATEGY2*** | ***STRATEGY3*** |
|---|---|---|---|
| **Preshock** | -27.25 (-1.71) | -9.10 (-1.34) | 0.15 (2.05) |
| **Shock** | 13.17 (1.80) | 2.77 (2.23) | -0.16 (-1.19) |
| **Postshock** | -1.75 (0.00) | 1.40 (0.00) | 0.12 (0.00) |

[a] T-statistics of coefficients in parentheses

Based on the change in cross-sectional variation between hedge fund returns and underlying factor returns, the exposure to investment risk of hedge funds in the sample declines postshock, until it becomes statistically indistinguishable from zero. Based on the pattern of decreasing exposure in *STRATEGIES* during (and following) shocks, those hedge fund managers engaged in equity arbitrage strategies (convertible arbitrage, equity market neutral, long/short equity) significantly curtail their exposure to the strategy (*STRATEGY1*). The absolute value of the coefficient for *STRATEGY1* declines 52% from a preshock level of 27.3 to a shock level of 13.2.

During shocks, event (merger) arbitrage exposure is also reduced by 70% (*STRATEGY2*) from preshock level of 9.1 to a shock level of 2.8. In addition, all of the equity variables (*S&P500*, *MSCIWRLD*, *MSCIEAFE*), with the exception of *RUSSELL*, become more statistically significant during shocks. The substantial contribution of underlying equity exposure exhibited by the sample is consistent with Asness, Krail and Liew (2000), who find that throughout the 1990's, the highest exposure for hedge funds is the equity market *Beta*.

# CHAPTER 8

# CONCLUSIONS

This paper develops and applies a methodology for empirically testing certain implications of the SV1997 model of the limits of arbitrage *LoA*, based on the returns for a sample of hedge funds. The documented evidence seems to indicate that despite incentives to maximize exposure to investment opportunities when volatility increases and expected returns to arbitrage are high, corresponding risks during shocks cause hedge funds to reduce their exposure during those periods. In identifying those capital constraints that may limit the investment activity of *professional arbitrageurs*, as described by SV1997, the change in the availability of investment capital employed by the arbitrageur is parameterized by the sensitivity of the hedge fund's performance to randomly occurring shocks.

In discussing the contributing role of leverage in the serial correlation of hedge fund returns, Getmansky, Lo, and Makarov (2003) note that the specific mechanisms by which a hedge fund changes leverage are complex and depend upon a number of factors, including market volatility. Goldman (2003) describes the well-accepted (but previously undocumented) tradeoff between risk and expected return as the basic motivation for the typical leverage dynamics of hedge funds: increasing leverage (proportionally) increases expected return, but also increases the volatility of return, and hence the risk of potential default and liquidation by the fund. Goldman also briefly refers to the posting of additional collateral or liquidation of investments by hedge funds when markets become more volatile.

The predictions tested in this paper are based on the commonly held presumption that when risk factors (for example, spread volatility) increase substantially, fixed income arbitrage hedge funds will (a) exhibit low or negative returns, and (b) reduce risk-based leverage. It follows from this hypothesis that fixed income hedge funds that exhibit higher risk-based leverage prior to increased spread volatility will delever more than those funds that exhibit lower leverage prior to increased spread volatility. The results confirm both incurred losses (as shown in Table 1), and reductions in leverage (shown in Tables 4 and 12), when shocks occur.

It also follows that fixed income hedge funds with higher SD of preshock returns show signs of being negatively correlated with option-like increases in the volatility of the swap spread. These funds, being more constrained by the occurrence of volatility shocks, and thereby having less investment capacity, will hence exhibit evidence of lower leverage preshock, but also will be *less* able to reduce leverage, by rebalancing their portfolios, than hedge funds with returns that are positively correlated with non-linear increases in the volatility of swap spread (Table 13). Although returns for all fixed income hedge funds tend to be inversely correlated with increased swap spread volatility when shocks occur, during pre- and postshock months, fixed income hedge funds may be either positively or negatively correlated with increases in swap spread volatility (Tables 12 and 13). Those funds exhibiting higher negative correlation with swap spread volatility also experience more severe losses when shocks occur, and recover less in periods following shocks (Table 13).

The results are consistent with the theory of *LoA*, that factors related to market risk, liquidity risk, and credit risk constrain the investment activity of hedge funds. Furthermore, the tendency is for funds with preshock returns positively correlated with increased spread volatility to be more able to modify risk-based leverage in order to weather the effects of more volatile market conditions. For broader samples of hedge funds, subsequent to the occurrence of shocks, we observe a similar albeit more pronounced reduction in exposure to investment risk.

In Table 1, for the entire sample of fixed income hedge funds, the failure of postshock returns to converge to preshock levels with the convergence of spreads may be evidence for the liquidation during the shock period of some investments that would exhibit positive postshock returns. In Tables 3 and 12, the persistent increase in gains related to swap spread volatility (*STRADDLE3M_10Y*) after spreads converge implies that the hedging demand, although positively correlated with shocks to spread, persists long after spreads converge.

One can also think of a relative value investment opportunity as a security with a market value that depends on the difference in the respective yields of two assets. When the *spread* (i.e., the difference between the yields) widens, the value of the investment declines; however, the expected return of the relative value investment opportunity also increases. It is reasonable to expect that periods when the spread is more volatile are periods of higher expected returns to the relative value investment.

However, these are also periods of potentially increased interim losses for the relative value investment, since prices diverge more frequently (and/or more significantly) from their long-run average price relationship during more volatile periods. The value of the relative value investment covaries with the change in the difference between common factors (duration, convexity, volatility) in the return of benchmark fixed income instruments, e.g. Treasury bills, Treasury bonds, swaps, and commercial paper (Longstaff, Santa Clara and Schwartz, 2000a,b).

Strategies may differ in their respective sensitivity to the magnitude of the realized change in the spread over the next period, according to differences in the specific investment instruments employed, as well differences in the financing and hedging of those instruments. By definition, the returns of higher variance strategies exhibit greater covariance with common factors in returns than lower variance strategies.

Rationing investment capital based on the volatility of a given trading or investment strategy is also consistent with industry practice, e.g. the calculation of haircuts for pledging margin, and the use of *Value-at-Risk* (*VaR*) models by banks and broker-dealers to extend credit to hedge funds based on the variability of the funds'

*NAVs*. This is consistent with general capital structure theory in which higher variance investments reduce financing capacity relative to lower variance investments.

More precisely, strategies may differ in their correlation with the increased volatility of common factors in return. As described by Shleifer (2000), a fund employing a strategy that exhibits significant negative correlation with increased volatility risk may suffer greater declines in fund value when shocks occur (than a fund that exhibits less negative correlation), and may also have more limited capacity to rebalance its portfolio without realizing capital losses through costly liquidation (Brown, Goetzmann, and Park, 2001).

Therefore, the increasing sensitivity of the hedge fund's returns to a more volatile spread environment may result in the adverse change in value outpacing the manager's efforts to reduce exposure in response to the shock. Therefore, the exposure and corresponding losses are greater during the shock than for a less constrained fund. Since the volatility-constrained fund has an incentive to reduce postshock exposure even more than a less constrained fund, postshock gains will also lower.

The evidence suggests that, in practice, a levered hedge fund facing a sufficiently severe shock, whenever possible, is likely to prudently reduce exposure to investment risk to avoid costly liquidation, in order to survive. However, some highly levered funds may be constrained from reducing their exposure. In the case of LTCM, which was extremely constrained – by a combination of leverage (in the form of swaps, forward and repurchase agreements) and unhedged exposure to volatility increases – the shock was sufficiently severe, and their positions so levered, that any attempt to delever would have resulted in the complete liquidation of the fund (Dunbar, 1999; Loewenstein, 2000).

In addition to possessing academic interest, the results within this paper suggest practical policy and regulatory implications, related to whether more robust liability structures would enable hedge funds to sustain more risk and therefore maintain higher levels of investment during periods when mispricing and therefore arbitrage opportunities are greatest (Krishnamurthy 2003), as also recently suggested by Geanakopoulos *et al* (2004) in theoretical research on collateral constraints, liquidity risk, and mispricing.

# APPENDIX A

## SUPPLEMENTARY TABLES

### Table 12. Full Sample of Fixed Income Hedge Funds[a]

This table reports the variables and coefficients for regressions of monthly fixed income hedge fund returns (sorted according to preshock, shock and postshock months) versus contemporaneous mean standard deviations of spreads (SWAPS30_2; ON/OFF_30) and the one-month mean daily returns of straddles (*STRADDLE3M_10Y*). *SWAPS30_2* is the difference in rates between 30-year and 2-year interest rate swaps. ON/OFF_30 is the difference in yield between on-the-run and off-the-run 30-year Treasury bonds. *STRADDLE3M_10Y* is the difference in rates between the 3-month treasury bill and 10-year swaps.

| **Three-factor Regression** | $b_1$ ***SWAPS30_2*** | **t-stat** | $b_2$ ***ON/OFF_30*** | **t-stat** | $b_3$ ***STRADDLE3M_10Y*** | **t-stat** | **N** | $\mathbf{R^2}$ | **F-stat** | **SE of Equation** |
|---|---|---|---|---|---|---|---|---|---|---|
| **Preshock** | -0.40 (0.097) | -4.16** | -0.30 (0.100) | -3.00** | 0.02 (0.073) | 0.27 | 201 | 0.072 | 6.178 | 0.032 |
| **Shock** | -0.11 (0.079) | -1.40 | -0.21 (0.077) | -2.68** | -0.06 (0.075) | -0.77 | 224 | 0.858 | 8.011 | 0.049 |
| **Postshock** | 0.06 (0.072) | 0.86 | 0.07 (0.067) | 1.00 | 0.21 (0.076) | 2.81** | 296 | 0.018 | 2.769 | 0.028 |

[a] Standard errors of coefficients in parentheses

## Table 13. Regressions of Monthly Returns of Fixed Income Funds Sorted by Standard Deviation of Preshock Returns [a]

This table reports the variables and coefficients for regressions of monthly returns for fixed income hedge fund (sorted according to preshock, shock and postshock months) versus contemporaneous mean standard deviations of spreads (*SWAPS30_2; ON/OFF_30*) and the one-month mean daily returns of straddles (*STRADDLE3M_10Y*). The first subgroup consists of funds with higher standard deviation preshock returns, the second subgroup consists of funds with lower standard deviation preshock returns.

| Three-factor Regression | $b_1$ *SWAPS30_2* | t-stat | $b_2$ *ON/OFF_30* | t-stat | $b_3$ *STRADDLE3M_10Y* | t-stat | N | $R^2$ | F-stat | SE of Equation |
|---|---|---|---|---|---|---|---|---|---|---|
| **SUBGROUP OF FUNDS WITH HIGHER STANDARD DEVIATION PRESHOCK RETURNS** | | | | | | | | | | |
| **Preshock** | -0.37 (0.148) | -3.06** | -0.26 (0.152) | -2.10** | -0.03 (0.107) | -0.28 | 219 | 0.06 | 3.631 | 0.013 |
| **Shock** | -0.08 (0.136) | -0.70 | -0.23 (0.132) | -1.89** | -0.10 (0.124) | -0.95 | 106 | .096 | 4.773 | 0.030 |
| **Postshock** | 0.12 (0.115) | 1.20 | 0.03 (0.095) | 0.31 | 0.17 (0.121) | 1.62 | 128 | 0.13 | 7.536 | 0.014 |
| **SUBGROUP OF FUNDS WITH LOWER STANDARD DEVIATION PRESHOCK RETURNS** | | | | | | | | | | |
| **Preshock** | -0.73 (0.122) | -4.95** | -0.58 (0.126) | -3.83** | 0.23 (0.095) | 2.16** | 82 | 0.210 | 8.242 | 0.041 |
| **Shock** | -0.29 (0.122) | -2.14** | -0.14 (0.120) | -1.04 | - 0.07 (0.108) | 0.56 | 80 | 0.093 | 3.720 | 0.065 |
| **Postshock** | -0.15 (0.097) | -1.31 | 0.21 (0.091) | 2.22** | 0.33 (0.103) | 2.75** | 168 | 0.001 | 0.955 | 0.035 |

[a] Standard errors of coefficients are in parentheses

## Table 14. Regression Coefficients for the Diverse Hedge Fund Sample

This table displays the coefficients from the regression of the full sample of monthly returns during the period from January 1997 through March 2000, as reported in the TASS database for 251 hedge funds engaged in diverse strategies. The returns are sorted according to preshock, shock, and postshock months, and regressed against contemporaneous returns for the following variables *ASSETS* (seven (7) indices representing returns of US and non-US stocks; currencies; commodities; and government, mortgage-/asset- backed, and corporate bonds), *STRATEGIES* (three (3) dominant trading strategies underlying the sample identified using principal components analysis), and *VOLEXPOSURE* (three (3) options-based proxies for sensitivities of returns to changes in volatility and volatility skews).

| | ***S&P500*** | ***US$INDEX*** | ***GSCI*** | ***MSWRLD*** | ***RUSSELL*** | ***MSEAFE*** | ***LEHCOM*** | ***STRGY1*** | ***STRGY2*** | ***STRGY3*** | ***STRADL*** | ***STRNGL*** | ***COLLAR*** |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Preshock | -- | -0.91 | -0.44 | 2.45 | 1.32 | -0.56 | -2.86 | -27.25 | -9.10 | 0.15 | 1.04 | -- | -- |
| n = 2730 | | (-1.62) | (-1.54) | (2.07)** | (1.90)* | (-1.52) | (-1.94)* | (-1.71)* | (-1.34) | (2.05)** | (1.53) | | |
| $R^2$=0.163 | | | | | | | | | | | | | |
| Shock | 3.45 | -1.66 | -0.96 | -4.93 | 0.29 | 0.64 | -0.93 | 13.17 | 2.77 | -0.16 | -74.13 | 77.25 | 10.16 |
| n = 3663 | (1.47) | (-1.22) | (-1.61) | (-1.40) | (2.46)** | (0.96) | (-1.18) | (1.80)* | (2.23)** | (-1.19) | (-1.72)* | (1.72)* | (1.71)* |
| $R^2$=0.147 | | | | | | | | | | | | | |
| Postshock | 0.29 | 0.06 | 0.18 | -0.17 | 0.47 | -0.42 | 0.08 | -1.75 | 1.40 | 0.12 | 0.38 | 0.58 | 0.34 |
| n = 3144 | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) |
| $R^2$=0.139 | | | | | | | | | | | | | |

*Fund Return* = Monthly hedge fund returns sorted according to preshock, shock and postshock months
*S&P500* = Monthly returns for the S&P500 Index
*US$INDEX* = Monthly percentage change for the US Dollar Trade-Weighted Index
*GSCI* = Monthly percentage change for Goldman Sachs Commodity Index
*MSWRLD* = Monthly returns for the Morgan Stanley World Equity Index (USD)
*RUSSELL* = Monthly returns for the Russell 2000 Index of small stocks
*MSEAFE* = Monthly returns for the Morgan Stanley Equity Index Europe, Australasia and Far East, Developed Markets only (USD)
*LEHCOM* = Monthly percentage change for the Lehman Composite Bond Index
*STRGY1* = Proxy for common "factor" returns correlated with convertible arbitrage and US equity hedge strategies as defined and reported by TASS
*STRGY2* = Proxy for common "factor" returns correlated with risk arbitrage and European equity hedge strategies as defined and reported by TASS
*STRGY3* = Proxy for common "factor" returns correlated with managed futures strategies as defined and reported by TASS
*STRDL* = *Long position* of 30-day at-the-money European puts and calls on the S&P500 Index
*STRNGL* = *Long position* of 30-day 20% out-of-the-money European puts and calls on the S&P500 Index
*COLLAR* = *Net long position* of 30-day *long* 25% out-of-the-money European puts and *short* 25% out-of-the-money European calls on the S&P500 Index

# APPENDIX B

# THE HOW AND WHY OF OFF-BALANCE SHEET "BORROWING" BY HEDGE FUNDS

## B.1. The Sources and Uses Leverage and the Role of Risk Based Leverage

The use of traditional credit lines (secured or unsecured) by hedge funds is extremely limited (and tends to be their most costly source of financing). Hedge funds usually obtain leverage through off-balance sheet transactions that may involve combinations of repos, margin loans, swaps, options, and futures.

Breuer (2000) cites a hypothetical example in which a financial institution simultaneously assumes multiple exposures to currencies, interest rates, and equities by iteratively leveraging an initial position in US Treasury securities with margin loans, short sales, repos and derivatives trades. Although these investments may appear unrelated, the respective financings of each position are implicitly interrelated. This example also illustrates that the off-balance sheet leverage employed by hedge funds is limited only by the amount of margin required to collateralize a trading position. In other words, in the absence of margin requirements, potential leverage would be unlimited.

Since margin requirements are not readily observable, off-balance sheet leverage is difficult to estimate. Margin requirements vary according to the following parameters: (a) the type and volatility of the underlying investment, (b) the type and volatility of the collateral being pledged, and (c) the notional amount being traded, relative to the liquidity of the underlying markets in which the respective instruments trade. Margin requirements also vary according to the particular counterparties involved in the transaction. The cost and the availability of leverage tend to be dictated by the size of the margin requirement relative to the notional exposure. For example, stock margins are 50%, futures margins vary between 2% and 8%, and margins on repo agreements vary between 1% to 2%.[1]

*B.1.1. Forwards, Swaps and Futures*

Forward contracts are equivalent to borrowing (lending) cash at the risk-free rate to buy (sell) the reference asset in the spot market.[2] Hence, the leverage of a forward (or

[1] According to Breuer (2000), during 1998, several hedge funds (including LTCM) were assessed 0% margin requirements by their counterparties in the repo market.

[2] A forward contract obligates the owner to purchase the underlying asset at a fixed *delivery price* at a specified future date. In a *long* forward contract, assets are borrowed for future delivery. The *NAV* of a forward contract at delivery date "*T*" initiated at date "*t*" for one unit of the underlying asset is $S_t$ - $K_T$, where $S_t$ is the spot price of the asset and $K_T$ is the forward delivery price. The price of the forward contract is $f_t^s = Ke^{-rt}$.

futures) position "$b_{forward}$" can be expressed as the ratio of the underlying asset price "$S$" relative to the price of the contract "$f$", as follows:

(9) $$b_{forward} = \frac{S_t}{f_t^s}$$

Swaps are over-the-counter forward contracts in which the first party pays a *variable payment equal to the change in* $S_t - S_{t-1}$ to the second party, while the second party pays to the first party a *fixed payment* $f_t^s$ equal to a spread over LIBOR. Swaps are simply a series of periodic forward contracts indexed by time ($t$ = 0, 1, …,$T$), such that $b_{swap} = \Sigma_t (S_t / f_t)$.[3] At each date, only the net difference between the two payments (i.e. *legs*) are exchanged by the two parties. In other words, *RBL* can be expressed as a function of the ratio of the change in the reference asset relative to the fixed payment.

Generally, swaps are the least costly source of leverage, because they are priced to have a zero value at inception. The cost of the swap is priced into the magnitude of the spread over LIBOR, which affects the differential in payments between the paying and receiving legs. Also, swaps frequently do not have margin requirements (aside from any net collateral required to be pledged against aggregate exposure as negotiated between the respective parties in the master swap agreement). Swap agreements usually include

[3] The exchange of fixed and variable payments in a swap is equivalent to borrowing (lending) at LIBOR plus a spread to buy (sell) an underlying forward exposure.

unwind provisions, by which either party can cancel the remainder of the swap, by paying a substantial breakage fee. In comparison, futures are essentially exchange-traded forward contracts with standardized maturity dates and notional values. Futures contracts tend to require higher initial margins, and are therefore more costly than forwards or swap contracts.

*B.1.2. Repo Agreements*

Leverage can also be obtained by lending securities for cash and then using the cash to purchase other securities. This procedure can be repeated until all margin collateral is exhausted. The leveraged asset position is equal to the value of the initial security position plus the sum of the cash obligations related to each repo transaction, all divided by the value of initial security position. The total leverage of repo positions in a portfolio "$b_{repo}$" is a function of the value of the underlying securities $S$ , and "$i$" the number of times those securities have been *on repo*.

(10) $$b_{repo} = \frac{S\left(1+\sum_{i=1}^{n}(1-\text{margin})^{i}\right)}{S}$$

The initial margin requirements for repos tend to be so small (1% to 2%) relative to the notional exposure of the securities being bought (or sold) that leverage in these transactions can vary between 50:1 and 100:1.

*B.1.3. Options*

As with forwards, options are equivalent to borrowing (lending) in order to invest in a long (short) position in an underlying asset, but there is one major difference. *RBL* is scaled by the sensitivity of the option value to the underlying asset value. Since an option represents a dynamically changing position in the underlying asset, the leverage (the elasticity of changes in equity value with respect to changes in asset value) varies with the *moneyness* of the option, i.e., the relationship between the strike price and the volatility of the asset ("$\sigma_s$"). This is commonly summarized by the option *delta* i.e., its *hedge ratio*("$\Delta_t^{Call}$"or "$\Delta_t^{Put}$"). For a European call option, the relationship between the leverage of the position and the option delta can be expressed as follows:[4]

(11) $$b_{Call} = \frac{dC_t}{dS_t} \cdot \frac{S_t}{C_t} = \frac{\Delta_t^{Call} S_t}{C_t}$$

The option delta tends to be less than (or equal to) one, and hence $dE \le dA$ for out-of-the-money options. The first-order variation in the value of the equity is linearly proportional to the first-order variation in the value of the asset. The underlying asset position continuously adjusts such that $dE = \Delta_t^{Option} dS$, where $E$ equals the price of the option and S equals the value of the underlying asset $A$. This is in contrast to a forward contract, where asset returns fully correspond with equity returns $df_t = dS_t$ (i.e.,

[4] The leverage ratio (expressed in Equation 11 as the delta multiplied by the current notional value of the asset, divided by the market value of call option) is generally referred to as the *lambda* of the option.

$dE = dA$).[5] As the spot price and the strike price of the option converge (and $\sigma$ is constant), $\Delta_t^{Option} \to 1$, and $dE \to dS_t$. In addition, options (whether exchange-traded or over-the-counter) tend to be the most costly forms of off-balance sheet leverage for hedge funds, due in part to their declining time value.

## B.2. Common Uses of Leverage by Hedge Funds

### *B.2.1. Increasing the Size or Number of Asset Exposures*

Hedge funds use interrelated borrowings to achieve economies of scale and scope, by scaling up returns or by diversifying the number of positions per unit of equity capital. By pledging assets to finance a portfolio of concentrated and idiosyncratic, but statistically uncorrelated investments, hedge fund managers often seek a *natural hedge* of the net investment spread at the portfolio level. However, statistical relationships between assets deemed to be close substitutes sometimes exhibit extreme variance. In addition to the changing correlation between separate investments (i.e. asset exposures), investments may also become adversely correlated through borrowing, i.e. liability exposures. In this manner, the interrelationships between investing and financing positions expose hedge

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[5] Borrowing to purchase an asset for future delivery is fundamental to the theoretical pricing of options. Borrowing the underlying security via an implicit forward contract is embedded within the Black-Scholes option hedging (i.e. replication) equation. For a call option $C(K_T)$, as the future spot price $S_t$ of the underlying asset grows large relative to the underlying volatility of the asset, the price of the call approaches the price of a forward contract with the delivery price $K_T$, i.e. $C(K_T) = \max[S_t - Ke^{-rt}, 0] \Rightarrow S_t - Ke^{-rt}$, where $Ke^{-rt} = f_t^s$.

funds to event risk where the extreme price deviations of either trading positions or collateral pledge as margin will force funds to delever.

*B.2.2. Hedging*

Certain market risks (e.g., interest rate risk) may be explicitly hedged. Many hedge fund strategies which make idiosyncratic bets (e.g., risk arbitrage, convertible arbitrage) are potentially exposed to unwanted systematic risk. The hedge fund managers that pursue these strategies usually hedge their positions against broad market movements. They will typically borrow the margin or premium to finance this hedge via futures or options. For example, a manager will take a small portion of the net proceeds from a repo transaction to post margin for S&P500 futures or interest rate futures contracts to offset directional changes in these markets. Alternatively, a manager can hedge by assuming an offsetting position in a swap, e.g., paying (receiving) the S&P500 or LIBOR.

*B.2.3. Short-selling*

Short selling involves simultaneously borrowing forward a stock (e.g. SPYDERs, an exchange-traded depository receipt that tracks the S&P500 index), and selling that same stock in the spot market. To repay the forward obligation, the hedge fund must repurchase that stock in the spot market at a specified future date. The hedge fund manager will realize a net gain if the stock price has fallen below the forward price on the forward date, or a net loss if the stock price has risen above the forward price on the forward date. The cost of borrowing SPYDERs forward is priced into the forward price of the SPYDERs relative to its spot price. Alternatively, a short position in SPYDERs can be assumed by simply receiving the fixed leg and paying the variable leg of a swap where the underlying security is a SPYDER.

# APPENDIX C

## THE FUNG AND HSIEH 1997 ASSET- AND RETURNS-BASED MULTIPLE-FACTOR MODEL

Let $R_t$ represent the return on a portfolio of assets in period *t*, where $x_{jt}$ is the weight of asset *j* within the portfolio during period *t* (from $t-1$ to *t*), and $r_{jt}$ is the return of the asset *j* within the portfolio during period *t,* $j = 0,...,J$, and $\sum_j$ denotes the summation operator overall values of *j*. For convenience, the asset $j = 0$ is the risk-free asset.

(12) $$R_t = \sum_j x_{jt} r_{jt}$$

By assumption, both the borrowing and lending rates are equivalent to the risk-free return. The number of assets (*J*) is assumed to be large (e.g., NYSE-listed US stocks alone exceed 2,000), and may include all US and non-US stocks, agency, government and corporate bonds, mortgages, commodities, currencies, and all related derivative instruments. Since the number of all investment instruments exceed the tens of thousands, and many may tend to exhibit high cross-correlation, in order to reduce the task to a manageable level, a factor structure for returns is assumed, as described by the standard arbitrage pricing theory model (APT):

(13) $$r_{jt} = \sum_k \lambda_{jk} F_{kt} + \varepsilon_{jt}$$

There are $K$ systematic factors, $F_{kt}, k = 1,...,K$; where $\lambda$ is the factor loading; and $\varepsilon$ represents the idiosyncratic returns. By assuming the systematic factors to be exogenously specified, one can interpret the factors as *asset classes*, following Sharpe (1992). Thus, using the factor model, the portfolio returns can be rewritten as:

(14) $$R_t = \sum_j \omega_{kt} F_{kt} + e_t$$

where, $\omega_{kt} = \sum_j x_{jt} \lambda_{jk}$ and $e_t = \sum_j x_{jt} \varepsilon_{jt}$. Thereby, instead of the portfolio's return being a weighted average of returns for a larger number of assets, it is now the weighted average of returns for a smaller number of *asset classes*. In this manner, the Sharpe (1992) style regression model (equation (15) below) works well in explaining the returns of mutual funds with returns that, in general, tend to be highly correlated with asset classes (e.g., US and non-US equities; government and corporate bonds).

(15) $$R_t = \alpha + \sum_k b_k F_{kt} + u_t$$

FH1997 modifies the Sharpe (1992) regression model in order to employ the empirical results for mutual funds as a background to compare with the returns of the more diverse sample of hedge fund returns. In order to compare, FH1997 frames the discussion of manager style in terms of an asset selection (i.e., “location”) and a trading strategy, which consists of both being long or selling short (i.e., “direction”) the asset, and weighting (i.e. “leverage”), of the asset [return] within the portfolio [return]. Mutual fund managers focus largely on asset selection, whereas hedge fund managers, as leveraged investors, also emphasize direction and weighting. As a result, FH1997 adds regressors as proxies for the returns to hedge fund trading strategies, by using factor analytic techniques to identify those strategies that serve as *principal components* to explain the highest percentage of the cross-sectional return variance. Proxies for dominant strategies can then be constructed using the returns of those hedge funds in the sample that are most highly correlated with those principal components.

## APPENDIX D

## PRINCIPAL COMPONENTS ANALYSIS

Johnson and Wichern (1998) describe principal components as *l* uncorrelated, linear combinations of *p* random variables $\mathbf{X}' = \lfloor \mathrm{X}_{1,} X_2, X_3, \ldots X_p \rfloor$, that are fewer in number ($l<p$, where *p* equals the number of hedge funds in the sample), *but also* more parsimoniously explain the variance-covariance structure of the original variables. This is achieved by maximizing sample variation, i.e. choosing the *l* out of $\mathbf{Y}' = \lfloor \mathrm{Y}_{1,} Y_2, Y_3, \ldots Y_p \rfloor$ linear combinations with maximum variance, such that the $Var(Y_1) > Var(Y_2) > \ldots > Var(Y_p)$.

Computing principal components depends solely on $\boldsymbol{\Sigma}$, the covariance matrix (or $\boldsymbol{\rho}$ the correlation matrix in the case of standardized returns) of $\mathbf{X}' = \lfloor \mathrm{X}_{1,} X_2, X_3, \ldots X_p \rfloor$ with eigenvalues $\lambda_1 \geq \lambda_2 \geq \lambda_3 \geq \ldots \geq \lambda_p \geq 0$. Hence, the assumption of multivariate normality, although useful for interpretation, is not necessary to compute principal components from the sample $\mathbf{X}'$, a multivariate "vector of vectors", in this case, of returns.

The linear combination $\mathbf{a'X} = a_1 X_1 + a_2 X_2 + a_3 X_3 + ... + a_p X_p$ has a mean equal to $E[\mathbf{a'X}] = \mathbf{a'\mu}$, and variance equal to $Var(\mathbf{a'X}) = \mathbf{a'\Sigma a}$, where $\mathbf{\mu} = E[\mathbf{X}]$ and $\mathbf{\Sigma} = Cov(\mathbf{X})$. The multivariate vector of linear combinations $\mathbf{Y} = \mathbf{AX}$ possess $\mathbf{\mu}_Y = E[\mathbf{Y}] = E[\mathbf{AX}] = A\mathbf{\mu}_Y$, and $\mathbf{\Sigma}_Y = Cov(\mathbf{Y}) = Cov(\mathbf{AX}) = \mathbf{A\Sigma_Y A'}$.

Hence, we obtain $Var(\mathbf{Y}) = \mathbf{a}'_k \Sigma\, \mathbf{a}_k$ and $Cov(\mathbf{Y}_k, \mathbf{Y}_l) = \mathbf{a}'_k \mathbf{\Sigma a}_l$, where $k \neq l$ and $k, l = 1,2,3,..., p$. The first principal component is the linear combination $\mathbf{a}'_1\mathbf{X}$ that maximizes $Var(\mathbf{a}'_1\mathbf{X})$ subject to $\mathbf{a}'_1\mathbf{a}_1 = 1$. The second principal component is the linear combination $\mathbf{a}'_2\mathbf{X}$ that maximizes $Var(\mathbf{a}'_2\mathbf{X})$ subject to $\mathbf{a}'_2\mathbf{a}_2 = 1$ and $Cov(\mathbf{a}'_2\mathbf{X}, \mathbf{a}_2\mathbf{X}) = 0$. The procedure repeats for *l*<*p* principal components, where the $l^{th}$ principal component is the linear combination $\mathbf{a}'_1\mathbf{X}$ that maximizes $Var(\mathbf{a}'_1\mathbf{X})$ subject to $\mathbf{a}'_1\mathbf{a}_1 = 1$ and $Cov(\mathbf{a}'_2\mathbf{X}, \mathbf{a}_2\mathbf{X}) = 0$.

Since $\boldsymbol{\Sigma}$ is a covariance matrix with eigenvalue-eigenvector pairs $(\lambda_1, e_1), (\lambda_2, e_2), (\lambda_3, e_3), ...(\lambda_p, e_p)$, such that $\lambda_1 \geq \lambda_2 \geq \lambda_3 \geq ... \geq \lambda_p \geq 0$, the $l^{th}$ principal component is given by $Y_{lth} = \mathbf{e}'_{lth}\mathbf{X} = e_{lth,1}X_1 + e_{lth,2}X_2 + e_{lth,3}X_3 + ... + e_{lth,p}X_p$. Hence, $Var(\mathbf{Y}) = \mathbf{e}'_k \Sigma\, \mathbf{e}_k = \lambda_{lth}$ and $Cov(\mathbf{Y}_{lth}, \mathbf{Y}_{kth}) = 0$ $Cov(\boldsymbol{Y}_{lth},\ \mathbf{Y}_{kth})=0$ (where $k \neq l$ and $k, l = 1,2,3,..., p$). If some of the $\lambda_l$ are equal, the choices of the corresponding coefficient vectors $e_l$ are not unique, and therefore, $\mathbf{Y_i}$ is not unique.

Note that the eigenvectors of $\mathbf{\Sigma}$ are orthogonal, if all the eigenvalues $\lambda_1, \lambda_2, \lambda_3, \ldots, \lambda_p$ are distinct. Furthermore, if the eigenvalues are not all distinct, the eigenvectors corresponding to the common eigenvalues may be chosen to be orthogonal, such that for any two eigenvectors, $e_l$ and $e_k, e_l' e_k = 0$. Therefore, the principal components are uncorrelated and have variances equal to the eigenvalues of $\Sigma$.

The principal components can be written as

(16) $$\mathbf{Y}_1 = \mathbf{e}_1'\mathbf{X}, \mathbf{Y_2} = \mathbf{e_2'}\mathbf{X}, \mathbf{Y_3} = \mathbf{e}_3'\mathbf{X}, \ldots \mathbf{Y}_p = \mathbf{e_p'}\mathbf{X}.$$

Therefore,

(17) $$\sigma_{1,1} + \sigma_{2,2} + \sigma_{3,3} + \ldots + \sigma_{p,p} = \Sigma_i^p Var(X_i) = \lambda_1 + \lambda_2 + \lambda_3 + \ldots + \lambda_p = \Sigma_i^p Var(Y_i).$$

Since the total population variance can then be written as $\sigma_{1,1} + \sigma_{2,2} + \sigma_{3,3} + \ldots + \sigma_{p,p} = \lambda_1 + \lambda_2 + \lambda_3 + \ldots + \lambda_p$, the proportion of total variance explained by the *l*th principal component is equal to:

$$\frac{\lambda_p}{\lambda_1 + \lambda_2 + \lambda_3 + \ldots + \lambda_p}$$

If a sufficient proportion of the total population variance for large *p* can be attributed to the first few components, then these can replace the original *p* variables with minimal loss of information.

Principal components analysis is performed in order to identify, from the returns of the entire sample, the subset of funds in the sample that best summarizes the dominant strategies employed by funds in the sample. This is equivalent to extracting the (orthogonal) subset(s) of hedge fund returns that best explain the return variation of the sample.

Since principal components are not scale invariant, standardized returns are employed to extract the principal components. The raw returns of funds most correlated with the extracted principal components, are identified and weighted to construct the proxies employed in the regression model.

## APPENDIX E

## PASSIVE OPTION PORTFOLIO STRATEGIES

To construct option-based proxies for sensitivity to increasing volatility, theoretical Black-Scholes (1973) option values are calculated for 30-day *European* options[1], using daily prices and implied volatilities for the S&P500 index, during the period from January 1997 to March 2000.[2]

$$(18)\ \mathrm{re}turn_{option,month"t"} = \Sigma_{Daily(t-1,t)} \lfloor return_{tradingdays(\tau-1,\tau)} \rfloor \times OptionValue_{monthend,t-1}$$

As shown in Equation (18), the value for an option position at month-end is equivalent to the cumulative sum of the daily returns during that month multiplied by the value of the position at the beginning of the month.

[1] European options can only be exercised at their expiration date.

[2] Mitchell and Pulvino find the difference between market-traded and theoretical option values to be 4 basis points, on average. This difference is too small to influence the pattern of the leverage estimates for the purposes of this paper.

From theoretical option values, monthly returns were calculated as follows. First, the daily one-month implied volatility of the index was estimated for the entire period. This was used to derive the daily value (i.e. the cost) of *at-the-money* ("ATM") puts and calls. Second, employing ATM and *out-of-the money* ("OTM") puts and call values, portfolios were constructed for each period and the values for the following strategies calculated: the daily return (i.e. the percentage change in value) for long positions in straddles, strangles and collars. Third, the daily return to each portfolio, based on the actual underlying index return for each period was used to calculate the monthly return to each passive option strategy. The monthly return is equivalent to the ratio of the cumulative net value of the position at the end of each month, less the value of the option position at the beginning of each month, all divided by the value of the option position at the beginning of each month.

*ATMCALL* and *ATMPUT* are included in the table below as basis instruments employed to construct each one of the three *VOLFACTORS* (*STRADDLE, STRANGLE, COLLAR*). In the regression, the long straddle position ("*STRADDLE*") is equivalent to being long an ATM put ***and*** long an ATM call of equal notional values and matching expiry dates. Hence, *STRADDLE* is equal to the net position $\{\max[0, S_T - S_t] + \max[S_t - S_T, 0]\}$. An increase (decrease) in the underlying asset price above the strike price is mitigated by a change in the value of the put (call) positions offsetting any directional changes in asset prices. Value changes in the net position do not result from directional changes in the price of the underlying asset, but from a shift in the volatility of the price of the asset. In effect, being long (short) a straddle is a bet that volatility will (not) increase. A long (short) straddle becomes more (less) profitable when volatility increases.

A long strangle position (*STRANGLE*) is equivalent to being long both an out-of-the-money put and an out-of-the-money call. In contrast, being long (short) a strangle is a bet that volatility will (not) exceed a certain level. As a combination of two out-of-the-money ("OTM") positions, the net return of a strangle may vary substantially from the net return of a straddle, depending on the level of the option strikes, relative to the volatility of the underlying asset. The cost of a strangle is lower than that of a straddle on the same asset (for the same notional amount), but provides less asset exposure since the strikes are further away from the initial value of the asset. A long (short) strangle only becomes more (less) profitable when volatility approaches or exceeds the strikes on the put and call options that comprise the position.

**Table 15. Proxies for Volatility Sensitivity of Hedge Fund Returns**

| ***VOLFACTORS*** **(Option-Based Proxies)** | **Passive Portfolio Position** [a] |
|---|---|
| ATMCALL | $C^{S}_{K=S_t,T} = \max[0, S_T - K]$ |
| ATMPUT | $P^{S}_{K=S_t,T} = \max[K - S_T, 0]$ |
| *STRADDLE* | $C^{S}_{K=S_t,T} + P^{S}_{K=S_t,T}$ |
| *STRANGLE* | $C^{S}_{K=120\%S_t,T} + P^{S}_{K=80\%S_t,T}$ |
| *COLLAR* | $-C^{S}_{K=125\%S_t,T} + P^{S}_{K=75\%S_t,T}$ |

[a] $S_T$ is the underlying stock price at maturity and $K$ is the "strike", i.e., the *exercise price* of the option. In the case of ATM options, $K=S_{t=0}$ the price of the underlying at the initial settlement date of the option. For OTM options, the strike or exercise price) is 20% or 25% higher or lower than the price of the underlying at the initial settlement date of the option.

For example, the value of *STRADDLE* is simply the sum of the values of *ATMCALL* and *ATMPUT*. Hedge funds that follow *relative-value* strategies, i.e., bets on the convergence in prices between assets that are close substitutes (e.g. *index arbitrage, statistical arbitrage* or *pairs-trading*), often seek to profit from overpriced options by *selling volatility* to collect option premium when the market estimate of future (implied) volatility, and therefore the price of the option, is "too high". Teturns to relative value strategies are short volatility and tend to be negatively correlated with straddles, in direct contrast to managed futures strategies, which tend to be *long* volatility (and hence become more profitable with increasing volatility).

Since option prices are nonlinear in volatility, the ratio of the option premium to the asset exposure – analogous to the leverage of the option – varies substantially, in proportion to the option delta, with the *moneyness* of the option (i.e. the proximity of the underlying asset value to the exercise price of the option). In the regressions, the long strangle position ("*STRANGLE*") is equivalent to being both long a 20% OTM put (i.e., $K_{call} = 120\%(S_t))$ ***and*** long a 20% OTM call (i.e., $K_{put} = 80\%(S_t))$ with equivalent notional values and matching expiry dates. Essentially, *STRANGLE* is equal to the net position $\{\max[0, S_T - 1.2(S_t)] + \max[0.8(S_t) - S_T, 0]\}$.

Hedge funds with returns that resemble collars engage in trading strategies that capture returns from *skewness*. The *volatility skew*, which has been exhaustively researched in the option pricing literature, is exhibited by the asymmetry in pricing between OTM puts versus OTM calls. Harvey and Siddique (1999) find evidence that the asymmetric variance of market returns is related to the *conditional skewness* of those returns. In other words, conditional skewness, conditioned on changes in the variance of stock returns, explains the higher increase in correlation between asset returns observed during extreme price declines, relative to increased correlation observed during extreme rallies. The results of Harvey and Siddique also suggest conditional skewness as a contributing factor to the covariation in the market prices for a broad market index, e.g., the S&P500.

Hedge funds that exhibit returns resembling returns to collars may borrow to make contrarian bets on the relative likelihood that the prices of certain assets will rally rather than decline. This is the same as providing insurance to others market participants that those assets are not over- (under-) valued, relative to fundamentals. In the regressions, the collar position ("*COLLAR*") is equivalent to being short a 25% OTM call (i.e., $K_{call} = 125\%(S_t)$) ***and*** long a 25% OTM put (i.e., $K_{put} = 75\%(S_t)$) with equivalent notionals and matching expiry dates. *COLLAR* is equal to the net exposure for the combined position $\{\max[0, S_T - 1.25(S_t)] + \max[0.75(S_t) - S_T, 0]\}$.

## APPENDIX F

## ESTIMATES OF ASSET MISPRICING USING STOCK RETURNS

Based upon daily returns for 30 of the stocks from Dow Jones Industrial Average (DJIA), two of the three methods from Richards (1999) are employed to estimate "$\hat{r}_{g,t}$", the residual variance exhibited by specific stocks in the DJIA relative to the remaining stocks in the index:

(A) The square root of the sum of squared differences over the period:

(19) $$\hat{r}_{g,t}{}^{1} = \Sigma(r_{g,t} - \Sigma\frac{1}{G}\left[r_{g,t}\right])^2$$

(B) The residual in the OLS regression: $r_{g,t} = a_{0,t} + a_{2,t}\, r_{2,t} + \ldots + a_{n-1,t}\, r_{n-1,t} + e_{g,t}$

(20) $$\hat{r}_{g,t}{}^{2} = e_{g,t} = r_{g,t} - \hat{a}_{0,t} - \Sigma_{h=1}^{n-1}\, \hat{a}_{h,t}\, r_{h,t}$$

These estimates of $\hat{r}_{g,t}$ are employed to identify periods when asset-specific volatility (as measured by cross-sectional dispersion in the one-month returns of stocks in the DJIA) is high. The first measure $\hat{r}_{g,t}{}^{1}$ is simply the cross-sectional dispersion of equity returns commonly employed in the previously cited literature on idiosyncratic risk. This simple measure of idiosyncratic risk is only valid if the underlying process generating asset returns is driven by only one common factor, e.g. if CAPM holds (or in the case of multiple factors, if all factors have a unitary factor loading). If the true model of market returns involves multiple factors (e.g. APT holds), and the variances of omitted factors are correlated to the variance of the factor in the one-factor model, the simple measure of average dispersion $\hat{r}_{g,t}{}^{1}$ will be spuriously larger during periods with large movements in the common component of returns. The second measure $\hat{r}_{g,t}{}^{2}$, is less susceptible than $\hat{r}_{g,t}{}^{1}$ to the missing variables problem; it does not account for time-varying factor coefficients in asset returns. [1]

Although weekly data is less susceptible to nontrading effects or asynchronous trading across time zones, estimates of residual variance based on higher frequency daily data are more relevant for short-term financing and hedging strategies than weekly data. The residual variance estimates $\hat{r}_{g,t}{}^{1}$ and $\hat{r}_{g,t}{}^{2}$ are based on 1344 observations, during the period January 1995 through April 2000, for each of the 30 stocks comprising the DJIA.

[1] A third measure is the difference between the actual return and the hedging portfolio return for each month, using a 90-Day rolling regression of the form (B), and applying the regression coefficients to form notional "one-month ahead hedging portfolios" for each asset: $\hat{r}_{g,t}{}^{3}$ = actual $r_{g,t}$ - hedging portfolio $r_{g,t}$. Although this third measure $\hat{r}_{g,t}{}^{3}$, is both less susceptible to the missing variables problem of the simple dispersion measure $\hat{r}_{g,t}{}^{1}$, and employs an out-of-sample element to account for time-variation, it is computationally intensive.

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