The Risk in Hedge Fund Strategies:
Theory and Evidence from Long/Short Equity Hedge Funds

By
William Fung and David A. Hsieh*

Abstract
Theory suggests that long/short equity hedge funds’ returns come from long/short as well as directional exposure to the stock market and the fees related to stock loans. Empirical analysis finds persistent net exposures to the spread between small versus large cap stocks in addition to the overall market. Together, these factors account for over 80% of return variation. Additional factors are price momentum and market activity. After adjusting for the risks associated with marketable securities, excess performance is positive and correlate to aggregate short interest. In comparison, equity mutual funds and long-bias equity hedge funds have lower excess performance and are uncorrelated to market activity and/or aggregate short interest. Consistent with theory, long/short equity hedge funds appear to derive excess performance from privileged access to the stock loan market.

* Fung is at the Centre for Hedge Fund Research and Education at the London Business School. Hsieh is at the Fuqua School of Business at Duke University. We acknowledge the LBS Centre for Hedge Fund Research and Education for providing the hedge fund data, and Mohan Gopalan for providing the short interest data in this paper. We also thank Ken French for the data from his website, Lubos Pastor and Robert Stambaugh for making their liquidity factor available, and Markus Brunnermeier and Stefan Nagel for making their Nasdaq “Tech” factor available. We received comments from seminar participants at Georgia State University and University of California at Irvine. We are responsible for any remaining errors.
The first known hedge fund was founded by A.W. Jones in 1949. Unlike the typical equity mutual fund, Jones’s fund took long and short positions in equities. This style of investing is now commonly referred to as Long/Short Equity (L/S Equity) to distinguish it from hedge fund styles, such as Global/Macro and Convertible Arbitrage that have come along since Jones’s time.

Even though L/S Equity is one of the oldest hedge fund styles, interest in it has remained strong over the years. As of December 2004, the TASS database has 4,147 hedge funds1 (excluding funds-of-hedge funds). Roughly 40 percent are classified as having L/S Equity as their primary investment style.2 By way of contrast, the next largest style (Managed Futures) accounts for 13 percent of the funds.

Long/Short Equity hedge funds generally have lower market exposure than equity mutual funds. For instance, the average L/S Equity hedge fund in the TASS database has a beta of 0.50 with respect to the Standard and Poor’s 500 index (SP500), while the average equity mutual fund (in the Morningstar database) has a beta of 0.96. Aside from the differences in risk exposures between L/S Equity hedge funds and equity mutual funds, there is also a substantial difference in the fees levied on investors of the fund. Typically, hedge fund managers charge a fixed fee of 1 to 2 percent per annum together with a performance-based fee of approximately 15 to 20 percent of new profits.3 In contrast, mutual fund fees are often a small fraction of the fees levied by hedge fund managers on investors.4 While there have been numerous studies on the efficiency of equity mutual funds, there is little documented evidence on whether L/S Equity hedge funds deliver value to their investors on a risk-adjusted and cost-adjusted basis.5

In this paper, we provide insight to three key questions that are essential to understanding why these two alternative forms of equity funds coexisted over the past few decades. One, what is the source of return in L/S Equity hedge funds? Two, what are the attendant risks in L/S Equity hedge funds? Three, is there any excess performance beyond compensation for bearing these risks?

The paper is organized as follows. Section I models the strategies used by L/S Equity hedge funds. Section II is devoted to an empirical analysis of the risks in L/S Equity hedge funds. Drawing from the results in Section II, Section III proceeds to empirically quantify the excess performance in L/S Equity hedge funds. By relating this excess performance to our theoretical models of L/S Equity strategies, we provide a theoretical interpretation of the observed excess performance. Given these insights on L/S Equity strategies, Section IV discusses two related research questions. First, what was the implied cost of L/S equity hedge funds and the attendant implications on optimal contract design for investors seeking excess performance from these hedge funds? Second, what is the potential impact of L/S Equity hedge funds on the stability of equity markets? Concluding remarks are offered in Section V.

I. The Primitive Long/Short Equity Strategy
In this section, we develop a simple theoretical model that captures the essence of L/S Equity strategies commonly used by hedge funds. As the description of the strategy suggests, a model of L/S Equity strategy will involve the market for borrowing and lending stocks—the stock loan market. Our description of this market is based on an adaptation and extension of D’Avolio (2002).

A. The Market for Borrowing and Lending Stocks—the Stock Loan Market

1. Stock Lenders

We begin our analysis of the stock loan market from the point of view of the lender. Institutional investors like pension funds often hold large inventories of stocks over long periods of time. In order to enhance the income from its long-term stock holdings, institutional investors often lend these stocks out to borrowers (typically short-term traders) for a fee while retaining their economic exposure to the underlying assets. In exchange for the stocks, the borrower typically pledges an amount equal to at least 100 percent of the market value of the stocks to the lender as collateral. The collateral is generally in the form of cash or cash equivalent (such as short-term interest bearing securities with minimal credit risk), which happens in 98 percent of stock loans analyzed in D’Avolio (2002). The lender will return the collateral when the borrower returns the stocks. Throughout this stock loan period, the economic value of the underlying stock resides with the lender.

According to D’Avolio (2002), stock loans are made on a day-by-day rollover basis. The lender can demand the return of the loaned stocks at any time. When that happens, the borrower has three days to return the stocks. If the stocks are not returned after three days, the lender has the right to use the collateral to repurchase the stocks in the open market.

Over the duration of the stock loan, the lender continues to receive from the borrower all distributions from the stocks. At the same time, the lender is expected to invest the cash collateral and pay the borrower the short-term interest rate on the collateral posted to secure the loan, less a stock loan fee. D’Avolio (2002) reported a stock loan fee of 20bp for 92 percent of stock loans in his sample. However, when a stock is hard to borrow (commonly referred to as being on special), the stock loan fee can be higher than 400bp.

Thus, from the point of view of the stock lender, the total return from a stock that is loaned to the stock loan market is

\[ r_L + fee_L \]  \hspace{1cm} (1) \]

where \( r_L \) denotes the return of the stocks and \( fee_L \) denotes the stock loan fee.

2. Prime Brokers
Before analyzing the economics of a stock loan transaction from the borrower’s perspective, a brief digression on the microstructure of the stock loan market helps to clarify our terminology. Typically, investing institutions that lend stocks do so via intermediaries. Financial intermediaries such as stockbrokers often offer custodian services to the clients who execute stock transactions with them. The phrase *prime broker* commonly refers to a brokerage house that acts as the primary location where stock transactions are settled on behalf of an investor. In general, the prime brokerage account is where the securities are held for safekeeping and where the attendant cash flows for transactions are consolidated. Because of other financial services that a prime broker offers its clients, prime brokers are better placed to source potential borrowers of stocks. Large prime brokers regularly borrow blocks of stocks from lending institutions at fixed terms to create an inventory from which they can then lend to stock borrowers at a spread to their own borrowing costs. At any point in time, not all stocks in inventory are borrowed. This will create unprofitable idle inventory for the prime broker. In contrast, periodically part of the prime broker’s inventory may go on *special* allowing the prime broker to earn abnormal spreads to their own borrowing costs. From a borrower’s perspective, it is the prime brokers that assume the market maker-like role in the stock loan market.

3. Stock Borrowers

Next, we consider the transaction from the point of view of the borrower of the stocks. Typically, a trader who borrows stocks intends to sell them short (the *short seller*) with the expectation of repurchasing them in the near future at a lower price. As discussed above, the short seller must post the equivalent of 100 percent of the proceeds from the short sale as collateral with the borrower. For the purpose of constructing our primitive long/short equity strategy, we shall assume the actual short sale proceeds are pledged as collateral. Under Regulation T in the U.S. (Reg-T), the short seller is required to post additional collateral equivalent to 50 percent of the short sale proceeds as variation margin with the prime broker, for the purpose of absorbing potential future losses should the price run up during the period of the loan. Although a short seller can pledge securities as variation margin; for simplicity, we shall assume in the construction of our primitive long/short equity strategy that cash margin which earns the risk-free rate is used. Thus, for each $1 of variation margin, the short seller’s return is

\[ 2 \left[ -r_s + (r_f - \text{fee}_S) \right] + r_f \]  

where \( r_s \) is the return on the shares shorted, \( r_f \) the return on the risk-free asset, and \( \text{fee}_S \) the stock loan fee.

4. Potential unequal access to the stock loan market

There are two common sources of unequal access to the stock loan market for borrowers. Like the Initial Public Offering (IPO) of a stock that is over subscribed, the allocation of *special* stocks to borrowers do not follow a regulated process. Access to special stocks at favorable terms can occur depending on the overall business relationship.
between the prime broker and the borrower. This tends to favor active traders such as hedge fund managers. Another potential source of unequal access is the spread between the interest earned by prime brokers from the collateral they post to secure stock inventory from institutional lenders and the interest paid on short sale proceeds, which they keep from individual stock borrowers as collateral. Once again active, professional traders such as hedge fund managers tend to receive more favorable spreads than the average retail investor. As we are analyzing hedge funds, in the construction of Equation (2), for simplicity we have assumed that the full risk-free rate is paid to the borrower on the short sale proceeds.

B. The Return on a Long/Short Equity Portfolio

Typically a L/S equity hedge fund holds a portfolio of long and short stock positions. Without loss of generality, assume that the hedge fund has $100 of capital. Suppose $L$ is used for outright purchases of long positions and $S$ is used as cash margin for $2S$ of short positions. The remaining $100-$L-$S$ is invested in the risk-free asset.

We assume that the long positions are loaned out. In this case, the $L$ of long position generates a gain of $L \left( r_L + \text{fee}_L \right)$. The short position generates a gain of $2S \left[ -r_S + (r_f - \text{fee}_S) \right] + S \ r_f$. Lastly, the cash position generates a gain of $(100-\text{L}-\text{S}) \ r_f$. Together, these positions lead to a return per $1 of capital to be

$$r_f + b_1 (r_L - r_f) + b_2 (r_L - r_S) + b_0$$

where

$$b_1 = (\text{L}-2\text{S})/100$$
$$b_2 = 2\text{S}/100$$
$$b_0 = \text{L}/100 \text{ fee}_L - 2\text{S}/100 \text{ fees}$$

In Equation (3), the first term represents the time-value of money. The second term is the return for bearing directional risk. The third term is the return for bearing spread risk—in the sense that the market values of the long and short positions can diverge from each other. The last term represents the net fees earned from lending out stocks over and above the fees paid for borrowing stocks.

While there are many factors that differentiate long-only mutual fund managers from L/S equity hedge fund managers, on average, the systematic distinction between these two groups of professional investors is the fact that hedge funds do take advantage of privileged access to the stock loan market—both in terms of preferential treatments on hard-to-borrow stocks and costs—whereas long-only mutual funds generally do not. Equation (3) is structured to highlight this differentiating feature between the two types of funds.

C. Empirical Proxies of the Primitive L/S Equity Strategies
In order to relate the primitive long/short equity strategy in Equation (3) to observable returns of L/S Equity hedge funds, the return interval used in the equation has to match available data of hedge fund returns—this tends to be monthly. However, as the return of the primitive long/short equity strategy in Equation (3) is not defined with respect to specific time intervals, we generate a monthly-return analog as follows.

First, we assume that the exposures, or b’s, are constant during each day. We can now express the return for day t as:

\[ r_{f,t} + b_{1,t} (r_{L,t} - r_{f,t}) + b_{2,t} (r_{L,t} - r_{S,t}) + b_{0,t} \]  

Here, \( r_{f,t} \) is the return of the risk-free asset, \( r_{L,t} \) the return of the long positions, and \( r_{S,t} \) the return of the short position, during day t. The exposure levels, \( b_{1,t} \) and \( b_{2,t} \) are constant during day t. \( b_{0,t} \) is the net fee for day t.

Next, we sum up the days in a month to arrive at the monthly return:

\[ \sum_t \{ r_{f,t} + b_{1,t} (r_{L,t} - r_{f,t}) + b_{2,t} (r_{L,t} - r_{S,t}) + b_{0,t} \} \]  

where the subscript t is summed over the days of the month, t=1,…,m.

Finally, we simplify the sums in Equation (5) for several types of strategy.

1. Models of Static Strategies

We define static strategies as those strategies where the risk exposures (i.e., b’s) remain constant within a month. Equation (5) now reduces to:

\[ r_{f,m} + b_{1,m} (r_{L,m} - r_{f,m}) + b_{2,m} (r_{L,m} - r_{S,m}) + b_{0,m} \]  

where \( r_{f,m} = \sum_t r_{f,t} \), \( r_{L,m} = \sum_t r_{L,t} \), \( r_{S,m} = \sum_t r_{S,t} \), and \( b_{0,m} = \sum_t b_{0,t} \).

We can now identify the variables \( r_{f,m}, r_{L,m} \) and \( r_{S,m} \) with standard asset returns. In the case of a passive index-like mutual fund, the coefficients \( b_{1,m} \) and \( b_{2,m} \) would be constant for all months. We can estimate them by regressing the mutual fund’s returns on standard asset returns as in Sharpe (1992). However, static strategies used by hedge funds tend to have time-varying exposure with respect to standard indices of assets. Empirically, these slow-moving exposures are difficult to detect in monthly returns. This problem is dealt with in three ways in the empirical analysis. One, we estimate the average coefficients from a linear regression. Two, we allow the coefficients to change once during our sample and test for the unknown sample break point. Three, we use rolling regressions to track time-varying coefficients.

2. Models of Dynamic Strategies
For a dynamic strategy, where the exposures (i.e., b’s) change within the month, there is no simple transformation of Equation (5) that can capture all possible time paths of the b’s, which can be arbitrary depending on the underlying strategy used. For tractability, we restrict our attention to dynamic strategies that can be represented as option returns. This approach is motivated by the observations that options can be replicated by dynamic trading strategies, as shown in Black and Scholes (1973), and likewise some dynamic trading strategies have the same payouts as options. For the purpose of our analysis we consider two such cases—market-timing and trend-following.

For market-timing strategies, we use the model described in Merton (1981). We illustrate this for the net long positions of a typical L/S Equity portfolio. If the underlying asset’s return is higher than that of the risk-free return, a perfect market timer would be long the asset. Otherwise the perfect market timer would hold the risk-free asset. Merton (1981) points out that the payout of the perfect market timer is the same as that of an at-the-money call option on the long asset. In other words, the exposure is simply the “delta” of the call option. Using the option return as a proxy for the market timer’s return allows us to eliminate the need to estimate the delta with respect to the underlying asset for each day of the month. Instead, both the time-varying delta and the underlying asset’s return are captured in the return of the option over the entire month.

For trend-following strategies we use an extension of Merton’s (1981) market-timer model as described in Fung and Hsieh (2001). The key difference is that the trend follower wants to buy at the low and sell at the high during the month. The payout of a perfect trend follower is that of a lookback straddle, and the exposure to the underlying asset is the same as the delta of such an option. As in the case of the market timer, we can proxy the monthly return of a trend follower using the return of a lookback straddle, without having to directly estimate the deltas of the straddle for each day of the month.

This provides a basic model of the dynamic behavior of L/S Equity hedge fund strategies—that the time-varying exposure to the underlying stocks can be approximated by the dynamic exposure of a market timer or a trend follower on the same underlying assets.

3. Treatment of Tail Risks

Lastly, we model the occurrence of nonlinear, option-like return behavior that manifest themselves only during market extremes. Observations on this type of return behavior has been conjectured in Hsieh (Plan Sponsor Magazine Interview, 1998) and observed by Mitchell and Pulvino (2001) where some hedge fund strategies exhibit characteristics similar to selling insurance policies against market extremes. This type of return behavior is consistent with the presence of arbitrage limits discussed in Shleifer and Vishny (1997) and convergence strategies in Kyle and Xiong (2001). We model this type of return behavior as out-of-the-money options as in Agarwal and Naik (2004).

II. Common Risk Factors in Primitive Long/Short Equity Strategies
In this section, we provide empirical estimates of the primitive L/S equity strategies using L/S Equity hedge fund returns. We begin our analysis on individual funds using L/S Equity hedge funds in the TASS database. As of March 17, 2005, the TASS database has 1,683 L/S Equity funds, of which 1049 are live and 634 are “defunct”. In order to avoid survivorship bias, we analyze both live and defunct funds, up through December 2004.

Most of the funds in our sample are denominated in U.S. dollars (USD)—867 live funds and 557 defunct funds. In order to avoid currency effects, we analyze only USD funds in this paper.

A. Principal Component Analysis

Following Fung and Hsieh (1997), we use principal component analysis to detect the number of common styles in hedge funds. The idea is simple. If two funds have the same investment style, their returns should be highly correlated. Principal component analysis allows us to identify the number of common covariations.

We performed the principal component analysis over five subperiods: 1995-6, 1997-8, 1999-2000, 2001-2, and 2003-4. The results in Table I are consistent with the presence of one main style in all three subperiods. In each of the subperiods, the first principal component explains more than 34 percent of the cross-sectional variation, while the second principal component accounts for less than 12 percent of the cross-sectional variation. This leads us to conclude that there is one major style. It turns out that the first principal component is highly correlated with the average fund return in all subperiods, as shown in Table II.

B. Identifying Static Risk Factors

We proceed in two steps to identify the common risk factors beginning with the static exposures before proceeding to identify dynamic exposures.

To identify common risk factors inherent in the static exposure of L/S Equity hedge funds, we regressed their average return on the standard four-factor model, consisting of the Fama-French (1992) three-factor model, augmented with the Jegadeesh and Titman (1993) momentum factor, as implemented in Cahart (1997). The four factors are RMRF, SMB, HML, and UMD. Here, RMRF denotes the return of a portfolio that is long stocks/short the risk-free asset; SMB is the return of long small cap stocks/short large
cap stocks; HML is the return to long high book-to-market stocks/short low book-to-market stocks and UMD is the return to long high momentum stocks/short low momentum stocks. It is interesting to note that UMD is correlated with the liquidity variable in Pastor and Stambaugh (2003). This is likely to be related with the net fee component in Equation (3). Further analysis of this assertion can be found in Section E below.

The first 3 columns of this table examine the standard 4-factor model. Column 1 has the two most important risk factors: the excess return of the market (RMRF) and the spread between small cap and large cap stocks (SMB). They jointly produce an adjusted $R^2$ of 0.865. We add the spread between high book-to-market and low book-to-market stocks (HML) in column 2. It is not statistically significant, and the adjusted $R^2$ remains unchanged. In column 2, we add the momentum factor (UMD). While it is statistically significant, it only raised the adjusted $R^2$ from 0.853 in the two-factor model to 0.868. These results are very similar to those found in Agarwal and Naik (2004) based on hedge fund indices provided by the database vendors. For comparison purposes, note that the four-factor model captures much more of the return variation in L/S equity hedge funds than the trend-following factors in Fung and Hsieh (2001).12

The remaining 9 columns of Table III provide a comparison with the average equity mutual fund in nine categories from the January 2005 Morningstar CD—Large Cap Growth (LCG), Mid Cap Growth (MCG), Small Cap Growth (SCG), Large Cap Blend (LCB), Mid Cap Blend (MCB), Small Cap Blend (SCB), Large Cap Value (LCV), Mid Cap Value (MCV), and Small Cap Value (SCV). The 4-factor model explains a high proportion of the variation in mutual fund returns. However, unlike hedge funds, mutual funds have no statistically significant alpha.

C. Identifying the Net Fee Variable

Beyond the standard four-factor model, we also need a proxy for the net fee variable, denoted as $b_{0,m}$ in Equation (6). As we cannot directly observe net fees in stock borrowing/lending for hedge funds, a proxy of the impact of net fees on hedge fund returns needs to be constructed. Here, we use trading activity as a proxy, based on the presumption that the impact of fees in stock borrowing/lending depends positively on the level of market activity. Four different proxies of market activity are analyzed. NYSETO is the turnover on the NYSE, calculated as the monthly share volume divided by the total outstanding shares at the end of the month. NASDTO is the turnover on the NASDAQ, defined as the monthly dollar volume divided by the total market value at the end of the month. NYSERVM is the NYSE monthly share volume, and NASDRVM is the NASDAQ monthly share volume. These two volume variables are “detrended” by dividing each month’s share volume with the average volume from the previous 12 months. Finally, all four proxies are recorded in natural logarithm.
The column labeled NYSETO in Table IV report the regressions of the average L/S equity hedge fund return on the four factor model plus the NYSE turnover ratio (NYSETO). It is not statistically significant. The next three columns (NASDTO, NYSERVM, NASDRVM) report the regression using the other proxies for the net fee variable. The results are similar. All are statistically significant and positive. NASDRVM add the most explanatory power, raising the adjusted $R^2$ from 0.868 in the 4-factor model to 0.902. It is also interesting to note that the constant term (i.e. “alpha”) is no longer statistically significant with the addition of these activity variables.

### D. Identifying Dynamic Risk Factors

Thus far, static exposures to the five common factors (RMRF, SMB, HML, UMD, and NASDRVM) explain nearly 90 percent of the return variation in the average L/S equity hedge fund. Since equity hedge funds appear to have alpha against the four market factors, we test for the presence of dynamic (option-like) risk factors. This is motivated by the observation in Glosten and Jagannathan (1994) that nonlinear payoffs, such as option returns, can appear to have alpha against a linear benchmark. In principle, we can add any number of dynamic risk factors into our regression, along with the five static risk factors. For tractability reasons, we restrict the analysis to dynamic risk factors that can be represented as option returns. Further, we limit the underlying risk factors to the two market risk factors that have the most explanatory power, RMRF and SMB.

We use three different proxies to capture option returns based on these two market factors. The Henriksson and Merton (1981) test for market timing in stocks is performed in the column labeled “HM” in Table IV. Here, Max{$0,\text{RMRF}$} and Max{$0,\text{SMB}$} are the proxies for the call option payout on market timing in stocks and in the spread between small and large cap stocks. The results reveal no evidence of dynamic strategies being applied to the management of these factors.\(^\text{13}\)

Next, we use option returns to test for market timing ability in stocks. The column labeled “ATM” uses exchange-traded at-the-money (ATM) options on the S&P futures contract as an alternative to Max{$0,\text{RMRF}$};\(^\text{14}\) they add little explanatory power. We try 5% and 10% out-of-the-money options in the columns labeled, respectively, “OTM 5%” and “OTM 10%” and 5. These, too, add little explanatory power. Based on these results, we conclude that there is no evidence to support the presence of nonlinear return behavior with respect to the overall stock market from the average L/S Equity hedge funds. A corollary to this observation is that, on average, L/S Equity hedge funds do not behave like market timers of the stock market.\(^\text{15}\)

Lastly, we test for dynamic exposure to the SMB spread factor. However, there is no verifiable price history on options on SMB as they do not trade in the public markets. A
reasonable alternative is to rely on the payout of a theoretical option and the change in its implied volatility. In addition, we assume that implied volatility is perfectly correlated with the 21-day historical volatility. We use the daily SMB returns from French’s data library to construct the historical volatility of the spread during a month.

To test market timing with respect to the level of SMB, we know the standard option’s return is correlated to SMB and the change in the historical volatility of SMB (DSMBVOL). Since SMB is already a factor in the regression, we only need to add the change in its historical volatility. To test trend following with respect to the level of the SMB, we know the lookback straddle’s return is correlated to the range of the SMB (labeled “PAYOUT” in Table IV) and the change in the historical volatility. Thus, we need to add two variables in the regression.

The column labeled “APPROX” in Table IV tests for both market-timing and trend-following strategies with respect to SMB. The regressions show that the change in the actual SMB volatility is statistically significant, but it adds little explanatory power to the regression, raising the adjusted R² from 0.899 to 0.903. The negative sign indicates that L/S equity hedge funds are short volatility, that is, they have lower returns as SMB volatility increases.

Thus far, we have performed an exhaustive set of tests for dynamic risk exposures, but we did not find any useful improvement to the results based on static factors in terms of adjusted R². Overall, given the high explanatory power of the static factors, it is not surprising to find little evidence of dynamic strategies. Consequently, we shall proceed with the five static risk factors model: RMRF, SMB, HML, UDM, and NASDRVM summarized in Equation (7):

\[ r_h - r_f = b_0 + b_1 \text{RMRF} + b_2 \text{SMB} + b_3 \text{HML} + b_4 \text{UMD} + b_5 \text{NASDRVM} + e \]  

where \( r_h \) is the return of the average L/S equity hedge fund.

E. Searching for Additional Risk Factors

Next, we turn to the issue of omitted risk factors. The obvious candidates are international equity movements and sector exposures, since the hedged return is obtained net of only the four standard U.S. factors. To address this issue, we add different variables to equation (7). Various world equity indices—MSCI Europe Ex UK, MSCI UK, MSCI Pacific Ex Japan, MSCI Japan, MSCI Emerging Markets—are also not statistically significant. Only two of the ten MSCI World Sector (Level 1) indices, Energy and Health, are statistically significant, although they do not contribute much explanatory power. Thus, it is unlikely that we have omitted any important risk factors.

F. Testing for Sample Breaks and Modeling for Slow-Drifting Static Risk Exposures

Next, we check for slow-changing risk exposures that are difficult to detect using monthly option-like returns. We use the Chow (1960) test, modifying the standard error
calculation to allow for conditional heteroskedasticity as in White (1980) and Hsieh (1983). We divide the sample into 3 subperiods based on major events in the financial markets. Period I starts in February 1994 (when the Federal Reserve raised interest rates) and ends in September 1998 (after the Russian debt default and during the near collapse of Long-Term Capital Management). Period II starts in October 1998 and ends in March 2000 (the peak of the internet bubble). Period III starts in April 2000 and ends in December 2004. The estimates of equation (7) for the three periods are given in Table V.

We conduct two tests of sample break. The first test determines whether the exposures change between Period I and III. The second test is for exposure changes between Period II and III. The chi-square statistics indicate that the exposures are different across the three subperiods.

Next, we check for persistent and slow-drifting exposure is to perform out-of-sample forecasts using rolling regressions. We accomplish this as follows. For each month, we use the previous 24 months to estimate equation (7). Then we predict the current month’s return using the estimated coefficients and the contemporaneous values of the regressors:

We perform this for each month from February 1994 until December 2004. The graphs of the actual and predicted values for the TASS average are in Figure 1. It shows that the predicted returns are highly correlated with the actual returns. This is strong evidence that the exposures do not change dramatically over time.

To recap the empirical analysis thus far, we have fund five static risk factors (RMRF, SMB, HML, UMD, and NASDRVM) that explain over 90 percent of the return variance of the average L/S equity hedge fund. In addition, exhaustive tests have not turned up any exposure to dynamic risk factors. There is, however, evidence that the exposures are slowly drifting over time, and they can be estimated using rolling regressions—summarized by the following empirical model:

\[ r_{h,m} - r_{f,m} = b_{0,m} + b_{1,m} \text{RMRF}_m + b_{2,m} \text{SMB}_m + b_{3,m} \text{HML}_m + b_{4,m} \text{UMD}_m + b_{5,m} \text{NASDRVM}_m + e_m \]  

(8)

where the \( b_{i,m} \) are estimated by means of rolling 24-month regressions. This addresses the first two questions we posed in this paper regarding the source of return and the attendant risks in L/S Equity hedge funds.
III. The Economics of Excess Performance

Given the conclusions in Section II, we can now proceed to address the third question: Do L/S equity funds generate return in excess to the major risk factors? The empirical model in Equation (8) allows us to examine the returns of L/S equity funds after adjusting for the effect of systematic risks—namely the four risk factors: RMRF, SMB, HML, and UMD. The analysis is done in two steps. First, we omit non-price variables, such as NASDRVM, from the analysis. The betas to the risk factors are based on 24-month rolling regressions. The monthly excess performance (refer to as the hedged returns for simplicity) beyond the four systematic risk factors are constructed as follows.

For each fund, we use the previous 24 months of data to run the following regression:

\[
\text{Fund return} - r_f = b_0 + b_1 \text{RMRF} + b_2 \text{SMB} + b_3 \text{HML} + b_4 \text{UMD}
\]

For the current month, we define the hedged return as:

\[
\text{Hedged return} = (\text{Fund return} - r_f) - b_1 \text{RMRF} - b_2 \text{SMB} - b_3 \text{HML} - b_4 \text{UMD},
\]

using the current month’s values of the risk-free return and the four factors.

The hedged return from the empirical analog of Equation (8) corresponds to the net fee (net return from stock lending and borrowing) term, b_{0,m}, of the primitive L/S equity strategy Equation (6). However, stock loan fees cannot be easily replicated using conventional securities. As such, these hedged returns are not truly alphas in the standard usage of the term.

A. Comparing Hedged Returns of Different Equity Fund Groups

Table VI reports the annualized average hedged return for L/S equity funds from TASS and in the first column. The hedged return is consistently positive for all three periods. They are unusually large in period II—potentially related to the Internet Bubble. However, only the hedged return in periods I and II are statistically different from zero.

The rest of Table VI provides some comparison fund groups. Column 2 is the average hedged return for Long-Biased (“Equity Non-Hedged”) funds from HFR, constructed in the same manner. While these hedged returns are also positive in the three periods, none are statistically significant. Column 3 to 12 display the average hedged return for the 9 categories of equity mutual funds. They are negative in roughly two out of three cases. None, however, are statistically positive.

The evidence suggests that, on average, equity hedge funds delivered better risk-adjusted performance than equity mutual funds. L/S equity hedge funds delivered superior excess performance to long-biased hedge funds. Specifically, the group of L/S equity hedge funds is the only strategy group that delivered statistically significant excess performance over the period of 1994-2004.
B. Relating Hedge Returns to Short Sales

1. Hedged Returns and Market Activity

Equation (8) and the empirical results in Table IV tell us that the hedged return from L/S Equity hedge funds is dependent on the level of market activity as proxied by the variable NASDRVM. This is perhaps not surprising as an important portion of hedge fund performance is akin to arbitrage-like activity. At the limit, when market activity approaches zero so would arbitrage opportunities. One example of this link can be found in Pastor and Stambaugh (2003). In that study, they directly modeled the relationship between the return from liquidity provision earned by market makers and stock volume. The low frequency nature of hedge fund data does not offer the luxury of modeling their return to such a level of detail. However, it is worthy of note that the Pastor and Stambaugh find that their liquidity measure exhibits significant correlation with UMD. It may well be that UMD is picking up liquidity effects in market making.23 However, the Pastor-Stambaugh liquidity measure has no correlation with NASDRVM, and is not statistically significant when added as a sixth regression in equation (7). This empirical phenomenon motivated us to relate equity hedge fund returns to short sales.

2. A Simple Qualitative Model of Short Sales and Hedge Fund Returns

Suppose there is a range of opinions about the value of a stock. The market price reflects the average opinion in the following sense. A trader who values the stock higher than its market price will attempt to buy the stock. A trader who values the stock lower than its market price will attempt to short the stock. In equilibrium, if there are no short constraints, the price of the stock should fully reflect the opinion of all traders.

Consider next the example of a stock that is on special (i.e., is hard-to-borrow). Then the opinion of the pessimistic trader can only be reflected in the market price at a higher cost relative to the optimistic trader. At the limit, when no stocks are available for borrowing, there is in effect a binding short-sale constraint on that stock. As a result, the market price will only reflect the opinion of the more optimistic trader. See Miller (1977), Harrison and Kreps (1978), and Morris (1996).

Empirical research provides some evidence to support this hypothesis. Asquith and Meulbroek (1996) show that stocks with higher short positions have lower future returns. Deither, Malloy, and Sherbina (2002) show that stocks with higher analyst disagreement also have lower future returns. Gopalan (2004) show that stocks with higher analyst disagreement and greater short constraint also have lower future risk-adjusted returns.

These theoretical and empirical results imply that traders can make excess returns if they can identify, borrow, and short-sell stocks that are hard to borrow (and have a tendency to be overpriced). This is the motivation behind our conjecture that excess performance of L/S equity hedge funds is systematically related to short sales activities (which is a subset of the overall level of market activities).24 Before we attempt to link
excess performance of hedge funds to short sales, we must ensure that the excess performance is not due to data biases and omitted risk factors.

C. Potential Measurement Errors in Hedged Returns

1. Data Biases

Hedge fund databases can suffer from a number of different biases, as described in Fung and Hsieh (1997, 2000), among others. Some of these biases, such as survivorship and incubation, may appear as excess performance. We show that this is not likely to be the case.

First, the hedged returns do not suffer from survivorship bias. We construct hedged returns in each month using all hedge funds that existed during that month. This includes nonsurviving as well as surviving funds.

Second, hedge returns are also not contaminated by incubation bias. When a fund enters a database, the vendor usually backfills the historical returns. The practice can induce an incubation bias for the following reason. A new fund typically starts with an incubation period, when the manager raises seed capital from friends and family members to try out a new trading strategy. If the strategy generates reasonable returns, the fund is entered into a database with the hope of attracting more capital. If not, the fund is closed down. Thus, when a fund first enters the database and the vendor backfills the incubation period’s returns, it causes a bias in the returns during the incubation period, which tends to be than the returns obtained during normal operations.

The incubation bias can be removed by deleting the returns during the incubation period. Since the incubation period is unknown, it must be estimated. Fung and Hsieh (2000) find that the median length of the backfilled periods for hedge funds was 12 months. This is a reasonable estimate of the incubation period. After all, running an experimental fund is costly for the manager, not only in terms of out-of-pocket expenses, but also in terms of the opportunity cost in forgoing income working as a trader for a proprietary trading desk or an established hedge fund.

It is important to realize that the backfilled history of a fund should not be attributed entirely to incubation. Sometimes, a fund may move from one database to another, as it tries to increase visibility with investors. The fund’s history is backfilled when it enters the new database, but only part of the backfilled history is related to the incubation period. Other times, funds enter a database when ownership of the database changes. A case in point is the acquisition of Tremont Capital Management (owner of the TASS database) by Oppenheimer Acquisition Corp. in March 1999. As a result of that transaction, a consolidation of two databases (TASS and Oppenheimer) led to a large number of hedge funds being added to the TASS database with backfilled histories from Oppenheimer’s database. Clearly, the backfilled history in TASS that came from nonbackfilled data in Oppenheimer would not contain incubation bias.
Given the reasonable assumption that the incubation period is less than two years, the hedged returns we calculate for the equity hedge funds are not contaminated by incubation bias, because they start on the 25th monthly observation of each fund. The first 24 monthly returns are used to estimate the factor exposure, which is needed to calculate the hedged return in the 25th month. Thereafter, rolling 24-month regressions are used to estimate factor exposures needed to generate the subsequent months’ hedged returns.

Furthermore, we note that the hedge returns for L/S Equity hedge funds and Long-Biased hedge funds suffer from the same biases, if they are present. These biases would cancel out when we compare the two sets of hedge returns, and do not affect our conclusion on relative excess performance.

D. Hedged Return Is Correlated to Short Interest

At this point, we relate hedged return to a more specific subset of market activity—short sales as measured by the short interest ratio. This ratio is defined as the outstanding number of stocks sold short as reported by the New York Stock Exchange (NYSE) divided by the number of stocks outstanding. This ratio is typically around one to two percent. Asquith and Meulbroek (1996) show that firms with high levels of short interest tend to have lower returns than their peers.

Here, we construct the NYSE short interest ratio from 1992 until 2000, using the aggregate short interest data in Gopalan (2004) and the number of outstanding shares reported by the NYSE. This variable is then extended to 2002 using the NYSE Monthly Short Interest Report. Since the short interest ratio has been trending up over time, we “detrend” it by dividing the short interest ratio with the average of the previous twelve months. This “detrended” variable is referred to as NYSERSI.

Table VII shows that the detrended short interest ratio has a statistically significant negative correlation with the TASS hedged returns and can be interpreted as follows. In the absence of inventory supply disruptions to the stock loan market, a low short interest ratio is consistent with high impediments to short sales—in terms of cost and risk. Either it is costly to short in terms of fees or there is a rising risk in managing short positions in terms of short squeezes. While there is no direct way of measuring the former, the latter is clearly present in active, rising markets with the attendant rise in transaction volume. In both cases stocks are more likely to be overvalued and the return to shorting is high. This in turn favors hedge fund managers who have better access to the stock loan market and who are presumably more experienced in managing the price risk of short positions. Conversely, when the short interest ratio is high, it is consistent with low impediments to short sales. Under this scenario, stocks are less likely to be overvalued and the return to shorting is low. Here, hedge fund managers will find it harder to exploit their comparative advantage of better access to the stock loan market and to utilize their risk management skills.
The NYSERSI variable provides a direct link to the short-sales subset of overall market activity (which was proxied by NASDRVM). It also provides a more explicit link between excess returns and the net fee variable in Equation (3). Table VII shows that the short interest ratio is more correlated to the hedged returns than the market activity variable (NASDRVM) for L/S equity hedge funds in TASS and HFR, providing empirical support to our interpretation.

To corroborate empirically this interpretation, Table VII looks at the correlation between the hedged returns of Long-Biased hedge funds and equity mutual funds to market activity (NASDRVM) and to short interest (NYSERSI). Except in one instance, these groups’ excess performance has no statistically significant correlation to market activity (NASDRVM) and short interest (NYSERSI). This reinforces the interpretation that excess returns of L/S equity hedge funds are short-sales related.

### IV. Implications for Future Research

#### A. The Cost of Excess Performance to Investors

Investors often question the supposedly handsome fees that hedge fund managers earn for their services. Clearly, excess performance is likely to attract excess fees; but at what cost? In the case of L/S Equity hedge funds, the excess performance (as proxied by the hedged returns) averaged 4.92 percent per annum (pa) for TASS funds, and the corresponding figure for HFR funds is 5.09 percent (see Table IV). However, these figures are estimated based on net-asset-value returns, which are net of all fees and expenses levied on investors of the fund. A natural question to ask is: How much fees did investors pay for this excess performance? Here, we provide an approximation of the cost to achieving this excess performance.

Over the period 1994-2002, the average L/S equity fund in TASS returned 17.73 percent pa, net of all fees and expenses. Of this, 4.92 percent pa is excess performance, which means 12.81 percent is due to exposure to the four standard risk factors. Assuming a fixed management fee plus administrative expenses of approximately 1.25 percent and an incentive fee of 20 percent of new profit (supposing for simplicity that no hurdle rate is enforced), the before-fee return would be approximately 23.42 percent pa (=17.73 percent/0.8 + 1.25 percent). The total cost to investors (management fees plus expenses) is 5.69 percent pa [=23.42 percent-17.73 percent]. This is just under 25 percent of the before-fee total return but is a little over 100 percent of the excess performance investors received.

Applying the same approximation to the average L/S equity fund in HFR, the total cost to investors comes to 5.24 percent pa and is also similar to the size of the average excess performance of 5.09 percent pa. The total return figures suggest an approximate 25 percent payout of total performance is paid to the hedge fund managers. However, in terms of excess performance, the payout to the hedge fund managers exceeded the payout to the investors.
It must also be noted that the incentive fee structure inherent in hedge funds creates a nonlinear payout function to the hedge fund managers based on total performance; see Goetzmann et al (2003) for an analysis. Given that index-like performance, such as mutual fund returns, do not attract such fees but delivers no excess returns, it is an important research question as to what is the optimal fee structure that best align the interest of investors seeking excess performance and that of hedge fund managers. The results in this paper provide useful clues to addressing this important question.

B. Do L/S Equity Hedge Funds Exert Destabilizing Influences on Markets?

The behavior of hedge fund risk exposures over time can provide interesting insight to the frequently asked policy question as to whether hedge funds destabilize markets. We analyze this question by examining the behavior of the risk exposure of long/short equity hedge funds (the largest subgroup of the hedge fund industry).

Figure 2 shows that the average market factor (RMRF) exposure of these hedge funds remained fairly stable from mid-1996 until the end of 2000, but began to decline in 2001. Figure 3 shows a similar pattern in the average exposure to the small/large cap spread factor (SMB), except that the exposure started to decline at the start of 2000. Together, these figures are consistent with the observation that L/S equity hedge funds did not exhibit unusual behavior during the bull run in Nasdaq stocks in the late 1990s. The evidence neither points to an unusual momentum-like buildup of market exposure leading to the peak of the Internet Bubble, nor does it point to aggressive shorting of stocks during the run-up. The evidence is more consistent with the average L/S equity hedge fund gradually reducing their exposure to small cap stocks prior to the burst of the Internet Bubble in early 2000. But, as a group, they were never net short. This is consistent with the findings in Brunnermeier and Nagel (2004). We note, however, that monthly returns cannot reliably pin point the exact time when long/short equity hedge funds started to change their risk exposures. Higher frequency data are required.

A corollary to the above discussion on the impact of L/S Equity hedge funds’ risk-taking behavior on market stability is the inverse relation between the short-sale ratio variable NYSERSI and the hedged returns. If excess performance is inversely correlated to the level of short open interest in the market, it is unlikely that L/S Equity hedge fund managers actively short stocks alongside the rest of the market. Our results suggest that the better environment for L/S Equity hedge funds to implement short-sale strategies occurs when the overall interest in short sales is low. This is consistent with the conjecture that L/S Equity hedge fund managers have a tendency to act as contrarians in their short-sale related activities. This in turn is consistent with the view that these managers, collectively, are a source of liquidity to momentum-like strategies in a manner similar to the convergence traders described in Kyle and Xiong (2001).
V. Conclusion

Based on an extensive sample of 1,738 L/S equity hedge funds, we show that their return generation process conforms to our theoretical specification—the primitive L/S equity strategy denoted in Equation (3). This conclusion is based on empirical results on the central tendency of L/S equity hedge funds’ returns over the sample period 1994 to 2002. In particular, we showed that there are two main risk factors in L/S Equity hedge funds: the excess return of the market (RMRF) and the spread between small and large cap stocks (SMB). These two risk factors together with the spread between value and growth stocks (HML) and momentum (UMD) from the standard four-factor model, can account for over 80 percent of the variation in the returns of these hedge funds. Exhaustive testing did not turn up important exposures to dynamic option-like factors. However, slow-moving, time-varying behavior of risk factor exposure is detected.

After adjusting for the risks associated with the four standard risk factors, the hedged returns show average positive performance. We showed that this observed excess performance is not contaminated by measurement errors from database biases and is unlikely to emanate from omitted market risk factors. Instead, this excess performance is market-volume related and more specifically short-sales volume related. The empirical results conform to our theoretical model that L/S Equity hedge funds have preferential access to the stock loan market and appeared to have capitalized this advantage in delivering excess performance. Further collaborative evidence is reported where neither equity mutual funds nor Long-Biased equity hedge funds exhibit return sensitivity to short-sale activities. Expressed differently, L/S Equity hedge funds, as the name suggests, derive excess performance from shorting. Besides differences in risk taking behavior, this is a key feature distinguishing L/S funds from Long-Biased funds.

Our empirical findings have interesting implications for future research on optimal contract design and market stability. Based on our estimate of excess performance, we showed that although L/S equity hedge fund managers’ share of total performance is within normal ranges. That share is approximately 25 percent of total trading profits based on the standard hedge fund compensation contract with its 20 percent profit-sharing feature. However, as a share of excess performance, L/S Equity hedge fund managers have rewarded themselves as much as their investors. Given that the current hedge fund contracts are designed to align the interest of investors and hedge fund managers in total performance space, it is a challenging problem to device a satisfactory analog in excess performance. In terms of risk-taking behavior, our empirical results show that L/S equity hedge fund managers do not exhibit momentum-like feedback trading behavior during stressful markets like the Internet Bubble. In contrast, their investment behavior is more consistent with the convergence traders in the model of Kyle and Xiong (2001)—in both directional and long/short activities.
REFERENCES


Footnotes:

1 As of December 2004, there are 3,309 live funds and 2,027 defunct funds in the TASS database. Of these, 1,049 are live equity funds and 634 are defunct equity funds.

2 As of December 2004, there are 1,049 live and 634 defunct Long/Short Equity funds in TASS. As of December 2004, about 23 percent of the funds in the Hedge Fund Research (HFR) database are classified as Equity Hedge, which is similar to Long/Short Equity in TASS. Similarly, as of June 2003, about 30 percent of the funds in the Morgan Stanley Capital International (MSCI) database are classified as Long Bias, which is similar to Long/Short Equity in TASS.

3 For a discussion on the nonlinear features of this type of fee structure, see Goetzmann, Ingersoll, and Ross (2003).

4 Both hedge funds and mutual funds pass on operating expenses of the fund to the investors.

5 Hints of excess returns from equity-related hedge fund indices have been reported in Agarwal and Naik (2004) and Fung and Hsieh (2004) as empirical regularities without a theoretical foundation.

6 Another commonly used term is the repo market for stocks.

7 This assumes that no other liens on the same assets exist.

8 Quite often, retail investors have no access to the use of the proceeds from short sales and are not paid interest over the duration of the stock loan.

9 We structured Equation (3) in this format to better reflect the empirical regularity that L/S Equity funds are typically net long, i.e., (L-2S)>0. Equation (3) can easily be reformulated to reflect the returns of hedge funds that are net short, i.e., (L-2S)<0.

10 It should also be noted here there are many factors that can differentiate one hedge fund manager from another.

11 Defunct means no information: ceased operation, or ceased reporting.

12 We tried the Pastor and Stambaugh (2003) liquidity factors, and the Brunnermeier and Nagel (2004) TECH factor. They did not improve the explanatory power of the four-factor model.

13 We tried |HML| and |UMD|, but they were not statistically significant.

14 Options have been used to model hedge fund returns in Fung and Hsieh (2001), Mitchell and Pulvino (2001), and Agarwal and Naik (2004).
This is in agreement with Agarwal and Naik (2004), who find option-like return features in other hedge fund styles but not in L/S Equity.

We do not rule out the possibility that some individual L/S equity funds may have strong exposures to dynamic risk factors. Our conclusion applies only to the average of these funds.

To conserve space, we do not report these results.

This is similar to a random parameter model, which can be estimated using Kalman filtering.

This out-of-sample forecast is similar to the one in Agarwal and Naik (2004).

Note, however, that any correlations between net fees to the four risk factors have been account for in the construction of Equation (8). What remains is that part of the net fee variable that has no correlation to the four risk factors.

While the average excess performance is negatively correlated with the *tech factor* in Brunnermeier and Nagel (2004), the relation is not statistically significant at conventional levels.

We note that, unlike our hedge fund sample, our mutual fund sample has only survivors. So it has survivorship bias. If we included dead funds, we should have an even lower excess performance, since dead funds have lower average returns than surviving funds. See, for example, Brown et al (1992) and Malkiel (1995).

This notion is reinforced by the fact that UMD is not important for equity mutual funds and long-only hedge funds. One would expect market makers to hedge their inventories.

Note, however, that the excess performance in the hedged returns cannot come from factors that are already reflected in market prices. Those would have been removed in the hedging process.

Our simple characterization of the stock loan market posits that the supply of stock lending inventory tends to follow a smooth pattern with long-term investing institutions regularly lending blocks of stocks at stable terms to the market.

The Brunnermeier-Nagel tech factor (available through December 2003) is not statistically significant when added as a sixth regressor in equation (7).
Table I  
Percent of Common Variation Explained by the First Five Principal Components

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>PC1</td>
<td>36%</td>
<td>46%</td>
<td>38%</td>
<td>34%</td>
<td>35%</td>
</tr>
<tr>
<td>PC2</td>
<td>7%</td>
<td>7%</td>
<td>12%</td>
<td>10%</td>
<td>8%</td>
</tr>
<tr>
<td>PC3</td>
<td>6%</td>
<td>6%</td>
<td>6%</td>
<td>6%</td>
<td>6%</td>
</tr>
<tr>
<td>PC4</td>
<td>4%</td>
<td>6%</td>
<td>4%</td>
<td>6%</td>
<td>6%</td>
</tr>
<tr>
<td>PC5</td>
<td>4%</td>
<td>5%</td>
<td>4%</td>
<td>5%</td>
<td>4%</td>
</tr>
</tbody>
</table>
## Table II
Correlation Between the First Principal Component and Fund Averages

<table>
<thead>
<tr>
<th>Period</th>
<th>TASSAVG</th>
<th>HFRI</th>
</tr>
</thead>
<tbody>
<tr>
<td>1995-6</td>
<td>0.976</td>
<td>0.914</td>
</tr>
<tr>
<td>1997-8</td>
<td>0.994</td>
<td>0.970</td>
</tr>
<tr>
<td>1999-0</td>
<td>0.992</td>
<td>0.985</td>
</tr>
<tr>
<td>2001-2</td>
<td>0.988</td>
<td>0.979</td>
</tr>
<tr>
<td>2003-4</td>
<td>0.992</td>
<td>0.982</td>
</tr>
</tbody>
</table>

**Notes:**

TASSAVG: Average of TASS Long/Short Equity funds

HFRI: HFRI Equity Hedge Index
## Table III. Regressions of Excess Returns of Equity Hedge Funds and Mutual Funds on the Four Factor Model (1994-2004)

<table>
<thead>
<tr>
<th></th>
<th>TASS</th>
<th>TASS</th>
<th>TASS</th>
<th>MUTFD</th>
<th>MUTFD</th>
<th>MUTFD</th>
<th>MUTFD</th>
<th>MUTFD</th>
<th>MUTFD</th>
<th>MUTFD</th>
<th>MUTFD</th>
</tr>
</thead>
<tbody>
<tr>
<td>AVG</td>
<td>0.0062</td>
<td>0.0064</td>
<td>0.0056</td>
<td>-0.0006</td>
<td>-0.0009</td>
<td>-0.0011</td>
<td>-0.0006</td>
<td>-0.0001</td>
<td>-0.0014</td>
<td>-0.0007</td>
<td>0.0000</td>
</tr>
<tr>
<td></td>
<td>0.0008</td>
<td>0.0010</td>
<td>0.0009</td>
<td>0.0007</td>
<td>0.00137</td>
<td>0.00136</td>
<td>0.00034</td>
<td>0.0009</td>
<td>0.00101</td>
<td>0.00076</td>
<td>0.00108</td>
</tr>
<tr>
<td>RMRF</td>
<td>0.4669</td>
<td>0.4570</td>
<td>0.4857</td>
<td>1.0001</td>
<td>1.1059</td>
<td>1.1278</td>
<td>0.9496</td>
<td>1.0206</td>
<td>0.9996</td>
<td>0.9342</td>
<td>0.9525</td>
</tr>
<tr>
<td></td>
<td>0.0234</td>
<td>0.0270</td>
<td>0.0247</td>
<td>0.0212</td>
<td>0.0383</td>
<td>0.0395</td>
<td>0.0098</td>
<td>0.0311</td>
<td>0.0323</td>
<td>0.0225</td>
<td>0.0374</td>
</tr>
<tr>
<td>SMB</td>
<td>0.2698</td>
<td>0.2604</td>
<td>0.2464</td>
<td>-0.0463</td>
<td>0.4123</td>
<td>0.7214</td>
<td>-0.0795</td>
<td>0.2743</td>
<td>0.6372</td>
<td>-0.0626</td>
<td>0.1824</td>
</tr>
<tr>
<td></td>
<td>0.0372</td>
<td>0.0352</td>
<td>0.0327</td>
<td>0.0229</td>
<td>0.0508</td>
<td>0.0432</td>
<td>0.0102</td>
<td>0.0347</td>
<td>0.0334</td>
<td>0.0195</td>
<td>0.0386</td>
</tr>
<tr>
<td>HML</td>
<td>-0.0242</td>
<td>-0.0076</td>
<td>-0.2638</td>
<td>-0.2002</td>
<td>-0.0728</td>
<td>0.0598</td>
<td>0.3000</td>
<td>0.5003</td>
<td>0.4236</td>
<td>0.5869</td>
<td>0.6805</td>
</tr>
<tr>
<td></td>
<td>0.0394</td>
<td>0.0345</td>
<td>0.0282</td>
<td>0.0569</td>
<td>0.0599</td>
<td>0.0126</td>
<td>0.0387</td>
<td>0.0433</td>
<td>0.0328</td>
<td>0.0430</td>
<td>0.0375</td>
</tr>
<tr>
<td>UMD</td>
<td>0.0689</td>
<td>0.0519</td>
<td>0.1299</td>
<td>0.1073</td>
<td>-0.0148</td>
<td>-0.0273</td>
<td>-0.0326</td>
<td>-0.0981</td>
<td>-0.1049</td>
<td>-0.1012</td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.0217</td>
<td>0.0164</td>
<td>0.0356</td>
<td>0.0350</td>
<td>0.0075</td>
<td>0.0211</td>
<td>0.0256</td>
<td>0.0185</td>
<td>0.0244</td>
<td>0.0216</td>
<td></td>
</tr>
<tr>
<td>Adj R²</td>
<td>0.853</td>
<td>0.852</td>
<td>0.868</td>
<td>0.976</td>
<td>0.940</td>
<td>0.953</td>
<td>0.993</td>
<td>0.949</td>
<td>0.946</td>
<td>0.956</td>
<td>0.916</td>
</tr>
</tbody>
</table>

TASSAVG: Average of TASS L/S Equity Funds  
LCG: Average of Morningstar’s Large Cap Growth Funds  
MCG: Average of Morningstar’s Mid Cap Growth Funds  
SCG: Average of Morningstar’s Small Cap Growth Funds  
LCB: Average of Morningstar’s Large Cap Blend Funds  
MCB: Average of Morningstar’s Mid Cap Blend Funds  
SCB: Average of Morningstar’s Small Cap Blend Funds  
LCV: Average of Morningstar’s Large Cap Value Funds  
MCV: Average of Morningstar’s Mid Cap Value Funds  
SCV: Average of Morningstar’s Small Cap Value Funds  
Standard errors in italics. Statistically significant coefficients (1% level) in bold.
Table IV
Panel A. Regression on TASS Average: 1994-2004 (132 observations)

<table>
<thead>
<tr>
<th></th>
<th>NYSETO</th>
<th>NASDTE</th>
<th>NYSERVVM</th>
<th>NASDRVM</th>
<th>HM</th>
<th>ATM</th>
<th>OTM 5%</th>
<th>OTM 10%</th>
<th>APPROX</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>0.0081</td>
<td>-0.0051</td>
<td>-0.0176</td>
<td>-0.0269</td>
<td>-0.0282</td>
<td>-0.0267</td>
<td>-0.0267</td>
<td>-0.0268</td>
<td>-0.0322</td>
</tr>
<tr>
<td></td>
<td>0.0036</td>
<td>0.0037</td>
<td>0.0074</td>
<td>0.0048</td>
<td>0.0051</td>
<td>0.0049</td>
<td>0.0048</td>
<td>0.0048</td>
<td>0.0050</td>
</tr>
<tr>
<td>RMRF</td>
<td>0.4838</td>
<td>0.4974</td>
<td>0.4955</td>
<td>0.4713</td>
<td>0.4335</td>
<td>0.4323</td>
<td>0.4634</td>
<td>0.4551</td>
<td>0.4698</td>
</tr>
<tr>
<td></td>
<td>0.0260</td>
<td>0.0243</td>
<td>0.0241</td>
<td>0.0220</td>
<td>0.0365</td>
<td>0.0577</td>
<td>0.0344</td>
<td>0.0311</td>
<td>0.0219</td>
</tr>
<tr>
<td>SMB</td>
<td>0.2481</td>
<td>0.2351</td>
<td>0.2613</td>
<td>0.2457</td>
<td>0.2473</td>
<td>0.2526</td>
<td>0.2462</td>
<td>0.2445</td>
<td>0.2389</td>
</tr>
<tr>
<td></td>
<td>0.0339</td>
<td>0.0301</td>
<td>0.0299</td>
<td>0.0242</td>
<td>0.0382</td>
<td>0.0248</td>
<td>0.0242</td>
<td>0.0243</td>
<td>0.0243</td>
</tr>
<tr>
<td>HML</td>
<td>-0.0077</td>
<td>-0.0222</td>
<td>0.0153</td>
<td>0.0083</td>
<td>0.0099</td>
<td>0.0060</td>
<td>0.0043</td>
<td>0.0053</td>
<td>0.0152</td>
</tr>
<tr>
<td></td>
<td>0.0347</td>
<td>0.0344</td>
<td>0.0336</td>
<td>0.0285</td>
<td>0.0272</td>
<td>0.0281</td>
<td>0.0286</td>
<td>0.0288</td>
<td>0.0282</td>
</tr>
<tr>
<td>UMD</td>
<td>0.0674</td>
<td>0.0742</td>
<td>0.0708</td>
<td>0.0727</td>
<td>0.0724</td>
<td>0.0718</td>
<td>0.0715</td>
<td>0.0723</td>
<td>0.0777</td>
</tr>
<tr>
<td></td>
<td>0.0219</td>
<td>0.0209</td>
<td>0.0203</td>
<td>0.0181</td>
<td>0.0173</td>
<td>0.0182</td>
<td>0.0180</td>
<td>0.0180</td>
<td>0.0167</td>
</tr>
<tr>
<td>Volume</td>
<td>-0.0030</td>
<td>0.0037</td>
<td>0.0212</td>
<td>0.0296</td>
<td>0.0292</td>
<td>0.0294</td>
<td>0.0295</td>
<td>0.0295</td>
<td>0.0319</td>
</tr>
<tr>
<td></td>
<td>0.0045</td>
<td>0.0014</td>
<td>0.0068</td>
<td>0.0044</td>
<td>0.0050</td>
<td>0.0044</td>
<td>0.0043</td>
<td>0.0044</td>
<td>0.0044</td>
</tr>
<tr>
<td>Max {0,RMRF}</td>
<td></td>
<td>0.0846</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>0.0639</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Max {0,SMB}</td>
<td></td>
<td>0.0027</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>0.0674</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Calls</td>
<td></td>
<td>0.0017</td>
<td>-0.00005</td>
<td>-0.00001</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>0.0021</td>
<td>0.00001</td>
<td>0.000003</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Puts</td>
<td></td>
<td>-0.0010</td>
<td>-0.0003</td>
<td>-0.0008</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>0.0022</td>
<td>0.0014</td>
<td>0.0011</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>DSMBVOL</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>-0.0704</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.0212</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>LB Payout</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.0065</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.0048</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Adj R²</td>
<td>0.868</td>
<td>0.875</td>
<td>0.874</td>
<td>0.902</td>
<td>0.902</td>
<td>0.901</td>
<td>0.902</td>
<td>0.901</td>
<td>0.906</td>
</tr>
</tbody>
</table>

Standard errors in italics. Statistical significance at the one-tailed 1% level in bold.
### Table V
#### Sample Break Test: Feb 1994-Dec 2004

<table>
<thead>
<tr>
<th></th>
<th>Period I</th>
<th></th>
<th>Period II</th>
<th></th>
<th>Period III</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Feb 94-Sep 98</td>
<td>Oct 98-Mar 00</td>
<td>Apr 00-Dec 04</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>0.0017</td>
<td>0.0010</td>
<td>0.0082</td>
<td>0.0020</td>
<td>0.0023</td>
<td></td>
</tr>
<tr>
<td>RMRF</td>
<td>0.5561</td>
<td>0.0353</td>
<td>0.5400</td>
<td>0.0365</td>
<td>0.4024</td>
<td>0.0319</td>
</tr>
<tr>
<td>SMB</td>
<td>0.3656</td>
<td>0.0327</td>
<td>0.2969</td>
<td>0.0362</td>
<td>0.1924</td>
<td>0.0360</td>
</tr>
<tr>
<td>HML</td>
<td>0.0586</td>
<td>0.0433</td>
<td>0.0130</td>
<td>0.1254</td>
<td>0.0291</td>
<td>0.0263</td>
</tr>
<tr>
<td>UMD</td>
<td>0.0434</td>
<td>0.0364</td>
<td>0.0228</td>
<td>0.0703</td>
<td>0.0361</td>
<td>0.0211</td>
</tr>
<tr>
<td>NASDRVM</td>
<td>0.0318</td>
<td>0.0063</td>
<td>0.0395</td>
<td>0.0108</td>
<td>0.0087</td>
<td></td>
</tr>
<tr>
<td>Adj R²</td>
<td>0.949</td>
<td>0.929</td>
<td>0.920</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>N</td>
<td>56</td>
<td>18</td>
<td>57</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\chi^2(5)$</td>
<td>50.5</td>
<td>36.4</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Standard errors in italics. Statistical significance at the one-tailed 1% level in bold.
The $\chi^2(5)$ statistics test for the equality of the slope coefficients between Periods I and II (individually) against Period III.
Table VI
Average Hedged Return for Hedge Funds and Mutual Funds

<table>
<thead>
<tr>
<th></th>
<th>TASS AVG</th>
<th>HFR AVG</th>
<th>MUTFD LCG</th>
<th>MUTFD MCG</th>
<th>MUTFD SCG</th>
<th>MUTFD LCB</th>
<th>MUTFD MCB</th>
<th>MUTFD SCB</th>
<th>MUTFD LCV</th>
<th>MUTFD MCV</th>
<th>MUTFD SCV</th>
</tr>
</thead>
<tbody>
<tr>
<td>Annualized Average</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Period I</td>
<td>3.49%</td>
<td>0.80%</td>
<td>-0.67%</td>
<td>-1.65%</td>
<td>-1.74%</td>
<td>-1.13%</td>
<td>-0.80%</td>
<td>-1.00%</td>
<td>-2.02%</td>
<td>-1.48%</td>
<td>1.02%</td>
</tr>
<tr>
<td>Period II</td>
<td>15.00%</td>
<td>10.03%</td>
<td>-2.05%</td>
<td>10.57%</td>
<td>7.05%</td>
<td>-1.14%</td>
<td>3.59%</td>
<td>-5.48%</td>
<td>-1.51%</td>
<td>0.65%</td>
<td>-8.10%</td>
</tr>
<tr>
<td>Period III</td>
<td>2.88%</td>
<td>0.76%</td>
<td>-2.99%</td>
<td>-3.42%</td>
<td>-4.06%</td>
<td>-1.79%</td>
<td>0.98%</td>
<td>-1.05%</td>
<td>-0.13%</td>
<td>1.81%</td>
<td>0.53%</td>
</tr>
<tr>
<td>Annualized SD</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Period I</td>
<td>2.79%</td>
<td>4.06%</td>
<td>1.93%</td>
<td>3.29%</td>
<td>3.40%</td>
<td>0.91%</td>
<td>2.22%</td>
<td>1.81%</td>
<td>1.39%</td>
<td>1.96%</td>
<td>2.12%</td>
</tr>
<tr>
<td>Period II</td>
<td>4.35%</td>
<td>7.57%</td>
<td>3.34%</td>
<td>6.82%</td>
<td>6.06%</td>
<td>1.97%</td>
<td>4.88%</td>
<td>5.83%</td>
<td>2.64%</td>
<td>5.33%</td>
<td>5.53%</td>
</tr>
<tr>
<td>Period III</td>
<td>3.82%</td>
<td>3.49%</td>
<td>3.17%</td>
<td>6.90%</td>
<td>6.21%</td>
<td>1.54%</td>
<td>3.74%</td>
<td>4.71%</td>
<td>3.77%</td>
<td>4.52%</td>
<td>4.38%</td>
</tr>
<tr>
<td>T-stat</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Period I</td>
<td>2.70</td>
<td>0.43</td>
<td>-0.75</td>
<td>-1.08</td>
<td>-1.11</td>
<td>-2.67</td>
<td>-0.78</td>
<td>-1.20</td>
<td>-3.14</td>
<td>-1.64</td>
<td>1.04</td>
</tr>
<tr>
<td>Period II</td>
<td>4.22</td>
<td>1.62</td>
<td>-0.75</td>
<td>1.90</td>
<td>1.43</td>
<td>-0.71</td>
<td>0.90</td>
<td>-1.15</td>
<td>-0.70</td>
<td>0.15</td>
<td>-1.79</td>
</tr>
<tr>
<td>Period III</td>
<td>1.64</td>
<td>0.47</td>
<td>-2.06</td>
<td>-1.08</td>
<td>-1.43</td>
<td>-2.54</td>
<td>0.57</td>
<td>-0.49</td>
<td>-0.07</td>
<td>0.87</td>
<td>0.26</td>
</tr>
</tbody>
</table>

HFR AVG: Average of HFR Equity Non-Hedge funds.
Table VII
Regression of Hedged Returns Against Volume and Short Interest

<table>
<thead>
<tr>
<th></th>
<th>TASS AVG</th>
<th>HFR AVG</th>
<th>MUTFD LCG</th>
<th>MUTFD MCG</th>
<th>MUTFD SCG</th>
<th>MUTFD LCB</th>
<th>MUTFD MCB</th>
<th>MUTFD SCB</th>
<th>MUTFD LCV</th>
<th>MUTFD MCV</th>
<th>MUTFD SCV</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>0.0212</td>
<td>-0.0017</td>
<td>-0.0108</td>
<td>-0.0040</td>
<td>-0.0110</td>
<td>-0.0105</td>
<td>-0.0148</td>
<td>-0.0287</td>
<td>-0.0031</td>
<td>-0.0123</td>
<td>-0.0254</td>
</tr>
<tr>
<td></td>
<td>0.0135</td>
<td>0.0209</td>
<td>0.0111</td>
<td>0.0218</td>
<td>0.0211</td>
<td>0.0064</td>
<td>0.0172</td>
<td>0.0184</td>
<td>0.0108</td>
<td>0.0178</td>
<td>0.0154</td>
</tr>
<tr>
<td>NASDRVM</td>
<td>0.0156</td>
<td>0.0103</td>
<td>0.0049</td>
<td>0.0150</td>
<td>0.0107</td>
<td>0.0044</td>
<td>0.0063</td>
<td>-0.0019</td>
<td>0.0025</td>
<td>0.0019</td>
<td>-0.0080</td>
</tr>
<tr>
<td></td>
<td>0.0066</td>
<td>0.0117</td>
<td>0.0052</td>
<td>0.0084</td>
<td>0.0077</td>
<td>0.0032</td>
<td>0.0075</td>
<td>0.0086</td>
<td>0.0048</td>
<td>0.0093</td>
<td>0.0081</td>
</tr>
<tr>
<td>NYSERSI</td>
<td>-0.0329</td>
<td>-0.0076</td>
<td>0.0037</td>
<td>-0.0126</td>
<td>-0.0019</td>
<td>0.0044</td>
<td>0.0080</td>
<td>0.0281</td>
<td>-0.0005</td>
<td>0.0101</td>
<td>0.0324</td>
</tr>
<tr>
<td></td>
<td>0.0088</td>
<td>0.0116</td>
<td>0.0081</td>
<td>0.0180</td>
<td>0.0169</td>
<td>0.0040</td>
<td>0.0115</td>
<td>0.0122</td>
<td>0.0083</td>
<td>0.0107</td>
<td>0.0104</td>
</tr>
<tr>
<td>Adj R²</td>
<td>0.162</td>
<td>0.010</td>
<td>-0.004</td>
<td>0.020</td>
<td>0.001</td>
<td>0.022</td>
<td>-0.001</td>
<td>0.034</td>
<td>-0.012</td>
<td>-0.010</td>
<td>0.080</td>
</tr>
</tbody>
</table>

Standard errors in italics. Statistical significance at the one-tailed test in bold.
Figure 2. RMRF-Betas from Rolling 24-month Regressions on 4 Factors
Figure 3. SMB-Betas from Rolling 24-month Regressions on 4 Factors