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

by

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Abstract

Theory suggests that long/short equity hedge funds' returns come from directional as well as spread bets on the stock market. 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 more than 80 percent of return variation. Additional factors are price momentum and *market activity*. Combining two major branches of hedge fund research, our model is the first that explicitly incorporates the effect of funding (stock loan) on alpha. Using a comprehensive data set compiled from three major database sources, we find that among the three thousand plus hedge funds with similar style classification, less than twenty percent of long/short equity hedge funds delivered significant, persistent, stable positive non-factor related returns. Consistent with the predictions of the Berk and Green (2004) model we find alpha producing funds decays to "beta-only" over time. However, we do not find evidence of a negative effect of fund size on managers' ability to deliver alpha. Finally, we show that non-factor related returns, or alpha, are positively correlated to market activity and negatively correlated to *aggregate short interest*. In contrast, equity mutual funds and long-bias equity hedge funds have no significant, persistent, non-factor related return. Expressed differently, L/S equity hedge funds, as the name suggests, do benefit from shorting. Besides differences in risk taking behavior, this is a key feature distinguishing L/S funds from long-bias funds.

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1. Introduction

The first-known hedge fund was founded by A.W. Jones around 1949. Unlike the typical equity mutual fund, Jones's fund took long and short positions in equities. This style of investing, commonly referred to as long/short equity ("L/S equity" for short), has stood the test of time and continued to attract investors' capital to this date. As of December 2008, the Lipper-TASS database has 8,558 hedge funds[1] (excluding funds-of-hedge funds). Roughly 40 percent are classified as having L/S equity as their primary investment style capturing 27 percent of the hedge fund industry's total assets under management (AUM) based on Lipper-TASS's estimate.[2]

In terms of risk characteristics, L/S equity hedge funds generally have lower market exposure than their brethren in the long-only world—equity mutual funds. For instance, the average L/S equity hedge fund in the Lipper-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. Hedge funds carry a substantially higher fee than equity mutual funds, typically charging a fixed fee of one to two percent per annum together with a performance-based fee of 15 to 20 percent of new profits.[3] In contrast, Investment Company Institute (2009) reports equity mutual fund fees and expenses averaged 0.99% in 2008.[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.

Hints of excess returns or alpha, adjusting for both risk and costs, from equity-related hedge fund indices have been reported in Agarwal and Naik (2004) and Fung and Hsieh (2004b) as empirical regularities with limited explanation as to the economic activities underlying the observed alpha. In a broader context, Kosowski, Naik and Teo (2007) reported persistent alpha across a broader spectrum of hedge fund styles. Using funds of hedge funds as a proxy for diversified portfolios of hedge funds, Fung, Hsieh, Naik and Ramadorai (2008) reported similar results. Both papers investigated the persistency of observed alphas. Following the model of Berk and Green (2004) both studies confirmed the negative impact of a fund's capital growth on its ability to deliver persistent alpha. Both Kosowski et al (2007) and Fung et al (2008) applied variants of the Fung and Hsieh (2004a) 7-factor model which was originally designed to proxy the general risk characteristics of diversified hedge fund portfolios. Consequently, observed alphas at the level of specific style categories (e.g. L/S equity) are a composite of risk model differences for that style category compared to the broad-based 7-factor model and other idiosyncratic sources. We know of no unambiguous way to disentangle these effects empirically. Although the Kosowski et al (2007) and Fung el al (2008) papers documented evidence that excessive capital hinders a hedge fund's ability to produce alpha, little is known about the economic conditions that are conducive to the production of alpha.

In order to gain insight on the risk of specific hedge fund strategies, Fung and Hsieh (2001) and Mitchell and Pulvino (2001) took a very different approach. By directly modeling the strategies pursued by trend followers (Fung and Hsieh (2001)) and merger arbitrageurs (Mitchell and Pulvino (2001)) these papers shed light on the explicit identification of favorable economic conditions to the respective strategies as a whole. Neither paper proceeded to investigate the question of alpha persistency in the respective groups of hedge funds. In this paper we combine both branches of hedge fund research and derive empirical conclusions using a comprehensive data base of hedge fund returns net of all fees and expenses. Our data sample spans several commercially available data bases. We model explicitly how L/S equity hedge funds differ from long-only equity funds by analyzing the effect of the stock loan market on the returns of L/S equity hedge fund managers. Approaching the problem this way allows us to investigate the persistency of alpha among L/S equity hedge fund managers and provide new insight on the drivers of alpha beyond the conventional approach of attributing them to commercial characteristics of a fund such as the age of the fund and, as a last resort, to "manager skill"[5]. In addition to combining two major branches of hedge fund research and applying it to a large universe of L/S equity hedge funds, our analysis is the first that explicitly models the effect of funding (stock loan) on alpha. This new approach is conceptually important in analyzing leveraged trading strategies which are used by the majority of hedge funds as well as timely as global markets emerge from the liquidity crisis of 2008. Our model is the first to empirically differentiate alpha from security selection skills (in this case stock picking) from alpha that is driven by artful management of leverage (in particular stock loans).

The empirical results in this paper provide insight to three key questions essential to understanding the performance of this major sector of the hedge fund industry. First, do L/S equity hedge funds exhibit persistent alpha, net of all costs, materially different from equity mutual funds? Second, do L/S equity hedge funds have similar risk factor exposure as equity mutual funds? Third, what kind of economic conditions are favorable to producing alpha? The answers to these questions help us better understand whether L/S hedge fund managers add value by taking advantage of the additional flexibility of shorting and leverage compared to their long-only peers.

The paper is organized as follows. Section 2 models the strategies used by L/S equity hedge funds. Section 3 develops the empirical analogue of these models, while Section 4 describes the data set used for the empirical tests which spans the past one and a half decade from 1994 to 2008. Section 5, is devoted to an empirical analysis of the risks in L/S equity hedge funds. Drawing from the results in Section 5 Section 6 proceeds to explore empirically the economics of *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. Concluding remarks are offered in Section 7.

2. 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.[6] Our description of this market is based on an adaptation and extension of D'Avolio (2002). Using the features of the stock loan market, we develop a simple (or "primitive") trading strategy for L/S equity hedge funds.

2.1. The market for borrowing and lending stocks—the stock loan market

2.1.1. Stock lenders

We begin our analysis of the stock loan market from the lender's vantage point. Institutional investors like pension funds often hold large inventories of stocks over long periods of time. In order to enhance the income from their 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.[7] 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 carrying 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 and the attendant price risk of the underlying stock reside 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 is entitled to receive from the borrower any distributions related to the stock—such as dividends, rights issues, etc.—as if the lender remains the stock holder-of-record. 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 exceed 400bp. Although D'Avolio (2002) did not explicitly model how and why stocks go on special, it is reasonable to assume that stocks with a limited floating supply (small original issuance size or large blocks being held by unwilling lenders) are prone to become hard-to-borrow candidates. For simplicity, we assume that stocks go on special when borrowers' interests exceed the inventory of stocks available from lenders. This implies that the hard-to-borrow status of a stock is not a static phenomenon. Stocks can go on special from time to time whenever there is a supply-demand imbalance, which can result in short squeezes in which short sellers are forced to cover their short positions in the open market pushing prices higher. It is important to note that while illiquid stocks are likely to be hard to borrow, ample liquidity in a stock does not necessarily imply ample lenders. Ultimately the liquidity of the repo market depends on the availability of lenders whose decision to lend stocks may be affected by other concerns such as credit risk and voting rights. Therefore there is no direct relationship between the trading volume of an active stock and its availability to stock borrowers.

From the stock lender's vantage point, the total return from a stock loaned to the stock loan market is

$$\textit{Return on loaned out stock} = r_L + fee_L \qquad (1)$$

where r_L denotes the return of the stocks, and fee_L denotes the stock loan fee.

2.1.2. 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* (PB) 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 house has the brokerage account in which the securities are held for safekeeping, and it consolidates any attendant cash flows from transactions. Because of other financial services that a PB offers its clients, PBs are better placed to source potential borrowers and lenders of stocks.

In addition, large PBs 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 the PB's inventory are borrowed. This will create unprofitable idle inventory for the PB. In contrast, periodically part of the PB's inventory may go on *special* allowing the PB to earn abnormal spreads to their own borrowing costs. In essence, it is the PB that assumes the market maker-like role in the stock loan market. Despite the functional similarity between PBs in the stock loan market and market makers in conventional stock markets, there is an important difference. Conventional market makers have, up to an extent, a contractual obligation to provide liquidity to the stock in which they maintain a market for buyers and sellers. PBs, on the other hand, are not contractually obliged to provide stocks to lenders beyond commercial self-interest. Therefore managing stock loan positions requires a level of skill quite different from managing the buying and selling of stocks out of a long inventory position.

We can model the inventory of stocks available for lending from a PB as comprising two components:

$$I_t = Z_t + Q_t \qquad (2)$$

where Z_t represents that part of the inventory from active investors whose holdings are are transitory and hard to predict, and Q_t is the long-term component of the inventory secured from institutional investors representing the more stable part of a PB's lending inventory.

2.1.3. Stock borrowers

Next, we consider the stock loan transaction from the borrower's vantage point. Typically, a trader who borrows stocks intends to sell them short (the *short seller*) with the expectation of repurchasing them at a lower price in the near future. 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* (PLSES), in line with common practice, we shall assume that the actual short sale proceeds are withheld by the lender as collateral. Under Regulation T in the United States (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 PB for the purpose of absorbing potential future losses should the price run up during the period of the loan. A short seller can pledge securities as variation margin. For notational simplicity, in constructing our PLSES, we assume that cash margin is pledged as collateral which earns the risk-free rate. Thus, for each \$1 of variation margin, the short seller's return on margin capital is implicitly leveraged two times, as follows:

$$\textit{Return on margin for shorted stock} = r_f + 2\,[\,-r_S + r_f)\,] - 2 * fees_S \qquad (3)$$

where r_S is the return on the shares shorted, $fees_S$ the stock loan fee, and r_f the return on the risk-free asset . Essentially the return from shorting comes from the interest earned from the margin capital pledged, two times the sum of the performance of the underlying asset and the interest earned from the short-sale proceed less the fees for borrowing the stocks.

2.1.4. 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 stocks that are hard-to-borrow does not have to conform to a regulated process. Access to stocks that are on special at favorable terms can occur depending on the overall business relationship between the PB 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 the PB 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 terms than the average retail investor.[8] There are similarities between lending stocks (stock loans) and lending money. Commercial bank lending decisions often take into account the overall business relationship of the borrower in determining terms. With an asset management industry that is dominated by passive long-only styles, active hedge fund managers are likely to be dominant users of the stock loan market. A valuable source of customer sought after by PBs because of the volume of business they transact, hedge fund managers often secure leverage funding from their PBs which adds to value as a business counterparty to PBs. Taken together, hedge fund managers are likely to receive favorable terms not only as dominant users of the stock loan market but also due to the attendant transactional business they conduct with their PBs. This speculator's advantage to the stock loan market is not without its peril. In times of market stress, short-sellers often bear the blunt of the regulator's wrath. This can trigger expensive, systemic unwinds of short positions like those we saw in 2007 and 2008 which in turn demands a different skill set to ensure survival.

In the construction of Eq. (2) we assume, for simplicity, that the full risk-free rate is paid to the borrower on the short sale proceeds.

While we know of no publicly available database that reports the time series properties of fee_L^j and fee_S^j for each stock j, one can infer first-order conditions between stock loan fees and the PB's inventory. For instance, one would expect

$$d(fee_L)/d(I) < 0 \text{ and } d(fee_S)/d(I) < 0 \qquad (4)$$

or that stock loan fees decline for lenders as well as for borrowers when the PB's inventory rises. From Equation (2), it is reasonable to expect that

$$d(Z)/d(V) > 0 \qquad (5)$$

where V denotes the volume of stock market transactions. In other words, as stock market activity rises, the transitory part of the PB's lending inventory can reasonably be expected to rise. Therefore, combining Eq. (4) and (5), it is reasonable to expect[9]

$$\delta(fee_L)/\,\delta(V) < 0 \text{ and } \delta(fee_S)/\,\delta(V) < 0 \qquad (6)$$

However, volume as a variable does not distinguish between activities in long purchases versus short sales. If shorting adds value to L/S equity hedge funds' performance, we need a more discriminating activity measure that directly relates to short sales activities. In order to do this, we need to look further into the information content of the aggregate short sales activities in the market.

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

Consider now the example of a stock that is on *special*. Here the opinion of pessimistic traders 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. Diether, 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 with greater short constraint (that 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.[10]

In the absence of inventory supply disruptions to the stock loan market,[11] a low level of aggregate short interest in the market is consistent with high impediments to short sales—in terms of cost (fees) and risk (short squeeze). 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 aggregate short interest in the market 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. Therefore if we narrow the market activity variable in Eq (6), V, to one that proxies short sale activities, V_s, then the extant literature tells us that

$$(\delta E(r_s)/ \delta V_s) < 0 \qquad (6a)$$

where $E(r_s)$ denotes the expected return from shorting .

While the above analysis applies under normal market conditions one additional case needs to be considered. When available liquidity to capital markets as a whole is under stress, similar to the conditions described in Brunnermeier and Pedersen (2009), the equity market is likely to be adversely impacted. Under such a scenario, an abrupt rise in the demand for shorts may be motivated by risk management needs rather than the for profit motive advanced above. When shorting is motivated by hedging long positions, equation (6a) may also apply albeit for quite different reasons.

To summarize, the unequal access to the stock loan market can induce a volume effect on Long/Short hedge fund returns through the volume impact on stock loan fees. In addition, the aggregate level of open short-sale interest in the market signals different profit potentials from short-sales of stocks under normal market conditions. Finally, when market-wide liquidity conditions are tight, shorting may no longer be driven by profit-motives but rather by risk management needs. In the empirical section of this paper we propose alternative variables to untangle these different effects on the performance of Long/Short equity hedge funds.

2.2. The return on a Long/Short equity portfolio

Using the description of the stock loan market, we build a simple long/short equity strategy in three steps. First, we describe the long-only strategy. Next, we describe the short-only strategy. Lastly, we combine them to form a long/short strategy, which we call the "primitive long/short equity strategy" (or PLSES for short).

Begin with a long-only fund having \$100 of capital. Suppose \$*L* is used for outright purchases of long positions. The remaining \$100-*L* is invested in the risk-free asset. We assume that the long positions are loaned out, earning a fee of fee_L. Applying Eq. (1), the \$*L* of long positions generates a gain of \$$L\ (r_L + fee_L)$. The remaining \$100-*L* invested in the risk-free asset generates a gain of (\$100-*L*) r_f, where r_f denotes the risk-free return. Hence, the long-only fund's return can be expressed as:

$$r_f + b_L\,(r_L - r_f) + a_L \tag{7}$$

where $b_L = L/100$, and $a_L = (L/100)\,fee_L$.

In Eq. (7), the first term is the familiar time-value of money. The second term is the return for bearing market risk. The last term, $a_{0,}$ is the additional adjustment for the net fees earned from stock lending, which are typically ignored in the calculation of standard performance benchmarks, such as the S&P 500 index or the Fama-French factors. Note that when \$*L* = \$100, Eq. (7) reduces to Eq. (1)—the return to a long-only stock lender. Sharpe (1992) showed that, for equity mutual funds, b_L is typically close to 1, consistent with the notion that equity mutual funds are long-only investors.

Consider next the return of a short-only fund with \$100 of capital. Suppose it holds \$2*S* of short positions. Under Regulation T (Reg-T), the fund must post \$*S* as margin for \$2*S* of short positions. Applying Eq. (3), the return on margin from the short sales generates a gain of \$$S\ \{2\ [\ -r_S + (r_f\text{-}fee_S)\ ] + r_f\}$. The remaining \$100-*S* of cash is invested in the risk-free asset. Hence the rate of return to the short-only fund with \$2S of short exposures can be expressed as:

$$r_f + b_S\,(-r_S + r_f) - a_S \tag{8}$$

where $b_S = 2S/100$, and $a_S = (2S/100)\,fee_S$. Here, the first term is the time-value of money. The second term is the return for bearing market risk from short sales. The last term is the additional adjustment for the net fees paid for stock borrowing. [12] Note that when \$*S* = \$100, Eq. (8) reduces to Eq. (3)—the return to a short-only stock borrower.

Consider now the general case of a L/S equity fund with \$100 of capital. \$*L* are invested in long positions. \$*S* are pledged as margin for \$2*S* worth of short position. The remaining \$100 - \$$L$ - \$$S$ are invested in the risk-free asset. Combining Eq. (7) and (8), we can express the rate of return to a L/S equity hedge fund as

$$r_f + b_1 (r_L - r_f) + b_2 (r_L - r_S) + a_0 \tag{9}$$

where $b_1 = (L\text{-}2S)/100$, $b_2 = 2S/100$, and $a_0 = (L/100)\, fee_L - (2S/100)\, fee_S$.

In Eq. (9), the first term represents the time value of money. The second term is the return for bearing long-side risk. The third term is the return for bearing spread, or relative performance, risk—in the sense that performance of the long and short positions can diverge from each other. The last term represents the net fees earned from lending out stocks minus the fees paid for borrowing stocks.

Although the treatment of short-sale margin under Reg-T engenders the impression that higher leverage is being applied to the short side of the portfolio, this is not necessarily the case. To see this, consider a dollar-neutral L/S portfolio where the market value of the long positions equals that of the short positions. This can be achieved by setting \$$L$ = \$2S in Eq. (9). In addition, Reg-T limits total leverage (i.e., \$$L$+\$2S) to two times margin capital (50 percent margin requirement for long positions, and 50 percent margin for short positions). Although the cash proceeds from the short sale of stock generate interest income to the short seller, they do not generate additional margin capital.[13]

Up to this point, the development of Eq. (9) is done in a format that highlights the return profile of a typical long-short hedge fund with a *net-long* bias (where \$$L$ > \$2S). For funds with a *net-short* bias, \$$L$ < \$2S, Eq. (9) can be suitably rearranged as follows:

$$r_f + w_1 (-r_S + r_f) + w_2 (-r_S + r_L) + w_0 \tag{10}$$

where $w_1 = (2S\text{-}L)/100$, $w_2 = L/100$, and $w_0 = (L/100)\, fee_L - (2S/100)\, fee_S$, so as to highlight the net directional exposure due to the short positions in the portfolio. Essentially the same structure as in equation (9) applies with minor adjustments to the interpretation of the asset rate of return and net fee term.

While there are many factors that differentiate long-only mutual fund managers from L/S equity hedge fund managers,[14] Eq. (9) highlights some key differences between them. L/S equity hedge funds typically have short positions (i.e., $S > 0$), and consequently a lower directional exposure than mutual funds (i.e., $b_1 < 1$). However, the presence of short positions implies that hedge funds will have some spread exposure (i.e., $b_2 \neq 0$). In order to equalize the amount of capital available to both the L/S hedge fund managers and a comparable mutual fund manager, we have implicitly assumed that L+2S <= 100 or that no leverage is used. In practice, most hedge funds are levered or L+2S> 100. Typically when a fund is leveraged, assets held long are pledged as collateral to secure additional risk capital in order to expand position exposure to reach L+2S> 100. We can incorporate the cost of borrowing the additional amount of risk capital into the a_0 term by adding the cost of leverage. Therefore, with only minor adjustments we can continue to use Eq. (9) to describe the return of the primitive L/S equity strategy (*PLSES*) without any constraint on the use of leverage.

3. Empirical proxies of the primitive L/S equity strategies

In this section, we provide details of how the PLSES in Eq. (9) is related to *observable* returns of L/S equity hedge funds. Empirically the return interval used in the equation has to match available data of hedge fund returns, which tend to be monthly. However, as the return of the PLSES in Eq. (9) is not defined with respect to specific time intervals, we generate a monthly-return analog of Eq. (9). This allows us to relate the actual monthly returns of L/S equity hedge funds to observed market returns.

The monthly return of the *PLSES* is constructed as follows. First, we assume that the exposures, or *b*'s, are constant during each day. We can now express the return of *PLSES* for day *t* as:

$$r_{f,t} + b_{1,t}\,(r_{L,t} - r_{f,t}) + b_{2,t}\,(r_{L,t} - r_{S,t}) + a_{0,t} \qquad (11)$$

by adding a second subscript *t* to each of the variables in Eq. (9), to denote their values during day *t* within a month.

Second, we sum up the daily returns in a month to arrive at the monthly return:

$$\Sigma_t \; \{r_{f,t} + b_{1,t}\,(r_{L,t} - r_{f,t}) + b_{2,t}\,(r_{L,t} - r_{S,t}) + b_{0,t}\} \qquad (12)$$

where the subscript *t* is summed over the days of the month, $t = 1,\ldots, m$. This allows us to examine static and dynamic versions of Eq. (12).

3.1. Models of static strategies

We define static strategies as those strategies in which the risk exposures (i.e., the slope coefficients *b*'s) remain constant within a month. Eq. (12) now reduces to:

$$r_{f,m} + b_{1,m}\,(r_{L,m} - r_{f,m}) + \mathrm{b}_{2,m}\,(r_{L,m} - r_{S,m}) + b_{0,m} \qquad (13)$$

where $r_{f,m} = \Sigma_t\, r_{f,t}$, $r_{L,m} = \Sigma_t\, r_{L,t}$, $r_{S,m} = \Sigma_t\, r_{S,t}$, and $b_{0,m} = \Sigma_t\, b_{0,t}$

The variables $r_{f,m}$, $r_{L,m}$ and $r_{S,m}$ can be proxied by standard asset returns. In the case of a passive index-like mutual fund, the coefficients $b_{1,m}$ and $b_{2,\mathrm{m}}$ would be virtually constant across months and can be estimated using familiar models such as Sharpe (1992). However, in the hands of hedge fund managers, strategies that are static over a daily time scale can exhibit time-variation over longer time scales. This forces a fixed coefficient regression to pick up the contribution of the time-varying exposure in the constant term, giving the appearance of excess performance. See Glosten and

Jagannathan (1994). The next three subsections deal with specific types of time variation in exposures.

3.2. Models of dynamic strategies

For dynamic strategies, the exposures (the slope coefficients *b*'s) change intra month, Eq. (12) cannot be readily transformed to capture all possible time paths of the *b*'s. For tractability, we limit our attention to those dynamic strategies that have option-like payouts. More specifically, our analysis focuses on two families of dynamic trading strategies—market-timing and trend-following.

For market-timing strategies, we use the model described in Merton (1981). As an illustration, think of the *net long (short)* positions of a typical L/S equity portfolio as the underlying asset. Focusing only on the timing of this net position, if the underlying asset's return is higher (lower) than that of the risk-free return, a perfect market timer would be long (short) 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 (put) option on the underlying asset. It follows that a marketing-timing strategy on the net exposure is simply the "delta" of the respective option, which changes with the underlying asset price. 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 net positions can be approximated by the dynamic exposure of a market timer or a trend follower on the same underlying assets.

3.3. Tail risk factors

As we do not observe trades or positions in hedge funds, we cannot be completely certain how returns are generated. For example, some hedge funds may be selling catastrophe insurance policies, as conjectured by Hsieh in Milner (1998), in which case the returns would be positive during the periods when the catastrophe did not occur, but large and negative when the catastrophe came to pass. Similar return patterns have been observed by Mitchell and Pulvino (2001) for merger arbitrageurs, who are providing insurance against merger failures. They found that merger failures are idiosyncratic in normal times, but mergers are systematically called off in market declines. These return profiles are very similar to short option positions, and they manifest themselves typically at 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).

3.4. Discrete changes in exposures

Finally, we test for discrete changes in exposures due to large market events by dividing the sample into three subperiods: Feb 1994 until Sep 1998, Oct 1998 until Mar 2000, and Apr 2000 until Dec 2004. The break points are based on three large market events. It was February 1994 was the month when the Federal Reserve raised interest rates and caused one of the largest declines in the bond market that year; September 1998 witnessed the LTCM debacle, while March 2000 saw the peak of the internet stock bubble. In light of the unprecedented events of 2008, we also include 2008 as period IV. These are the sample break periods identified in Fung and Hsieh (2004a) and Fung et al (2008). We test for the equality of the exposures using a modified Chow (1960) test described in Fung et al. (2008).

4. Dataset and measure biases

Our analysis uses 9,411 L/S equity hedge funds from three databases and 7,662 equity mutual funds from the CRSP survivorship-bias free database. In this section, we provide details of the construction of these datasets, and some of the potential biases in the hedge fund database.

4.1. Long/Short equity hedge fund data

We merge hedge funds data from three databases: 3,142 Long/Short Equity funds from Lipper-TASS, 3,801 Equity Hedge funds from HFR, and 2,468 Equity Long/Short funds from CISDM using the following procedure. Funds are first grouped according to their respective management companies. Duplicate funds in the same management company are eliminated if they have the same name or identical returns. We then eliminate funds that have very similar names and highly correlated returns. The table in the Data Appendix summarizes the resulting unique set of funds. There are 1,269 funds from Lipper-TASS, 1,202 from HFR, and 567 from CISDM, totaling 3,038 funds. As a control group, we included long-bias hedge funds that are classified as "Equity Non-Hedge" in the HFR database. A summary table of our data set can be found in the data appendix.

4.2. Equity mutual fund data

Equity mutual funds from the CRSP survivorship-bias free database are extracted as follows. Starting with the names of all the mutual funds that existed during 1994 until 2008, we removed funds that have very similar names. We then selected funds in 35 investment objectives based on the S&P classification. This yields 7,662 funds for our analysis. Monthly returns from both data sets—hedge funds, mutual funds are based on net-asset-values and are returns to investors net of all costs.

4.3. Potential measurement errors in hedge fund returns

Hedge fund databases can suffer from a number of different biases, as described in Ackerman et al. (1999), Fung and Hsieh (1997, 2000), and Liang (2000). Some of these biases, such as survivorship and incubation, can impact estimates of excess performance. Fortunately, after minor adjustments to the data, the effect of these measurement errors on the present study is *de minimis*.

First, to control for survivorship bias, we construct returns in each month using all funds that existed during that month. This includes non-surviving as well as surviving funds.

Second, to minimize the effect of incubation bias, we need to understand its cause. 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. However, when a new fund is added to a database, vendors usually include the incubation period's returns as part of its history. This causes an upward bias in the returns, since the incubation period tends to have higher returns than the normal times.

In principle, 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. It is clear that 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 not appropriate to treat all of a fund's backfilled returns as arising from 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. At 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 non-backfilled data in

Oppenheimer would not contain incubation bias. See Fung and Hsieh (2009) for further discussions of these issues.

In this paper, we apply an asset-under-management (AUM) filter of $5 million to help circumvent some of the effect of incubation bias. This is a compromise solution to choosing a fixed cutoff point at which "actual operating" return history is assumed to have started. This coupled with additional persistency tests in our search for alpha producer funds should go a long way towards mitigating the bias of backfilled returns on our findings.

5. Common risk factors in primitive Long/Short equity strategies

In this section, we analyze the common risks in long/short equity funds. Using principal component analysis, we verify the presence of a main strategy in the long/short equity funds. This allows us to use the average of the funds to represent this main strategy. We then link the average return to static and dynamic risk factors. Lastly we study the cross section of funds to assess their ability to generate returns after adjusting for the observed risk factors. We also contrast the return characteristics of equity hedge funds to those in mutual funds.

5.1. Principal component analysis

Due to lack of standardized reporting format in the hedge fund industry, classification of hedge funds according to their *stated* styles by existing database vendors still relies on inspections of the fund's offering documents. Fung and Hsieh (1997) recommended the use of principal component analysis of fund returns to supplement this commonly used qualitative classification of hedge funds. The intuition is to supplement the classification of hedge funds according to *what hedge funds do*, and not rely solely on *what they say they do*. Following Fung and Hsieh (1997), we use principal component analysis to detect the number of common styles in hedge funds.

Insert Table 1

We begin our empirical analysis using non-overlapping two-year subsamples, so we can examine the consistency of the results over time. Principal component analysis over seven subperiods—1994-5, 1996-7, 1998-1999, 2000-1, and 2002-3, 2004-5 and 2006-7—show results (Table 1, panel A) that are consistent with the presence of one main style in all subperiods. In each of the subperiods, the first principal component explains more than 33 percent of the cross-sectional variation, while the second principal component accounts for less than 17 percent of the cross-sectional variation. A similar set of results hold for long-bias hedge funds that are classified by HFR as being a member of the Equity Non-Hedge category.

In each case, the first principal component is highly correlated with the average fund return in all subperiods, as shown in Table 2. This is so for both the average of our data set, as well as the reported returns of hedge fund indices of comparable styles—the HFR Equity Hedge index, the Credit Swiss Tremont L/S equity index (which uses the Lipper-TASS data set as input), and the CASAM/CISDM L/S Equity Hedge Fund index.

Insert Table 2

5.2. Identifying static risk factors

To identify common risk factors inherent in the static exposure of L/S equity hedge funds, we extend earlier results of Fung and Hsieh (2004b). The Fung and Hsieh (2004b) study applied 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) on commonly used L/S equity Hedge Fund indices. 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 denotes the return of long small cap stocks/ short large cap stocks; HML denotes the return to long high book-to-market stocks/short low book-to-market stocks, and UMD denotes the return to long high momentum stocks/short low momentum stocks. Given the results in Tables 1 and 2, the Fung and Hsieh (2004b) results essentially tell us about the time series characteristics of the average L/S equity hedge fund's performance. Here we expand their model to examine both the time series characteristics of individual L/S equity hedge fund returns as well as the cross-sectional dispersion of returns—which are much more pronounced than that of equity mutual funds as the principal component analysis shows.

Beginning with the same four-factor model as in Fung and Hsieh (2004b), the regressions are performed in the same two-year subperiods as the principal components—1994-5, 1996-7, 1998-9, 2000-1, 2002-3, 2004-5 and 2006-7. Table 3 reports the average and median across the funds that have all 24 monthly returns in each subperiod. The median adjusted-R^2 is between 0.30 and 0.51. The median exposure to the market (RMRF) declined from a high of 0.62 in 1994-5 to a low of 0.30 in 2002-3, and then rising back to 0.43 in 2006-7. The median exposure to SMB remained around the 0.30 range in the first three subperiods, dropping to 0.17 in the last subperiod with a low of 0.07 during the 2004-5 subperiod. The median exposure to HML is low, between 0.04 and 0.20; the median exposure to UMD is even less, between –0.02 to 0.15. These two factors have less importance relative to the earlier period in Fung and Hsieh (2004b). Interestingly, the median value of the Durbin-Watson (DW) statistic is between 1.84 and 2.03, which indicates that there is not much serial correlation in the regression residuals.[15] The constant term, which represents the monthly alpha, is consistently positive, between 0.14 and 0.37 bp per month, except for 1998-9 when it jumped to 0.79 bp per month. L/S equity hedge funds consistently have alpha relative to these four factors.[16]

In contrast, equity mutual funds have much higher adjusted-R^2, greater exposure to the market (RMRF), and roughly the same exposure to the other three factors: SMB, HML, and UMD. Interestingly, the median monthly alpha is slightly negative.

Long-bias equity hedge funds tend to fall between L/S equity hedge funds and equity mutual funds. They have more market exposure than the L/S equity funds and less market exposure than mutual funds. Their median alphas are generally positive but smaller than L/S equity funds.

Insert Table 3

5.3. Identifying alpha producing funds

Although the Fung and Hsieh (2004b) study reported the presence of significant nonfactor related returns (alpha) at the level of hedge fund indices, it is important to know whether this is a wide-spread characteristic among L/S equity hedge funds or just a localized phenomenon in the hands of a small fraction of population. At the level of a diversified portfolio of hedge funds such as the broad-based hedge fund indices and funds-of-hedge funds, Fung et al. (2008) has documented that abnormal good performance (alpha producing) is the property of the minority. Moreover, both risk factor exposures and alpha production varied over time. In particular, observed alpha among funds-of-hedge funds appeared to be declining over time in line with the predictions of the Berk and Green model (2004) as the demand for hedge funds rose.

Given that equity hedge funds comprise, consistently throughout history, approximately 40 percent of the industry's capacity, it is important to understand whether their managers are subject to the same empirical phenomenon, and to what extent contributed to the phenomenon reported in Fung et al (2008). In order to gain insight into this question, we must first identify the alpha producing funds among the universe of equity hedge funds and then analyze the factors that affect alpha production.

In order to provide a robust and distribution-free test of the presence of alpha in equity hedge funds and mutual funds, we use the cross-sectional bootstrap from Kosowski et al. (2006) that allows for cross-sectional correlation among funds, together with the stationary bootstrap from Politis and Romano (1994) allowing for time-series correlation. This is the same procedure in Fung et al. (2008).

As an illustration, we describe the bootstrap procedure for the Class of 1995--the 149 hedge funds with data during 1994-5. Least-squares regressions for each fund are performed, and the slope coefficients, the residuals, and the *t*-statistic of the constant term are recorded. Next, we simulate a new 24-months sample as follows. Draw randomly one month from the 24 months. Then with probability Q (set to 0.5)[17] we use the following month, and with probability 1-Q, we draw a different month. We continue in this manner until we have a sample of 24 months. In each month, we simulate the return of each fund using the actual value of the regressors, together with the previously saved slope coefficients and the previously saved residuals. The constant term is set to zero, as per the null hypothesis. We then regress the simulated return on the regressors, and we recorded the *t*-statistic of the constant term. This yields 149 simulated *t*-statistics, one for each fund. Repeating this procedure 1,000 times, we end up with 149,000 *t*-statistics. This simulated distribution is used to determine the statistical significance of the original 149 *t*-statistics.

Using a 5 percent significance level based on the simulated distribution, we find that 15 percent of the 149 L/S equity hedge funds have statistically significant alpha. In contrast, only 4 percent of the 1,406 mutual funds and 9 percent of the 22 long-bias equity hedge funds have statistically significant alpha.

Over the 13 two-year subsamples, about 22 percent of the L/S equity hedge funds have significant alpha, while only 4 percent of the equity mutual funds and 13 percent of the long-bias equity hedge funds have significant alpha. This supports the view that equity hedge funds are more likely to have alpha than equity mutual funds.

To investigate if alphas persist over time, we divide funds in each category (L/S equity hedge funds, equity mutual funds, and long-bias equity hedge funds) into two groups. Starting with the Class of 1995 (i.e., those funds with 24 monthly returns in the 1994-5 subperiod), L/S equity hedge funds that have statistically significant alpha are assigned to the Alpha-H group. The remaining L/S equity hedge funds constitute the Beta-H group. We then calculate the equally-weighted monthly returns for each of these two groups during the post-selection year 1996. This process is repeated each year ending with the last Class of 2006 (i.e., those funds with returns in the 2005-6 subperiod), which provides the post-selection return in 2007. The same procedure is used to create the Alpha-N and Beta-N groups from the long-bias equity hedge funds, and the Alpha-M and Beta-M groups from equity mutual funds.

Table 4 reports the result from regressing the one-year post-selection returns of each of the six portfolios on the four-factor model. The four equity hedge fund groups have positive alpha, while the two equity mutual fund groups have negative alpha. In particular, the Alpha-H group has a statistically significant positive alpha, while the Beta-M group has a statistically significant negative alpha. Within each of the three categories, the Alpha group has a larger alpha than the Beta group.[18] These results provide support that the sorting procedure is not random, and that alpha of the Alpha-H group persists over time.

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Insert Table 4

Table 5 provides transition probabilities between the Alpha-H and Beta-H groups. In Panel A, we calculate the one-year transition probabilities, as follows. At the end of each year, we classify each fund as an Alpha-H fund, or a Beta-H fund base on the prior

24 months of returns. At the end of the following year, we check to see if a fund continues to be an Alpha-H fund, becomes a Beta-H fund, or exits the sample. In Panel B, we perform the same verification procedure two years after the initial classification at which point there is no overlapping data used in the calibration of funds into the different groups and the subsequent verification period. In our data, 41% of Alpha-H funds continue to have alpha at the end of 1 year, but only 20% of them continue to have alpha at the end of 2 years. For Beta-H funds, 77% continue to have no alpha at the end of 1 year, and 63% have no alpha at the end of 2 years. This is strong evidence of alpha decaying over time, similar to the behavior of FOF alpha in Fung et al (2008) and consistent with the prediction of Berk and Green (2004) that alphas are being competed away over time.

Insert Table 5

5.4. Cross-sectional fund characteristics and alpha

In Table 6, we focus on L/S equity hedge funds, the group having the largest fraction of funds with alpha, to investigate if the fund characteristics of a hedge fund, such as age, asset under management, market exposure, etc., can predict alpha. In row 1, we sort funds by the t-statistic of alpha, as follows. For each two-year evaluation period, we divide funds into deciles, ranked by the *t*-statistic of the alpha, and follow the equally-weighted return of each decile portfolio for the next year. This yields 10 decile portfolios. The monthly excess returns of each portfolio are regressed against the Fama-French-Carhart four factors. The constant term of the regression is the alpha of that portfolio. The lowest decile has an alpha of -0.0023 per month, while the highest decile has an alpha of 0.0024 per month. The difference is statistically significant. This serves to confirm the results of the coarser sort, into the Alpha-H and Beta-H portfolios.

In the remaining rows of Table 6, we perform the same procedure using different sorting criteria, based on AUM, age, etc. Interestingly, there is little difference in alpha across the deciles based on these sorts. Fund size and fund age do not help to predict alpha. Taken together with the results in Table 4, it appears that the observed decay of alpha over time is primarily driven by competitive pressure and less driven by excessive capital growth of alpha producing funds. A plausible explanation to this deviation from the conventional interpretation of Berk and Green (2004) is that the barrier to entry for L/S equity hedge funds is low—being lightly regulated and trading in liquid markets—compared to conventional equity funds. Therefore, the existence of alpha may attract pursuing capital, but they tend to be more broadly distributed among competing managers.

Finally, only in the cases of the Adjusted Rsq and the Durbin-Watson statistic there are differences between the alphas across the decile-portfolios. To the extent that a higher Adjusted Rsq is consistent with a larger factor content of a fund's total return and therefore less alpha-like, the significant negative spread between the top Adjusted Rsq-decile and the bottom ones is consistent with a lack of factor timing ability. The extant literature generally attributes serial correlation of hedge fund returns to smoothing of returns by hedge fund managers typically arising from the lack of liquidity of the underlying assets. The significant spread of the intercept term among top and bottom decile funds sorted by the DW Statistics suggests that observable alphas are unlikely to be a result of return smoothing behavior as one would expect from liquid strategies like Long-Short equity.

Insert Table 6

Thus far we have identified those hedge funds in our sample that exhibit statistically significant alpha based on the familiar four-factor model commonly used in literature, controlling both for cross-sectional correlation among funds as well as for time-series correlation in returns. Our results point to a substantial difference between L/S equity hedge funds and equity mutual funds in terms of their ability to deliver alpha with persistency. Characteristics of hedge funds add little value in identifying the alpha producers among them. We proceed to examine the impact of time-varying coefficients on our conclusions thus far.

5.5. Market-timing ability and alpha

We test for the presence of dynamic (option-like) risk factors, 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 four static risk factors. For tractability we limit the analysis to dynamic risk factors that can be empirically represented as option returns to focus on the two market risk factors that have the most explanatory power, RMRF and SMB.

Three different proxies to capture option returns based on these two market factors are used. The Henriksson and Merton (1981) test for market timing in stocks is performed in the column labeled "HM" in Table 7. Here, Max{0,*RMRF*} and Max{0,*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.[19]

Insert Table 7

Option returns are used 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,*RMRF*};[20] they add little explanatory power. Similar results are found in the tail exposure tests, using 5 percent and 10 percent out-of-the-money options in the columns labeled, respectively, "OTM 5 percent" and "OTM 10 percent"—reported in Table 7. There is no empirical 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.[21]

To test for dynamic exposure to the SMB spread factor, another approach is needed as options on SMB 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. Assuming that the implied volatility is perfectly correlated to 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, as the SMB is already a factor in the regression, we only need to add the change in its historical volatility (*DSMBVOL*).[22] To test trend following with respect to the level of the SMB, we note that the lookback straddle's return is correlated to the range of the SMB (labeled "PAYOUT" in Table 7) and the change in the historical volatility. Taken together, these represent two additional variables in the regression model.

The column labeled "LBSMB" in Table 7 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 not statistically significant.[23] Overall, we do not find dynamic factor exposures in the Alpha-H group—a conclusion that holds also for the Beta-H group. Similarly, we do not find any evidence of dynamic exposure in the Alpha-N group. Except for LBSMB, there is also no evidence of dynamic exposure in the Beta-N group.

5.6. Testing for discrete adjustments in factor exposure

The option-like factors in the last section are designed to capture continuous adjustments in factor exposures. It is possible that alphas are generated based on discrete changes in factor exposures. Here, we use the Chow (1960) test, modifying the standard error calculation to allow for conditional heteroskedasticity as in White (1980) and Hsieh (1983) to the four subperiods in our data sample—Period I starts in February 1994 and ends in September 1998, period II starts in October 1998 and ends in March 2000 period III starts in April 2000 and ends in December 2007. Finally, period IV covers the 2008 calendar year.

Insert Table 8

Panel A of Table 8 provides various modified Chow tests. The first row, labeled 'I vs II', tests for changes in the factor exposures between Periods I and II. The second row, labeled 'I vs III', tests for changes in the factor exposures between Periods I and III and similarly for ‘I vs IV’ in the third row. The fourth row, labeled ‘II vs III’, tests for changes in the factor exposures between Periods II vs III followed by tests for changes between Periods II vs IV and finally III vs IV. For the Alpha-H group, the modified Chow test does not find any statistically different factor exposures in subperiods 1 to III. Only in subperiod IV (2008) are significant changes observed. The results for all the other groups are broadly similar except that for Beta-H and Beta-M where subperiod I’s factor exposures are significantly different from that of subperiod III. These results are in contrast to the findings of Fung et al. (2008) on funds-of-hedge funds where they found time-varying behavior to factor exposures. Two interpretations stand out. First, the results here are consistent with L/S equity hedge fund managers being less dependent on market-timing strategies.[24] Second, it is consistent with the conjecture that L/S equity hedge fund managers are more dependent on security selection as the main source of performance.

Panel B of Table 8 tests for the stability of alpha between subperiods. It finds that the average level of alpha of the Alpha-H group changed between Periods I vs III and II vs III as well as subperiods II vs subperiods III. Taken togeher these results point to subperiods changes to the level of Alpha not caused by changes in factor exposure. The results for the other non-alpha producing groups in Panel B of Table 8 are generally less informative.

5.7. Omitted variables, market liquidity and alpha

In this section we tackle the question of omitted variables. We first check for the presence of non-US risk factors, since the Fama-French-Carhart four factors are based on US stock returns. We added, one at a time, returns of various world equity indices—MSCI Europe Ex UK, MSCI UK, MSCI Pacific Ex Japan, MSCI Japan, and MSCI Emerging Markets, to the regression of Alpha-H on the four factor model. None of the world equity indices exhibited statistically significant coefficients. Next, we added the Brunnermeier-Nagel (2004) tech factor, based on the knowledge that the excess performance of funds-of-funds in Fung et al (2006) is most evident in the period after the LTCM debacle through the peak of the internet stock bubble. But the tech factor was also not statistically significant.

Another possible omitted variable is market liquidity. One explanation of hedge fund alpha offered by Asness et al. (2001) and Getmansky et al. (2004) is that hedge funds earn a premium for holding illiquid assets, which can show up as “alpha”. Illiquid assets, such as high yield corporate bonds, often exhibit serially correlated returns. Table 9 provides the first-order serial correlation of returns. The Alpha-H and Alpha-N groups have the highest first-order serial correlation of 0.203 and 0.202, respectively; both are statistically different from zero. The other three groups (Beta-H, Alpha-M, Beta-M, and Beta-N) all have statistically insignificant first-order serial correlation.

Insert Table 9

Since equity hedge funds have strong exposure to small cap stocks, which are less liquid than large cap stocks, we check if the serial correlation in small cap stocks can explain serial correlation in equity hedge funds returns. If we return to Table 4, we can see that this is indeed the case for the Alpha-N group of long-bias equity hedge funds. After accounting for the exposure to the four factors, the residuals of Alpha-N are no longer serially correlated, as indicated by the Durbin-Watson (D.W.) statistic of 1.80. However, this is not the case for the Alpha-H group of L/S equity hedge funds. The D.W. statistic in the Alpha-H regression is 1.57, which tells us that the serial correlation in small cap stocks is not sufficient to account for the serial correlation of Alpha-H.

In order to further explore the presence of liquidity premium in equity hedge funds, we need a more direct approach. Along with the four-factor model, we included different measures of the return to illiquidity, such as the liquidity factors proposed in Acharya-Pedersen (2005), Pastor-Stambaugh (2003) and Spiegel-Wang (2005). These proxies for return to liquidity did not contribute additional explanatory power beyond the four-factor model.[25] However, it should be noted that within the broad category of L/S equity hedge funds, there are variations in investment styles. Therefore we cannot rule out the possibility that some subgroup of L/S equity hedge funds may exhibit significant correlation to these measures of equity market liquidity from time to time. In the next section, we explore non-price variables that more directly reflect transaction volume and short sales activities.

5.8. Liquidation bias and alpha

As noted in section 4.3, we constructed the hedge fund sample taking great care to minimize the effects of survivorship bias. Here, we deal with another potential bias called liquidation bias. This bias can arise when hedge funds stop reporting returns to data vendors prior to liquidation, typically due to poor performance. This raises the possibility that the observed alpha from the Alpha-H group can be due to liquidation bias.

To investigate this possibility, we conducted an extensive search to determine the status of 114 equity hedge funds in the Alpha-H group that dropped out of the sample from 1996 through 2007. We found that 57 funds are still alive while 37 were liquidated, as of the end of December 2007, based on subsequent updates of the databases, searches in SEC filings and conversations with knowledgeable sources in the hedge fund industry.

Twenty of the 114 funds remain unaccounted for. Examining the returns and assets-under-management, 5 funds most likely would have been liquidated, given poor performance and outflow of capital towards the end of their reported history. The other 15 funds did not exhibit any behavior different from the live funds. However, we will assume that all 20 unaccounted for funds were liquidated in the assessment of liquidation bias.

To assess the impact of liquidation on our estimate of alpha, we need to make an assumption about the last return of a liquidated fund, which is typically not included in our sample. We entered a return of -50% in the month following the last reported return of a liquidated fund. This lowered the average return of the Alpha-H group by 23 bp per month, which would still leave 35 (=58-23) bp per month of alpha, which is statistically significant at the standard error of 8 bp.

We would argue that a liquidation return of -50% is a very rare occurrence for long/short equity hedge funds. Many of the famous "blow ups" in the hedge fund industry occur in funds that employ highly levered strategies involving securities that are not publicly traded. However, by its very nature, long/short equity is not a highly levered strategy and typically only transact in publicly traded markets. As our discussion in Section 2 indicates, equity hedge funds, like any other equity investor transact in US public equity cannot stray too far from Regulation T which limits the amount of leverage these funds can undertake.

6. The economics of excess performance

So far, we have shown that a substantial variation in equity hedge fund returns can be explained by observed market risk factors, using the standard Fama-French-Carhart four factor model. Beyond the compensation for these four risk factors, we found that equity hedge funds generate "alpha" or excess return. However, we were not able to link these excess returns to dynamic strategies, such as market timing, or to various liquidity factors based on research on equity markets. We further showed that biases in data reporting cannot account for the observed level of alpha. This leaves the more likely explanation that observed alphas are coming from the skillful management of short positions in the stock loan market, as modeled in section 2. A direct test of this model would be to relate the alphas to the "net fee" variable in our model. Unfortunately, there is no reliable, comprehensive data base on the cost of stock loans. We are, therefore, unable to construct a direct, systematic measure of the net fee variable. In this section, we explore proxies for the net fee variable, using trading activity and short sales.

6.1. Trading activity and the net fee variable

In Eq. (13), our empirical model of the PLSES includes a proxy for the net fee variable, denoted as $b_{0,m}$ which has not been brought into the empirical analysis. In Section 2.1.4, we argued that although we cannot directly observe net fees in stock borrowing/lending for hedge funds, a proxy of the time series properties of the net fee impact on hedge fund returns can be constructed via Eq. (4), (5) and (6). In this section, we investigate proxies for the net fee variable and analyze the role they play in that part of the returns from long/short equity funds that cannot be attributed to the standard four-factor model.

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.

Insert Table 10

The column labeled NYSETO in Table 10 reports the regressions of the excess return of the Alpha-H group on the four-factor model plus the NYSE turnover ratio (*NYSETO*). The next three columns (*NASDTO, NYSERVM, NASDRVM*) report the regression using the other proxies for the net fee variable. The results are similar—the first three variables are statistically insignificant and positive, the exception being the variable *NASDRVM*, which raises the adjusted R^2 from 0.804 in the four-factor model to 0.818 (see Panel A of Table 10).

On the face of it, these results are consistent with the prediction of Equation (6) that L/S equity hedge fund managers benefit from the general decline in the cost of accessing the stock loan market from the short side as market activity rise. However Eq. (6) also tells us that both lending fees (which add to return from long positions) and borrowing fees (which lower return from short positions) are impacted. To see the total effect of an increase in market activity on the nonfactor related return of the PLSES, we need to take the total derivative of the b_0 term with respect to transaction volume of the market, V as follows:

$$db_0/dV = (\$L/\$100) * (\delta fee_L/ \delta V) + (fee_L/\$100) * (\delta \$L/\delta V) - (\$2S/\$100) * (\delta fee_S/ \delta V) - (2fee_S/\$100) * (\delta S/ \delta V) \quad (14)$$

The first two terms of Eq. (14) tell us that the total impact of an increase in market activity depends on the trade off between the income from lending out stocks that are held long and the effect on fee income from changes in the dollar value of long positions. On the short side of the portfolio, the last two terms of Eq. (14) tell us that the impact of an increase in market activity depends on the reduction in fees paid for stocks borrowed and the change in rebate interest earned from changes in short-sale proceeds.

In order to gain insight into the effect of these compensating components of Eq. (14), we perform the same analysis for the Alpha-M and Alpha-N groups for control comparisons to the results for the Alpha-H group. The results are reported in Panels B and C of Table 10. It can be seen none of the market activity variables is statistically significant for Alpha-M and Alpha-N. As these are the long-only mutual funds (Alpha-M) and long-bias hedge funds (Alpha-N), we interpret these results as corroborating evidence that the impact of the market volume variables on L/S equity funds comes primarily through the positions that are held short by L/S equity hedge funds consistent with the analysis put forward in Section 2.1.4.

6.2. Hedge fund returns as correlated to short interest

Following from the analysis in Section 2.1.4., we relate the returns of the Alpha-H group 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.

Specifically, 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 2008 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* and is used to proxy the specific subset of total market activity (or volume) pertaining to short sales.

Applying Eq. (6a) from Section 2.1.4 and substituting the variable *NYSERSI* for V_s, Table 10 shows that the detrended short interest ratio has a statistically significant negative correlation with the Alpha-H group's return as Eq. (6a) predicts.

The *NYSERSI* variable provides a direct link to the short-sales subset of overall market activity (which was proxied by *NASDRVM*). It disentangles the positive impact of an increase in market activity on the reduction of stock borrowing fees from the negative impact of risking cumulative short interest on profitable shorting opportunities in a manner consistent with the extant literature.

To corroborate this interpretation empirically, the last columns of Panels B and C in Table 10 show that there is no significant correlation between the returns of the Alpha-M and Alpha-N with this short sales variable *NYSERSI*. This reinforces the interpretation that excess returns of L/S equity hedge funds are short-sales related.

Beyond the statistical significance of the volume and short interest variables, the serial correlation of the residuals in these regressions give another indication of the role these variables may play in explaining the returns of equity hedge funds. For the L/S equity hedge funds, the D.W. statistics for the Alpha-H group rises above 1.90, when the volume variable (*NASDRVM*) is included in the regressions.

Finally when the non-price variables (*NASDRVM* and *NYSERSI*) are included in the sample break tests performed in Table 8, the constant terms for the Alpha-H group no longer differ across the subperiods. The three test statistics for Alpha-H (5.3, 8.2, and 20.0 in Table 8, Panel B) drop to 0.7, 3.9, and 4.4, respectively. These non-price variables have accounted for all the changes in alpha of the Alpha-H group across the subperiods.

We provide two additional corroborating pieces of evidence. When we replaced the NYSE short interest variable with the equivalently constructed variable using Nasdaq short interest data, the results are basically unchanged. We also added institutional ownership, as Asquith et al (2005) showed that stocks with high institutional ownership are easier to borrow. It turns out that higher institutional ownership is correlated with higher returns, but it is not statistically significant in any of the regressions. This could be the result of the much smaller sample size -- as ownership data are reported quarterly, our sample size shrinks by 75 percent.

In light of the unprecedented events of 2008, we include 2008-9 as an additional subperiod in our analysis. There is, however, one caveat. HFR overhauled its strategy definition in May 2008. Consequently, we adapted the new (post-May 2008) classification scheme to the pre-May 2008 classifications to extend our hedge fund sample to the end of 2009 in a consistent manner. Given the dramatic change in the economic environment in 2008, it is no surprise that sample break tests show that the risk exposures of all six groups changed in 2008-9. We therefore estimated the net fee regressions in the last column of each panel in Table 10 only using the additional 24 months in 2008-9. The results are in Table 11. While the smaller number of observations reduced the statistical significance of the regressions, consistent with the last column of Table 10, Table 11 shows that the constant terms remain statistically insignificant under the same specification.

Insert Table 11
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7. Conclusion

Using an extensive sample of 3,038 L/S equity hedge funds over the sample period 1994 to 2008, we show that their return generation process conforms to our theoretical specification—the primitive L/S equity strategy, *PLSES* denoted in Eq. (9). Empirically we find the *PLSES* conforms to the familiar four-factor model: the excess return of the market (RMRF), the spread between small and large cap stocks (SMB), the spread between value and growth stocks (HML), and momentum (UMD).

After adjusting for the risks associated with the four standard risk factors, less than 20 percent of our sample of L/S equity hedge funds exhibit significant, persistent, positive alpha. Consistent with the extant literature, the evidence point to alpha decaying over time. Although alpha producers are limited to a small subset of this hedge fund sector, it nonetheless compares favorably to equity mutual funds in which no alpha was detected in our data sample. In addition, we find that alpha producers are typically found among L/S equity hedge funds and much less so among equity hedge funds that are classified as being long-only.

In terms of risk, the standard four-factor model accounts for over 80 percent of the variation in the returns of these hedge funds. Contrary to studies in other hedge fund strategies, exhaustive testing of our data set did not turn up important exposures to dynamic option-like factors. There are no discernable risk factor differences between the equity hedge funds and equity mutual funds. Both groups appear to be betting on a similar set of risk factor albeit with different factor loadings. However, slow-moving, time-varying behavior of risk factor exposure is detected for both equity hedge funds and equity mutual funds.

We showed that the observed excess performance (alpha) for L/S equity hedge funds is not contaminated by measurement errors from database biases such as survivorship and back-filled biases. The observed alphas do not appear to emanate from omitted systematic risk factors. Instead, this excess performance is market-volume related (positively correlated) and more specifically short-sales volume related (negatively correlated). The former observation leads us to the conclusion that alpha is sensitive to the level of market activities (as proxy by volume). The latter observation is consistent with our model's prediction in which L/S equity hedge fund managers have privileged access to the stock loan market benefiting from the attendant funding advantage. After including these non-price variables into the four-factor model, the intercept term in this expanded model is no longer significant. In addition, no discernable serial correlation in the residuals of the expanded model is detected and earlier observed sample break points are now rejected. Therefore, although the delivery of persistent alpha to investors is, on average, limited to less than 20 percent of the population of L/S equity hedge funds, the good news is these alphas appear to be stable over time at approximately 36 basis points per month in excess of the risk-free rate. These alphas do not come without risks. In particular the empirical evidence conforms to our theoretical model that L/S equity hedge funds depends on preferential access to the stock loan market and appeared to have capitalized this advantage in delivering excess performance. This advantage is also positively associated with the level of stock market activity (proxy by stock market volume). In contrast, lower levels of aggregate short sales interest appear to be more conducive to L/S equity managers in establishing short positions that deliver alpha in future periods. Put differently, active markets may be conducive to the production of alpha but shorting is best done before aggregate short interest peaks. Further collaborative evidence is reported in which we show that neither equity mutual funds nor long-bias equity hedge funds exhibit return sensitivity to short-sale activities. Expressed differently, L/S equity hedge funds, as the name suggests, do benefit from shorting. Besides differences in risk taking behavior, this is a key feature distinguishing L/S funds from long-bias funds.

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Footnotes:

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[1] As of December 2008, there are 4,285 live funds and 4,273 defunct funds in the Lipper-TASS database.

[2] As of December 2008, about 28 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 November 2008, about 38 percent of the funds in the CISDM database are classified as *Equity Long/Short*.

[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] There are at least two additional dimensions to the set of fund characteristics that could be determinants of alpha producing L/S equity funds. First, in a forthcoming paper, Agarwal and Jorion (2009) reported a time-decaying series of alphas from Emerging Managers. This could be an alternative explanation of manager alpha as a more precise interpretation of what one means by skill. It must also be noted that non-factor related returns can be correlated to idiosyncratic fund characteristics such as the educational background of the hedge fund mangers in question—see for example Li, Zhang and Zhao (2009).

[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] There is also the idiosyncratic risk that the lender, which tends to be one of the major prime brokers, undergoes financial distressed and are forced to unwind their stock loan facilities thereby triggering borrowers to unwind stock-loan positions prematurely. This in turn can constrict the supply of available stocks to borrowers as well as exerting upward pressure on fees and can occur irrespective of market-wide activities.

[10] Here we are referring to the excess performance net of the systematic components of the strategies employed by Long/Short equity hedged funds.

[11] 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.

[12] Cohen et al. (2006, Table I, Panel B) found that the median stock loan fee is 25 basis points below the general collateral interest rate.

[13] In practice, L/S Equity hedge fund managers can leverage beyond the limits of Reg-T through special arrangements with their prime brokers, who frequently lend additional margin capital to L/S portfolios with low volatility.

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

[15] Based on the tables in Durbin (1969).

[16] We repeated the analysis for L/S equity funds in Panel A of Table 3 using the Fung and Hsieh (2004a) factors. The average (median) alpha, over all 7 two-year subsamples, was 0.0044 (0.0038), very similar to 0.0036 (0.0032) using the four factor model.

[17] For robustness, we also tried Q = 0, and obtained qualitatively similar results.

[18] Only the alpha of Alpha-H is statistically different from that of Beta-H. The alpha of Alpha-M (Alpha-N) is not statistically different from that of Beta-M (Beta-N).
[19] We tried |HML| and |UMD|, but they were not statistically significant.
[20] Options have been used to model hedge fund returns in Fung and Hsieh (2001), Mitchell and Pulvino (2001), and Agarwal and Naik (2004).
[21] 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.
[22] This follows from the fact that the standard option's return is correlated to SMB and the change in the historical volatility of SMB (*DSMBVOL*).
[23] We have calculated the analogous proxies for the lookback strategy on HML and MOM. None of them were found to be statistically significant in the regressions.
[24] Or that they engage in very slow market-timing strategies.
[25] To save space, we do not report these regressions. They are available upon request.

Table 1: Principal Component Analysis on Equity Hedge Funds and Mutual Funds

The percent of cross-sectional variance explained by the first five principal components in Long/Short equity hedge funds, CRSP equity mutual funds, and Long-Bias equity hedge funds, for non-overlapping two-year periods.

Panel A: Long/Short Equity Hedge funds:

Period:	1994-5	1996-7	1998-9	2000-1	2002-3	2004-5	2006-7
# of Funds:	149	243	373	481	539	1145	1333
PC1	33%	40%	43%	33%	37%	38%	38%
PC2	8%	8%	9%	16%	9%	9%	8%
PC3	6%	5%	6%	6%	7%	5%	6%
PC4	5%	5%	4%	5%	4%	5%	5%
PC5	5%	4%	4%	4%	4%	4%	4%

Panel B: CRSP Equity Mutual Funds:

Period:	1994-5	1996-7	1998-9	2000-1	2002-3	2004-5	2006-7
# of Funds:	149	243	373	481	539	4341	4673
PC1	72%	73%	77%	69%	86%	76%	75%
PC2	6%	9%	7%	15%	4%	7%	6%
PC3	6%	7%	5%	4%	3%	3%	4%
PC4	2%	2%	3%	2%	1%	3%	4%
PC5	2%	1%	2%	2%	1%	2%	2%

Panel C: Long-Bias Hedge Funds:

Period:	1994-5	1996-7	1998-9	2000-1	2002-3	2004-5	2006-7
# of Funds:	22	51	63	51	41	55	47
PC1	42%	53%	50%	46%	60%	57%	53%
PC2	11%	8%	7%	16%	6%	6%	8%
PC3	8%	6%	6%	6%	5%	5%	5%
PC4	7%	5%	5%	5%	4%	4%	5%
PC5	6%	4%	5%	4%	4%	3%	4%

Table 2: Correlation of First Principal Component of L/S Equity Hedge Funds with Hedge Fund Indices

Correlation coefficient between the first principal component of Long/Short equity hedge funds and different hedge fund indices: The average of Long/Short equity hedge funds, the HFRI Equity Hedge Index, the CSFB/Tremont Long/Short Equity Index, and the CASAM/CISDM LS Equity Index, during non-overlapping two-year periods.

Period	L/S Equity Hedge Funds Average	HFRI Equity Hedge	CTI LS Equity	CASAM LS Equity
1994-5	0.981	0.899	0.953	0.982
1996-7	0.993	0.937	0.958	0.985
1998-9	0.986	0.973	0.953	0.986
2000-1	0.989	0.983	0.858	0.963
2002-3	0.994	0.984	0.807	0.970
2004-5	0.982	0.990	0.972	0.977
2006-7	0.989	0.992	0.971	0.989

Source: HFR, CSFB/Tremont, CASAM/CISDM.

Table 3: Regression of Excess Returns on Fama-French-Carhart Four-Factor Model

This table shows the average and median of the regressions of fund excess returns on the Fama-French-Carhart four-factor model. RMRF is the excess return of the market portfolio. SMB is the return of small stocks minus the return of large stocks. HML is the return of high book-to-market stocks minus low book-to-market stocks. UMD is the return of high momentum stocks minus low momentum stocks. In each two-year period, all funds with monthly returns are included in the regression. The fund returns are in excess of the risk free return (RF). RMRF, SMB, HML, UMD, and RF are obtained from Ken French's Data Library.

Panel A: Long/Short Equity Hedge Funds:

Period	Adj R^2	Constant	RMRF	SMB	HML	UMD	D.W.	# of Funds
	Average of Regressions							
1994-5	0.343	0.0010	0.5841	0.3595	0.0752	0.0844	1.88	149
1996-7	0.431	0.0042	0.5603	0.3830	0.0418	0.0655	1.87	243
1998-9	0.468	0.0088	0.5655	0.3986	0.1064	0.0481	1.95	373
2000-1	0.423	0.0038	0.4506	0.1942	0.0489	0.0370	1.82	481
2002-3	0.407	0.0024	0.3438	0.2136	0.1349	-0.0454	1.93	543
2004-5	0.336	0.0009	0.6678	0.1037	0.3371	0.1815	1.83	1,145
2006-7	0.326	0.0044	0.4653	0.2241	0.0825	0.2041	2.03	1,333
	Median of Regressions:							
1994-5	0.364	0.0020	0.6207	0.2956	0.0371	0.0741	1.86	149
1996-7	0.478	0.0025	0.6076	0.3151	0.1150	0.0259	1.84	243
1998-9	0.508	0.0079	0.5501	0.3366	0.0760	0.0361	1.95	373
2000-1	0.427	0.0037	0.3755	0.1765	0.0288	0.0196	1.86	481
2002-3	0.404	0.0021	0.2993	0.1379	0.1258	-0.0192	1.95	543
2004-5	0.312	0.0014	0.4859	0.0678	0.1959	0.0648	1.84	1,145
2006-7	0.307	0.0029	0.4283	0.1723	0.0798	0.1491	2.03	1,333

Panel B: CRSP Equity Mutual Funds

Period	Adj R^2	Constant	RMRF	SMB	HML	UMD	D.W.	# of Funds
	Average of Regressions:							
1994-5	0.743	-0.0021	0.9312	0.2077	-0.0986	0.0631	1.82	1,406
1996-7	0.779	-0.0041	0.9525	0.2210	0.0624	-0.0149	1.84	2,163
1998-9	0.826	0.0006	0.9293	0.2470	0.0201	-0.0040	2.06	3,226
2000-1	0.839	-0.0021	0.9814	0.1780	0.1421	0.0049	2.04	3,941
2002-3	0.901	-0.0024	0.9807	0.2012	0.1299	0.0191	1.97	4,625
2004-5	0.787	0.0005	0.99531	0.09165	-0.0276	0.1206	1.92	4,341
2006-7	0.809	0.0003	0.97996	0.19943	-0.0161	0.0938	2.08	4,673
	Median of Regressions:							

1994-5	0.827	-0.0011	0.9421	0.1628	-0.0175	0.0299	1.77	1,406
1996-7	0.871	-0.0022	0.9584	0.1472	0.1101	-0.0155	1.84	2,163
1998-9	0.890	-0.0002	0.9491	0.1845	0.0439	-0.0045	2.06	3,226
2000-1	0.871	-0.0002	0.9451	0.1398	0.1281	-0.0155	2.02	3,941
2002-3	0.931	-0.0021	1.0082	0.0918	0.1519	0.0141	1.95	4,625
2004-5	0.864	0.0004	0.9722	0.0267	0.0398	0.0755	1.89	4,341
2006-7	0.855	-0.0002	0.9762	0.1233	0.0301	0.0592	2.07	4,673

Panel C: Long-Bias Hedge Funds

Period	Adj R^2	Constant	RMRF	SMB	HML	UMD	D.W.	# of Funds
	Average of Regressions:							
1994-5	0.432	0.0005	0.8809	0.5705	-0.0552	0.0289	1.99	22
1996-7	0.531	0.0016	0.8897	0.6158	0.0143	-0.0656	1.77	51
1998-9	0.536	0.0073	0.7352	0.5726	-0.0984	-0.0217	2.01	63
2000-1	0.556	0.0049	0.8088	0.3033	0.1094	-0.0269	1.95	51
2002-3	0.613	0.0021	0.6626	0.4148	0.2203	-0.0703	1.99	41
2004-5	0.566	0.0009	0.8425	0.2571	0.1153	0.0592	1.83	55
2006-7	0.499	0.0034	0.7779	0.2814	0.0004	0.1989	2.03	47
	Median of Regressions:							
1994-5	0.550	-0.0008	0.8457	0.4354	-0.1236	-0.0844	1.99	22
1996-7	0.626	0.0016	0.9044	0.5388	0.0424	-0.0654	1.78	51
1998-9	0.582	0.0033	0.7227	0.4172	-0.0191	-0.0060	2.01	63
2000-1	0.608	0.0034	0.7595	0.3163	0.2073	-0.0631	1.93	51
2002-3	0.723	0.0004	0.6600	0.3002	0.1859	-0.0262	1.99	41
2004-5	0.629	-0.0001	0.9111	0.2407	0.1488	0.0040	1.88	55
2006-7	0.541	0.0013	0.7239	0.2583	-0.0190	0.0554	1.98	47

Table 4. Test for Persistence of Alpha, 1996-2007

In December of each year, we run the excess return regression on the Fama-French-Carhart four-factor model, using data from the previous 2 years. Those funds with statistically significant positive constant terms are grouped into an 'alpha' portfolio, and the equally-weighted returns of the subsequent year is calculated. The remaining funds are grouped into a 'beta' portfolio, and the equally-weighted returns of the subsequent year is calculated. Alpha-H and Beta-H are the portfolios of L/S equity hedge funds. Alpha-M and Beta-M are the portfolios of CRSP equity mutual funds. Alpha-N and Beta-N are the portfolios of Long-Bias equity hedge funds.

	L/S Equity Hedge Funds		CRSP Equity Mutual Funds		Long-Bias Equity Hedge Funds	
	Alpha-H	Beta-H	Alpha-M	Beta-M	Alpha-N	Beta-N
Constant	**0.0058**	0.0021	0.0001	**-0.0013**	0.0065	0.0020
	0.0008	*0.0010*	*0.0010*	*0.0006*	*0.0031*	*0.0013*
RMRF	**0.3122**	**0.5784**	**0.9519**	**0.9673**	**0.5001**	**0.8237**
	0.0250	*0.0304*	*0.0297*	*0.0158*	*0.1277*	*0.0391*
SMB	**0.2060**	**0.2663**	**0.3479**	**0.1690**	**0.3372**	**0.4304**
	0.0315	*0.0316*	*0.0361*	*0.0176*	*0.0740*	*0.0437*
HML	-0.0070	0.0507	-0.0165	**0.1013**	-0.0693	-0.0251
	0.0251	*0.0357*	*0.0322*	*0.0216*	*0.0932*	*0.0411*
UMD	0.0248	0.0433	0.0456	0.0148	-0.0200	0.0004
	0.0187	*0.0238*	*0.0224*	*0.0145*	*0.0590*	*0.0312*
D.W.	1.57	1.79	1.79	1.63	1.78	2.04
Adj R^2	0.79	0.87	0.95	0.98	0.46	0.91
No. of Obs	144	144	144	144	144	144

Notes: Heteroskedasticity-consistent standard errors are in italics. Coefficients in bold are statistically significant at the 1% one-side significance level.

Table 5. Transition Probabilities

In December of each year, we run the excess return regression on the Fama-French-Carhart four-factor model, using data from the previous 2 years. Those funds with statistically significant positive constant terms are grouped into an ‘alpha’ portfolio, and the equally-weighted returns of the subsequent year is calculated. The one and two year transition probabilities between the alpha and beta groups are then calculated.

Panel A. One-Year Transition Probabilities

From\To	Alpha-H	Beta-H	Exit
Alpha-H	41%	45%	14%
Beta-H	8%	77%	15%

Panel B. Two-Year Transition Probabilities

From\To	Alpha-H	Beta-H	Exit
Alpha-H	20%	56%	24%
Beta-H	8%	63%	29%

Table 6. Monthly Alphas of Post-Selection Returns for Decile Groups of L/S Equity Hedge Funds using Different Sorts, 1996-2007

In December of each year, we run the excess return regression on the Fama-French-Carhart four-factor model, using data from the previous two years. Funds are sorted into decile portfolios, ranked by different criteria using the regression results. The equally-weighted portfolios are followed for the subsequent year. The excess returns of the decile portfolios are regressed against the Fama-French-Carhart four-factor model. and the constant terms (i.e. alpha) are reported under each column. DEC01 is the lowest decile, and DEC10 is the highest decile. DEC10-DE01 is the difference between the first and tenth decile.

	DEC01	DEC02	DEC03	DEC04	DEC05	DEC06	DEC07	DEC08	DEC09	DEC10	DEC10-DEC01
t(alpha)											
Constant	-0.0023	-0.0020	-0.0019	-0.0014	-0.0024	-0.0007	0.0009	-0.0005	0.0042	0.0024	0.0047
S.e.	*0.0022*	*0.0018*	*0.0016*	*0.0015*	*0.0020*	*0.0020*	*0.0014*	*0.0012*	*0.0013*	*0.0010*	*0.0024*
AUM											
Constant	-0.0003	0.0012	0.0013	-0.0008	-0.0003	-0.0010	-0.0011	0.0001	-0.0015	-0.0018	-0.0015
S.e.	*0.0014*	*0.0014*	*0.0014*	*0.0012*	*0.0014*	*0.0013*	*0.0016*	*0.0014*	*0.0016*	*0.0011*	*0.0012*
AGE											
Constant	0.0003	0.0021	-0.0013	-0.0005	-0.0012	0.0000	-0.0006	-0.0004	-0.0021	-0.0007	-0.0010
S.e.	*0.0011*	*0.0014*	*0.0023*	*0.0012*	*0.0013*	*0.0011*	*0.0010*	*0.0011*	*0.0010*	*0.0016*	*0.0015*
RMRF											
Constant	0.0000	-0.0012	-0.0003	0.0011	0.0004	0.0000	-0.0016	-0.0017	-0.0007	0.0000	0.0001
S.e.	*0.0016*	*0.0009*	*0.0010*	*0.0012*	*0.0010*	*0.0010*	*0.0014*	*0.0010*	*0.0013*	*0.0031*	*0.0033*
SMB											
Constant	0.0030	-0.0006	-0.0008	-0.0018	0.0001	0.0003	-0.0018	0.0000	-0.0011	-0.0013	-0.0043
S.e.	*0.0016*	*0.0011*	*0.0009*	*0.0012*	*0.0009*	*0.0010*	*0.0011*	*0.0013*	*0.0013*	*0.0032*	*0.0032*
HML											

Constant	-0.0007	-0.0018	-0.0017	0.0005	-0.0010	-0.0013	-0.0009	0.0011	-0.0002	0.0024	0.0031
S.e.	*0.0025*	*0.0011*	*0.0010*	*0.0009*	*0.0007*	*0.0009*	*0.0015*	*0.0014*	*0.0016*	*0.0024*	*0.0031*
UMD											
Constant	0.0019	0.0002	-0.0010	0.0009	-0.0019	-0.0024	-0.0007	-0.0012	-0.0008	0.0013	-0.0005
S.e.	*0.0030*	*0.0016*	*0.0011*	*0.0009*	*0.0008*	*0.0010*	*0.0012*	*0.0012*	*0.0013*	*0.0021*	*0.0031*
Adj Rsq											
Constant	0.0006	0.0015	-0.0017	-0.0003	0.0014	-0.0004	0.0011	-0.0022	-0.0006	-0.0035	-0.0041
S.e.	*0.0012*	*0.0014*	*0.0012*	*0.0017*	*0.0012*	*0.0014*	*0.0014*	*0.0019*	*0.0013*	*0.0010*	*0.0014*
DW											
Constant	-0.0027	0.0002	-0.0013	0.0002	-0.0003	0.0002	0.0011	-0.0007	-0.0018	0.0011	0.0037
S.e.	*0.0018*	*0.0010*	*0.0011*	*0.0014*	*0.0011*	*0.0011*	*0.0015*	*0.0012*	*0.0012*	*0.0017*	*0.0018*
Auto1											
Constant	0.0003	0.0021	-0.0013	-0.0005	-0.0012	0.0000	-0.0006	-0.0004	-0.0021	-0.0007	-0.0010
S.e.	*0.0011*	*0.0014*	*0.0023*	*0.0012*	*0.0013*	*0.0011*	*0.0010*	*0.0011*	*0.0010*	*0.0016*	*0.0015*
Kurtosis											
Constant	0.0005	0.0009	-0.0002	-0.0010	-0.0015	0.0004	-0.0017	-0.0013	0.0002	-0.0004	-0.0009
S.e.	*0.0012*	*0.0013*	*0.0016*	*0.0010*	*0.0014*	*0.0012*	*0.0013*	*0.0010*	*0.0014*	*0.0017*	*0.0014*

Notes: Heteroskedasticity-consistent standard errors are in italics. Coefficients in bold are statistically significant at the 1% one-side significance level.

Table 7. Tests for Market Timing Ability in Equity Hedge Funds, 1996-2007

Excess return regressions of Alpha-H, Beta-H, Alpha-N and Beta-N on Fama-French-Carhart four-factor model and market timing variables. HM-RMRF is the Henrickson-Merton variable Max{0, RMRF}. HM-SMB is Max{0, SMB}. CALL (PUT) is the return on call (put) options on the S&P500 futures contract using the quarterly expirations. ATM is at-the-money options; 5% OTM is 5% out-of-the-money options; and 10% OTM is 10% out-of-the-money options. DSMBVOL is the change in the change in the 21-day historical volatility of SMB. PAYOUT is the range of SMB within each month as a percent of its value at the start of the month.

Panel A: Apha-H Group

	H-M	ATM	5% OTM	10% OTM	LB SMB
Constant	**0.0036**	**0.0061**	**0.0062**	**0.0063**	0.0013
	0.0015	*0.0008*	*0.0008*	*0.0009*	*0.0015*
RMRF	**0.3153**	**0.3990**	**0.3882**	**0.3804**	**0.3164**
	0.0381	*0.0581*	*0.0555*	*0.0532*	*0.0224*
SMB	**0.1273**	**0.1993**	**0.1993**	**0.2012**	**0.2052**
	0.0365	*0.0308*	*0.0315*	*0.0315*	*0.0224*
HML	0.0027	-0.0048	-0.0046	-0.0017	-0.0025
	0.0223	*0.0238*	*0.0239*	*0.0238*	*0.0235*
UMD	0.0234	0.0234	0.0233	0.0233	0.0273
	0.0179	*0.0184*	*0.0185*	*0.0186*	*0.0167*
HM-RMRF	0.0074				
	0.0650				
HM-SMB	0.1410				
	0.0783				
CALL		-0.0006	-0.0018	-0.0020	
		0.0021	*0.0022*	*0.0022*	
PUT		0.0054	0.0034	0.0028	
		0.0026	*0.0018*	*0.0016*	
DSMBVOL					-0.0244
					0.0226
PAYOUT					**0.1079**
					0.0323
D.W.	1.64	1.58	1.57	1.57	1.66
Adj R^2	0.79	0.79	0.79	0.79	0.80

Panel B: Beta-H Group

	H-M	ATM	5% OTM	10% OTM	LB SMB
Constant	0.0023	0.0022	0.0021	0.0020	-0.0005
	0.0020	*0.0011*	*0.0011*	*0.0012*	*0.0021*
RMRF	**0.6146**	**0.5756**	**0.5472**	**0.5455**	**0.5782**
	0.0481	*0.0760*	*0.0755*	*0.0744*	*0.0304*
SMB	**0.2240**	**0.2678**	**0.2702**	**0.2697**	**0.2613**

	0.0613	*0.0339*	*0.0341*	*0.0336*	*0.0308*
HML	0.0545	0.0500	0.0493	0.0481	0.0552
	0.0356	*0.0356*	*0.0352*	*0.0348*	*0.0360*
UMD	0.0429	0.0429	0.0435	0.0436	0.0475
	0.0236	*0.0238*	*0.0239*	*0.0239*	*0.0223*
HM-RMRF	-0.0717				
	0.0792				
HM-SMB	0.0715				
	0.0877				
CALL		0.0006	0.0011	0.0013	
		0.0030	*0.0030*	*0.0031*	
PUT		0.0004	-0.0010	-0.0010	
		0.0034	*0.0025*	*0.0023*	
DSMBVOL					-0.0505
					0.0267
PAYOUT					0.0609
					0.0481
D.W.	1.82	1.78	1.79	1.79	1.76
Adj R^2	0.87	0.87	0.87	0.87	0.87

Panel C: Alpha-N Group

	H-M	ATM	5% OTM	10% OTM	LB SMB
Constant	-0.0033	**0.0099**	**0.0104**	**0.0114**	0.0052
	0.0059	*0.0040*	*0.0041*	*0.0042*	*0.0045*
RMRF	0.2676	0.4898	0.5144	**0.5767**	0.5004
	0.2421	*0.2164*	*0.2306*	*0.2369*	*0.1245*
SMB	**0.3306**	**0.3789**	**0.3739**	**0.3755**	**0.3353**
	0.1299	*0.0782*	*0.0815*	*0.0810*	*0.0710*
HML	-0.0588	-0.0901	-0.0871	-0.0679	-0.0673
	0.0880	*0.0903*	*0.0889*	*0.0836*	*0.0935*
UMD	-0.0227	-0.0321	-0.0338	-0.0357	-0.0183
	0.0568	*0.0569*	*0.0573*	*0.0569*	*0.0586*
HM-RMRF	0.5106				
	0.3619				
HM-SMB	0.0418				
	0.1980				
CALL		0.0198	0.0147	0.0108	
		0.0118	*0.0107*	*0.0109*	
PUT		0.0181	0.0142	0.0153	
		0.0137	*0.0112*	*0.0102*	
DSMBVOL					-0.0206
					0.0692
PAYOUT					0.0310
					0.1079
D.W.	1.68	1.73	1.70	1.67	1.77
Adj R^2	0.47	0.49	0.49	0.50	0.45

Panel D: Beta-N Group

	H-M	ATM	5% OTM	10% OTM	LB SMB
Constant	0.0007	0.0019	0.0017	0.0015	-0.0009
	0.0021	*0.0015*	*0.0014*	*0.0015*	*0.0031*
RMRF	**0.8720**	**0.7768**	**0.7484**	**0.7397**	**0.8223**
	0.0618	*0.0954*	*0.0977*	*0.0971*	*0.0399*
SMB	**0.3212**	**0.4357**	**0.4384**	**0.4375**	**0.4224**
	0.0818	*0.0475*	*0.0477*	*0.0471*	*0.0412*
HML	-0.0135	-0.0271	-0.0281	-0.0317	-0.0190
	0.0402	*0.0408*	*0.0405*	*0.0399*	*0.0407*
UMD	-0.0010	0.0007	0.0015	0.0018	0.0066
	0.0307	*0.0313*	*0.0315*	*0.0315*	*0.0289*
HM-RMRF	-0.0862				
	0.0997				
HM-SMB	0.1901				
	0.1172				
CALL		0.0012	0.0023	0.0029	
		0.0039	*0.0041*	*0.0043*	
PUT		-0.0021	-0.0029	-0.0030	
		0.0040	*0.0030*	*0.0026*	
DSMBVOL					-0.0749
					0.0417
PAYOUT					0.0693
					0.0767
D.W.	2.05	2.03	2.04	2.05	2.01
Adj R^2	0.92	0.91	0.91	0.91	0.92

Note: Definitions of Alpha-H, Beta-H, Alpha-N, and Beta-N given in Table 4.
Coefficients in bold are statistically significant at the 1% level.

Table 8. Sample Break Analysis, 1996-2007

This table contains the Chow (1960) test of sample breaks in the Fama-French-Carhart 4 factor regressions on the six different “alpha” and “beta” portfolios, using the heteroskedasticity-consistent covariance matrix in place of the standard OLS covariance matrix. The entire sample is divided into three periods: Period I is Jan 1996 to Sep 1998, Period II is Oct 1998 to March 2000, and Period III is Apr 2000 to Dec 2007. Panel A tests for sample breaks in the slope coefficients. The test statistic is asymptotically distributed as chi-square with, respectively 4 degrees of freedom in all cases. Panel B tests for sample breaks in the constant term. The test statistic is asymptotically distributed as chi-square with 1 degree of freedom in all cases.

	Alpha-H	Beta-H	Alpha-M	Beta-M	Alpha-N	Beta-N
Panel A. Equality of Coefficients:						
Period I vs II, $\chi^2(4)$	4.3	4.7	3.7	1.4	2.6	2.3
Period I vs III, $\chi^2(4)$	2.5	**13.9**	**45.8**	5.3	5.5	8.9
Period II vs III, $\chi^2(4)$	16.4	8.7	30.8	2.6	4.7	4.5
Panel B. Equality of Constants:						
Period I vs II, $\chi^2(1)$	5.3	**19.3**	1.1	**10.9**	0.4	**20.2**
Period I vs III, $\chi^2(1)$	**8.2**	1.1	0.0	3.8	0.0	3.6
Period II vs III, $\chi^2(1)$	**20.0**	**12.8**	1.4	5.5	1.5	**16.6**

Note: Test statistics in bold are significant at the 1% level. Definitions of Alpha-H, Beta-H, Alpha-M, Beta-M, Alpha-N and Beta-N given in Table 4.

Table 9. Tests of Illiquidity: First order serial correlation,1996-2007

This table tests for illiquidity in the six "alpha" and "beta" portfolios. ρ(1), is the estimated first-order autocorrelation coefficient. Its standard error is 1/√N where N is the number of observations. (There are 108 monthly observations.) The t-statistic is ρ(1) divided by the standard error.

	Alpha-H	Beta-H	Alpha-M	Beta-M	Alpha-N	Beta-N
p(1)	**0.203**	0.131	0.109	0.078	**0.202**	0.117
Std Err	*0.084*	*0.084*	*0.084*	*0.084*	*0.084*	*0.084*
t-stat	2.43	1.57	1.31	0.93	2.42	1.40

Notes: Standard errors in italics. Test statistics in bold are significant at the 1% level. Definitions of Alpha-H, Beta-H, Alpha-M, Beta-M, Alpha-N and Beta-N given in Table 4.

Table 10. Regressions including Proxies for Net Fee Variable,1996-2007

Excess return regressions of Alpha-H, Beta-H, Alpha-M and Alpha-N on Fama-French-Carhart four-factor model and various proxies for the net fee variable. NYSETO is the turnover of 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, both detrended by dividing each month's share volume with the average volume from the previous 12 months. NYSERSI is the aggregate short interest outstanding on the NYSE, divided the number of outstanding shares, and detrended by dividing this ratio with its average in the previous twelve months.

Panel A: Alpha-H Group

	NYSETO	NASDTO	NYSERVM	NASDRVM		NASDRVM
Constant	**0.0134**	0.0016	**-0.0031**	**-0.0177**	0.0409	0.0118
	0.0033	*0.0051*	*0.0078*	*0.0047*	*0.0092*	*0.0111*
RMRF	**0.3035**	**0.3178**	**0.3173**	**0.3077**	**0.3060**	**0.3034**
	0.0251	*0.0269*	*0.0250*	*0.0214*	*0.0235*	*0.0202*
SMB	**0.2050**	**0.2030**	**0.2111**	**0.2038**	**0.2003**	**0.1997**
	0.0321	*0.0300*	*0.0315*	*0.0240*	*0.0305*	*0.0240*
HML	-0.0147	-0.0103	0.0020	0.0065	-0.0117	0.0013
	0.0255	*0.0266*	*0.0246*	*0.0213*	*0.0243*	*0.0206*
UMD	0.0204	0.0270	0.0262	0.0301	0.0247	0.0294
	0.0188	*0.0199*	*0.0190*	*0.0174*	*0.0182*	*0.0173*
VOLUME	**-0.0081**	0.0014	0.0082	**0.0217**		**0.0191**
	0.0033	*0.0017*	*0.0073*	*0.0044*		*0.0045*
NYSERSI					-0.0338	-0.0257
					0.0087	*0.0086*
D.W.	1.58	1.59	1.64	1.91	1.67	1.95
Adj R^2	0.790	0.785	0.786	0.818	0.804	0.828

Panel B: Beta-H Group

	NYSETO	NASDTO	NYSERVM	NASDRVM		NASDRVM
Constant	0.0009	-0.0045	0.0057	**-0.0151**	0.0221	-0.0002
	0.0048	*0.0060*	*0.0094*	*0.0061*	*0.0122*	*0.0160*
RMRF	**0.5798**	**0.5871**	**0.5764**	**0.5750**	**0.5748**	**0.5729**
	0.0305	*0.0316*	*0.0320*	*0.0282*	*0.0311*	*0.0286*
SMB	**0.2665**	**0.2617**	**0.2643**	**0.2647**	**0.2631**	**0.2627**
	0.0313	*0.0305*	*0.0317*	*0.0272*	*0.0309*	*0.0269*
HML	0.0520	0.0456	0.0471	0.0606	0.0480	0.0580
	0.0354	*0.0359*	*0.0372*	*0.0329*	*0.0354*	*0.0323*
UMD	0.0440	0.0467	0.0427	0.0472	0.0432	0.0468
	0.0239	*0.0225*	*0.0238*	*0.0217*	*0.0236*	*0.0218*
VOLUME	0.0013	0.0022	-0.0033	**0.0159**		**0.0146**
	0.0054	*0.0020*	*0.0088*	*0.0057*		*0.0060*
NYSERSI					-0.0193	-0.0131

					0.0120	*0.0123*
D.W.	1.80	1.83	1.77	1.91	1.81	1.91
Adj R²	0.866	0.867	0.866	0.874	0.869	0.874

Panel C. Alpha-M Group

	NYSETO	NASDTO	NYSERVM	NASDRVM		NASDRVM
Constant	-0.0017	0.0049	0.0194	0.0013	0.0125	0.0162
	0.0036	*0.0060*	*0.0101*	*0.0071*	*0.0112*	*0.0148*
RMRF	**0.9540**	**0.9456**	**0.9410**	**0.9521**	**0.9497**	**0.9500**
	0.0306	*0.0298*	*0.0289*	*0.0300*	*0.0292*	*0.0294*
SMB	**0.3481**	**0.3512**	**0.3368**	**0.3480**	**0.3458**	**0.3459**
	0.0360	*0.0354*	*0.0412*	*0.0361*	*0.0355*	*0.0361*
HML	-0.0147	-0.0128	-0.0358	-0.0172	-0.0182	-0.0198
	0.0323	*0.0329*	*0.0317*	*0.0318*	*0.0324*	*0.0320*
UMD	0.0466	0.0430	0.0426	0.0453	0.0455	0.0449
	0.0227	*0.0224*	*0.0220*	*0.0227*	*0.0225*	*0.0227*
VOLUME	0.0019	-0.0016	-0.0176	-0.0011		-0.0024
	0.0037	*0.0020*	*0.0093*	*0.0065*		*0.0067*
NYSERSI					-0.0119	-0.0130
					0.0106	*0.0108*
D.W.	1.81	1.77	1.72	1.78	1.79	1.78
Adj R²	0.948	0.948	0.950	0.948	0.949	0.948

Panel D. Alpha-N Group

	NYSETO	NASDTO	NYSERVM	NASDRVM		NASDRVM
Constant	0.0011	0.0066	0.0677	0.0014	0.0003	-0.0081
	0.0158	*0.0160*	*0.0233*	*0.0178*	*0.0316*	*0.0394*
RMRF	**0.5063**	**0.4999**	**0.4655**	**0.4991**	**0.5012**	**0.5005**
	0.1360	*0.1363*	*0.1311*	*0.1272*	*0.1301*	*0.1295*
SMB	**0.3378**	**0.3373**	**0.3020**	**0.3367**	**0.3382**	**0.3380**
	0.0738	*0.0743*	*0.0739*	*0.0736*	*0.0757*	*0.0750*
HML	-0.0638	-0.0691	-0.1307	-0.0664	-0.0684	-0.0647
	0.0996	*0.0956*	*0.0934*	*0.0905*	*0.0948*	*0.0925*
UMD	-0.0169	-0.0201	-0.0294	-0.0189	-0.0200	-0.0187
	0.0605	*0.0631*	*0.0581*	*0.0606*	*0.0590*	*0.0605*
VOLUME	0.0057	-0.0001	**-0.0560**	0.0047		0.0055
	0.0145	*0.0049*	*0.0219*	*0.0165*		*0.0167*
NYSERSI					0.0060	0.0083
					0.0297	*0.0302*
D.W.	1.80	1.78	1.74	1.79	1.79	1.80
Adj R²	0.455	0.454	0.475	0.454	0.454	0.451

Notes: Standard errors in italics. Coefficients in bold are significant at the 1% level. Definitions of Alpha-H, Beta-H, Alpha-M, and Alpha-N given in Table 4.

Table 11. Regressions including Proxies for Net Fee Variable, 2008-9

Excess return regressions of Alpha-H, Beta-H, Alpha-M and Alpha-N on Fama-French-Carhart four-factor model, NYSERSI and NASDRVM. NYSERVM is the NYSE monthly share volume, and NASDRVM is the NASDAQ monthly share volume, both detrended by dividing each month's share volume with the average volume from the previous 12 months. NYSERSI is the aggregate short interest outstanding on the NYSE, divided the number of outstanding shares, and detrended by dividing this ratio with its average in the previous twelve months.

	Alpha-H	Beta-H	Alpha-M	Beta-M	Alpha-N	Beta-N
Constant	0.0150	0.0181	0.0374	0.0106	0.0368	0.0051
	0.0324	*0.0288*	*0.0250*	*0.0143*	*0.0239*	*0.0330*
RMRF	**0.4498**	**0.5529**	**1.0790**	**1.0459**	0.0139	**0.8285**
	0.0487	*0.0576*	*0.0503*	*0.0260*	*0.0482*	*0.0554*
SMB	-0.0261	-0.0184	**0.3351**	**0.1302**	0.1541	0.0844
	0.0854	*0.1134*	*0.1010*	*0.0534*	*0.0854*	*0.1028*
HML	**-0.3834**	**-0.2600**	-0.1846	**-0.1073**	0.0067	**-0.3482**
	0.1085	*0.0931*	*0.0794*	*0.0432*	*0.1116*	*0.1099*
UMD	0.0097	-0.0082	0.0269	-0.0028	-0.0104	-0.0142
	0.0269	*0.0296*	*0.0412*	*0.0163*	*0.0436*	*0.0245*
NYSERSI	-0.0047	-0.0191	-0.0267	-0.0090	**-0.0343**	0.0106
	0.0211	*0.0193*	*0.0170*	*0.0082*	*0.0138*	*0.0173*
NASDRVM	-0.0127	0.0033	-0.0124	-0.0019	0.0059	-0.0188
	0.0237	*0.0217*	*0.0216*	*0.0120*	*0.0216*	*0.0232*
D.W.	2.21	2.02	2.10	2.27	2.96	2.31
Adj R^2	0.767	0.835	0.969	0.992	0.006	0.940

Data Appendix

1. Long/Short Equity Hedge Fund data:

We merge hedge funds from three databases: 3,142 Long/Short equity funds from Lipper/TASS, 3801 Equity Hedge funds from HFR, and 2,468 Equity Long/Short from CISDM, as follows. We first identify funds by management companies. We eliminate duplicate funds in the same management company if they have the same name, or identical returns. We then eliminate clone funds if they have very similar names and highly correlated returns. The following table summarizes the resulting unique funds:

	TASS	HFR	CISDM	Row Total
Unique	1,269	1,202	567	3,038
Live	621	724	142	1,487
Dead	648	478	425	1,551
Duplicates*	1,873	2,599	1,901	6,373
Col Total	3,142	3,801	2,468	9,411

* Includes non-USD funds.

2. Equity Mutual Fund data:
We obtain equity mutual funds from the CRSP survivorship-bias free database, as follows. We start with the names of all the mutual funds that existed during 1994 until 2008. We then selected equity funds in 44 investment objectives based on the Lipper classification. For funds with multiple share classes, we kept the one with the longest track record. This yields 7,662 funds for our analysis.

3. Long-Bias Equity Hedge Fund data:
We use the hedge funds classified as Equity Non-Hedge in the HFR database. There were 200 funds in this category.