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Asian Hedge Funds: Return Persistence, Style, and Fund Characteristics

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Abstract

This study explores the return persistence properties, styles, and fund characteristics of hedge funds that mainly invest in Asia. We examine, for the first time, a high resolution hedge fund dataset which includes monthly return information as well as detailed fund characteristics data. We find that the returns of Asian hedge funds persist most strongly at monthly horizons to quarterly horizons. This persistence weakens considerably when we lengthen the measurement period beyond a quarter, and does not appear to be due to the imputation of fees or to systematic risk as measured by a simple factor model. Further, we show that Asian funds comove largely with a common Asian equity markets component. Other major components that explain the cross-sectional variation in Asian hedge fund returns include a CTA component, two macro components, and three multi-strategy components. The seven style components in total explain about 64% of the variation in returns. Next, we study the relationship between the cross-section of fund returns and fund characteristics. We document a positive relationship between holding firm size and fund returns which is consistent with an "economies of scale" explanation. Moreover, we find that funds with higher redemption (lockup) periods achieve higher returns on average due to their ability to extricate from their positions in a timely fashion in the face of redemptions. However, there is no evidence to suggest that funds with higher expenses (management and performance fees) achieve higher returns.

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Since 1990, the complex and esoteric world of hedge funds has garnered much attention from the press. Hedge funds are often in the media spotlight with their spectacular gains and losses. For example, George Soros, the manager of Quantum Fund, a macro hedge fund, is famous for his attack on the British Sterling in September of 1992 when he made $1 billion on his short position on the Pound. Long Term Capital Management (LTCM) will always be remembered for its spectacular fall in October of 1997 when its highly leverage positions took a huge hit with the sudden devaluation of the Russian Rouble and the subsequent liquidity crunch. It required the combined efforts of several of the world's largest banks to save LTCM from its shell-shocked creditors. In the heat of the Asian financial crisis of 1997-1998, macro hedge funds were sharply criticized by the Prime Minister of Malaysia, Dr. Mahathir bin Mohamad, for being "share- and financial-market manipulators" who were needed in the same way that "travelers in the good old days needed highwaymen."[1]

In addition to media coverage, hedge funds have been getting increasing attention from high net worth individuals and institutional investors. Brooks and Kat (2002) estimates that as at April 2001, there are around 6000 hedge funds in existence with an estimated US$400 billion in capital under management and US$1 trillion in total assets. The reason why hedge funds appeal to so many investors is partly due to their widely-reported ability to generate impressive absolute returns. It is also partly due to the lack of regulation in the hedge fund industry which allows hedge funds to follow complex trading strategies, and invest in a wide range of assets and instruments, thus increasing the return space available to investors.

It is also this same lack of regulation that makes it harder to understand hedge funds. Relative to what we know about mutual funds, little is known of hedge funds. The problem is exacerbated by the relative dearth of data on hedge funds. The situation is improving with the increase in research interest in this area. Recent research on hedge funds has shown that there exist significant survivorship issues with respect to hedge funds (Liang (2000), Fung and Hsieh (1997), and others) and that fund returns persist at the quarterly horizons (Agarwal and Naik, 2000) but not at annual horizons (Brown, Goetzmann, and Ibbotson, 1999). Further, Fung and Hsieh (1997) and Brown and Goetzmann (2003) show that the multitude of hedge fund styles can be reduced to five to eight styles which explain the contemporaneous and future cross-sectional variation in fund returns.

However, little if any is known about a fund's returns in relation to its fees and other fund characteristics. Given the hedge funds' unique and relatively complicated fee structures, which often comprise of a compulsory management fee, a performance fee contingent on returns exceeding a hurdle rate, minimum investments, and a redemption period, it will be interesting to examine the relationship between returns and funds' fee components. Amongst other issues, an analysis of the relationship between fund fees and returns will also allow us to test if hedge funds compensate their investors for their higher fees. Further, testing the relationship between returns and other fund characteristics will allow us to address perennial questions like: "Do larger funds provide investors with higher returns?"

In the existing literature, most hedge fund studies examine US-centric hedge funds. Very little is known about the rapidly growing group of funds which invest in Asia. Based on data from two Asian fund databases, AsiaHedge and EurekaHedge, the number of funds which invest predominantly in Asia have risen dramatically from around 75 in January of 1999 to around 282 in March 2003. This represents a 276% increase over a span of around four years. It will be interesting to see if the quarterly return persistence documented for funds which invest globally and in US also apply to Asian funds as well. Further, it may be instructive to try to understand the multitude of style/investment region combinations of Asian hedge funds using returns-based style analysis (Fung and Hsieh, 1997; Brown and Goetzmann, 2003). Such an exercise will have important implications for investors seeking diversification benefits in Asian hedge funds.

In this paper, we examine for the first time a high resolution Asian database that is constructed from the union of two Asian hedge fund databases: AsiaHedge and EurekaHedge. This unique database has monthly fund return data as well as detailed fund characteristics data including fund size, holding company size, inception date, management fee, performance fee, redemption period, and minimum investment. We structure our analysis of the Asian funds sample around three fundamental questions: Do Asian hedge fund returns persist? What styles are relevant for explaining Asian fund returns? Is there a relationship between fund characteristics and returns?

One of our key findings is that the returns in Asian hedge funds persist strongly at monthly to quarterly horizons. A hypothetical strategy that longs the best performing decile last month and shorts the worst performing decile last month and holds the funds for a month yields a mean annual excess return of 24.1% per annum. However at longer horizons of greater than a quarter, there is very little evidence of return persistence. This short-term return persistence is due neither to persistence/imputation of expenses nor to greater risk-taking amongst winner funds. Our persistence results are robust to the use of different non-parametric methodology as well.

To gain further insight, we perform returns-based principal components analysis on the funds in our sample. This exercise allows us to uncover a strong common underlying component for Asian funds which is highly correlated with Asian equity indices. This component explains up to 33% of the cross-sectional variation in fund returns and is highly correlated with many fund style/investment region combinations (e.g. Long/Short Asia including Japan, Long/Short Asia excluding Japan, Fixed Income Emerging Asia, Macro Asia including Japan, etc.). Additionally, we identify six other major components. These include one Commodity Trading Advisors (CTA), three multi-strategy, and two macro components. These seven components are able to explain 64% of the cross-sectional variation in Asian hedge fund returns. An implication of our style analysis is that the diversification benefits of investing in various Long/Short equities funds which target different investment regions within Asia appear to be minimal. Investors will likely reap greater diversification benefits by investing in macro, multi-strategy, and CTA funds as well. This finding is significant as to-date, little is known about the merits of within-region diversification strategies in Asia.

Finally, we test the relationships between returns and various fund characteristics in a cross-sectional regression setting. The objective of this exercise is to understand if fund characteristics play a role in the return performance of Asian hedge funds. Our regression results yield a number of salient observations. First, we find no evidence to suggest that funds with higher fees (management and performance fees) reap greater post-fee and pre-fee returns. Second, funds managed by larger holding companies appear to attain greater returns on average than funds managed by smaller holding companies. This finding is consistent with the market view that funds managed by large companies benefit from economies of scale. Third, funds with longer redemption (lockup) periods tend to perform better than funds with shorter redemption periods. An increase in redemption period of 10 days is associated with a non-trivial 11 basis point increase in fund monthly post-fee return. We show further that the reason for the differential performance is because longer redemption periods allow funds to close out of their positions in a more timely fashion and incur less transactions costs while doing so.

This study connects to the recent hedge fund literature in a number of ways. The result that bigger hedge funds do not fare better than smaller hedge funds is consistent with the idea by Goetzmann, Ingersoll, and Ross (2003) that funds face decreasing returns to scale. We find instead that there is evidence of increasing returns to scale at the management company level. Our finding that investing in CTA funds adds diversification to an Asian hedge fund portfolio lends support to the results of Liang (2003) and Caglayan and Edwards (2001) who find low correlations between the returns to CTA funds and the returns to other hedge funds. The finding that the majority of the Asian hedge funds co-move with a common Asian component which is in turn highly correlated with Asian markets echoes the results of Asness, Krail, and Liew (2001) who find that contrary to popular belief, hedge funds have significant market exposures.

It may be interesting to relate our results to the literature on mutual funds. Carhart (1997), Hendricks, Patel, and Zeckhauser (1993), and others find that mutual fund returns persist for 1 to

3 years. However much of the returns persistence is concentrated in the worst performing funds. Even the momentum factor does not appear to explain the anomalous and persistently low returns of such funds. Our redemption period results suggest a possible explanation for their abnormal negative returns: that massive redemptions force funds to close positions in an untimely manner. The transactions cost incurred and the opportunity costs forgone from closing potentially lucrative positions hurt the returns of such funds. On fund families, Nanda, Wang, and Zheng (2002) find that high ability mutual fund families, through sharing of information and strategies, are likely to have more correlated performance across funds. Our holding fund size results nicely complements their findings that fund family characteristics matter to the returns of mutual funds.

The remainder of this paper is structured as follows. Section I describes the data. Section II presents the results from the return persistence tests. The returns-based style analysis is discussed in Section III, while Section IV examines the relationship between funds returns and fund characteristics. Section V concludes and offers avenues for further research.

I. Data

We cull our Asian hedge fund data from the union of the databases of EurekaHedge Advisors Pte Ltd (hereafter EurekaHedge) and HedgeFund Intelligence AsiaHedge (hereafter AsiaHedge). Both databases include funds which invest a significant portion of their assets in Asian countries. Our data sample includes monthly return data which runs from January 1999 to March 2003. While the EurekaHedge dataset contains return data since a fund's inception, AsiaHedge only includes return data starting January 1999. Hence we only perform our analysis on returns starting January 1999 to accommodate the later start date of the AsiaHedge database.

Both of these rich hedge fund databases include fields for a host of relevant fund characteristics which include management fee, performance fee, redemption period, investment style, geographical region, fund size, fund capacity, total assets, minimum investment, and inception date. These fund characteristics are recorded for the 2002 year and for our purposes we take the fund characteristics as constant throughout its life span. The minimum investment is usually quoted in US dollars but is also sometimes quoted in Australian dollars, Euros, or Japanese Yen. To effect a meaningful comparison, we convert everything to US dollars using the exchange rates on May 29th 2003[2].

The returns listed in EurekaHedge and AsiaHedge are post-fee returns. Since fees are imputed but not paid intra-year, such a return adjustment for fees may introduce spurious persistence in returns measured, particularly at horizons less than a year (Agarwal and Naik, 2000). For example, it could be that the persistent "winners" are actually funds with low fees while the persistent "losers" are funds with high fees. Carhart (1992; 1997) argues that post expense return persistence could be an artifact of persistence in expenses. Hence we back out pre-fee returns from post-fee returns using management fee and performance fee information (which are only available for the EurekaHedge database). To do so, we sum the post-fee monthly returns and compute the performance fee off these annual returns.[3]One twelfth of the annual performance fee is then added back to the post-fee monthly returns. Then we add back a twelfth of the annual management fee each month. All our persistence tests are done with pre-fee and post-fee returns.

In this study, we include both living as well as dead funds in our data. EurekaHedge has both listings of obsolete funds and live funds. AsiaHedge, however, only records live funds. Nonetheless, since EurekaHedge has 313 funds and AsiaHedge has only 104 funds that are not in EurekaHedge, the effect of the missing dead funds in AsiaHedge is likely to be second order. Moreover, our dead funds to total funds ratio of 32 to 417 is higher than the dead funds to total funds ratio of 27 to 746 from the Hedge Fund Research (hereafter HFR) database (Agarwal and Naik, 2000), a large, popular dataset for hedge fund research (Ackermann, McEnally, and Ravenscraft, 1999; Liang, 1999; Agarwal and Naik, 2000). To the extent that true survival rates are comparable for these different sets of funds, this suggests that survivorship issues (Brown etal, 1992) are mitigated in our combined dataset. Finally, to address any lingering survivorship concerns, we adopt methodologies which have proven robust to survivorship issues (e.g. the chi-squared test, (see Carpenter and Lynch, 1999)).

Our sample of funds differs markedly from the two traditional datasets used in the hedge fund literature: TASS Management Limited (hereafter TASS) and HFR. TASS has been used by many researchers including Fung and Hsieh (1997). Both EurekaHedge and AsiaHedge contain funds which have an Asian bent. Our combined dataset includes mostly funds that invest exclusively in the Asia-Pacific, and some funds that are based in the Asia-Pacific but invest globally. HFR and TASS, on the other hand, include onshore and offshore funds that invest in the US. The degree of overlap is very small. Out of our total of 417 funds, only 27 (less than 7%) funds in our dataset are featured in TASS.

Table I shows the number of dead and live funds broken down by investment style and investment region in our combined database. While Figure 1 highlights the five best and worst performing funds in our sample.

II. Persistence of returns in Asian hedge funds

The issue of fund return persistence has a long and illustrious history in the mutual fund literature. Hendricks, Patel, and Zeckhauser (1993), Goetzmann and Ibbotson (1994), Brown and Goetzmann (1995), and Wermers (1997) show that mutual fund performance persists in the short term (one to three years). They credit their results to the existence of "hot hands" or common investment strategies. Meanwhile, Grinblatt and Titman (1992), Elton, Gruber, Das, and Hlavka (1993), and Elton, Gruber, and Blake (1996) find that mutual fund performance is predictable over long horizons of between five and ten years. They ascribe their results to mutual fund managers having different information or different stock-picking ability. Carhart (1997) offers a different take on mutual fund return persistence. He finds that much of the persistence can either be attributed to managers following momentum strategies or to persistence in expenses. On the other hand, Wermers (2000) investigates fund holdings data and finds that fund managers do possess stock picking ability. However their stock picking abilities do not compensate for their expenses.

Since the hedge fund industry is relatively new, less is known about hedge fund return persistence. Brown, Goetzmann, and Ibbotson (1999) find no evidence of return persistence at annual horizons for their sample of offshore hedge funds. They do not find persistent winners or losers with either raw fund returns or style-adjusted fund returns. Agarwal and Naik (2000) examine the quarterly, semi-annual, and annual returns of the funds in the HFR database. They find using the methods of Brown, Goetzmann, and Ibbotson (1999) evidence of persistence in fund returns. They show that evidence of persistence is concentrated at quarterly horizons and weakens considerably when one moves to annual horizons. Their tests control for style and the imputation of fees.

A. Single-period tests of persistence

In this section, we follow the methodology of Brown, Goetzmann, and Ibbotson (1999) and test our sample of Asian fund returns for evidence of persistence. We include both two-period tests of persistence as well as multi-period tests of persistence in our empirical repertoire. We aim to find out if winners / losers persist in our Asian funds sample, and if so, at what frequencies such persistence occurs. Our unique monthly returns database allows us to examine the issue of persistence at frequencies higher than those tested in the existing literature.

First, we construct a contingency table of winners and losers. A fund that beats the median fund in any period is labeled a winner, and one that doesn't is labeled a loser. We compare a fund's performance in the current period (where a period ranges from one month to one year) to its performance in the previous period. Hence, persistence in this context refers to the existence of funds that are winners in two consecutive periods (denoted by WW) or losers in two consecutive periods (denoted by LL). Letting WL denote winners in the first period and losers in the second period, and LW denote the reverse, we can calculate the cross-product ratio (CPR), which is defined as $(WW*LL)/(WL*LW)$. The CPR ratio captures the ratio of the funds that exhibit persistence in performance to those that do not. Under the hypothesis of no persistence in gross returns, the probability of winning or losing in each period equals one-half and is independent of the return horizons. So, one would expect that the four categories WW, WL, LW, and LL each have 25% of the funds, and CPR equals 1. Since the standard error of the natural logarithm of the CPR is given by

$$\sigma_{\ln(CPR)} = \sqrt{\frac{1}{WW} + \frac{1}{WL} + \frac{1}{LW} + \frac{1}{LL}} \tag{1}$$

(see Christensen, 1990), we can test for the statistical significance of the CPR.

We also conduct a chi-square test comparing the observed frequency distribution of WW, WL, LW, and LL with the expected frequency distribution. Carpenter and Lynch (1999) study the specification and power of various persistence tests and find that the chi-square test based on the number of winners and losers is well-specified, powerful, and more robust to the presence of survivorship bias compared to other test methodologies. We compute the chi-square statistic as

$$\frac{(WW-D_1)^2}{D_1} + \frac{(WL-D_2)^2}{D_2} + \frac{(LW-D_3)^2}{D_3} + \frac{(LL-D_4)^2}{D_4} \text{ where} \tag{2}$$

$$\begin{aligned}
D_1 &= (WW+WL)*(WW+LW)/N,\ D_2 = (WW+WL)*(WL+LL)/N, \\
D_3 &= (LW+LL)*(WW+LW)/N,\ D_4 = (LW+LL)*(WL+LL)/N, \text{ and} \\
N &= WW+WL+LW+LL,
\end{aligned}$$

and test this statistic at the 1% significance level, which corresponds to a critical value of 6.63 (one degree of freedom). Our analysis covers both post-fee and pre-fee fund returns

Table II showcases the CPR and chi-squared test results. We find that at the two-period level, winners and losers tend to persist for horizons spanning one month to nine months. This evidence appears to be even stronger for pre-fee returns. Our results corroborate the findings of Agarwal and Naik (2000) that return persistence weakens as one lengthen the measurement horizons. Like us, they also find that pre-fee returns exhibit greater persistence than post-fee returns. However, in general we find stronger evidence of return persistence than Agarwal and Naik (2000) who find very mild evidence of persistence at semi-annual and annual horizons. Both the CPR and the chi-squared statistic are statistically greater than zero at the 1% level for measurement horizons of up to and including nine months. We believe that a reason for the sharper results that we obtain in this paper is the higher frequency of our returns data. This allows us to test say all consecutive three-month periods for persistence and not just consecutive calendar quarters. Our finding that persistence at annual horizons is very weak also corroborates the results of Brown, Goetzmann, and Ibbotson (1999).

B. Multi-period tests of persistence

Next, to further investigate persistence, we turn to a multi-period framework and compare the observed frequencies of strings of wins and losses with that generated by a normal distribution (since a normal distribution approximates a binomial distribution in large samples). The Kolmogorov-

Smirnov statistic is a convenient tool with which to test whether the observed distribution is statistically different from a normal distribution (DeGroot and Schervish, 2002).

The results of the Kolmogorov-Smirnov test are displayed in Table III. They show again that we have stronger evidence of persistence at shorter measurement periods. As we lengthen the measurement period to six months and beyond, the evidence of persistence diminishes greatly. It may be interesting to note that while winners persist as much as losers with pre-fee returns, with post-fee returns, the former group of funds are more persistent than the latter group of funds. One interpretation may be that the performance fee (which is conditional on returns exceeding the hurdle rate) insulates the investor somewhat from the poor performance of persistent losers.

In the above investigations, we have utilized gross returns that have not been adjusted for style. It is widely known that hedge funds follow disparate strategies. Hence an adjustment for style may be in order. A simple way of doing so is to subtract the average style returns from the fund's returns. However, Brown, Goetzmann, and Ibbotson (1999) and Agarwal and Naik (2000) find that their results are unaffected by their adjustments for style. Moreover since most of the funds in our sample belong to the Long/Short Equities style, the benefits of doing so may be suspect. Further, there are some styles for which are not well represented in our sample (see Table I). Hence, the adjustment for style may not be meaningful in these cases since the average style return may be a very noisy indicator of their styles' performance. Nonetheless, we perform separate CPR, chi-squared, and Kolmogorov-Smirnov tests on sub-samples of funds belonging to the long/short equity, macro, relative value and multi-strategy styles. These are styles with at least twenty funds in our dataset. Tests are done on funds one style at a time. None of our inferences change when we perform these tests.

C. Persistence and factors

The results in this section so far have shown that there is persistence in Asian hedge fund returns. However, a few questions remain. For instance, it remains to be seen whether funds are persistent winners because they take on more systematic risk (and hence are rewarded with greater returns) or because they have better stock picking skills. Conversely, we also do not know if funds are persistent losers because they undertake less systematic risk or because they have poorer stock picking skills.

In order to test whether persistence in returns is due to persistence in risk taking, we next conduct a simple risk adjustment exercise. We hypothesize that Asian hedge fund return can be spanned by an Asian equity factor, an Asian bond factor, and a US equity factor[4], as well as Fama French (1993) factors for size (SMB), book-to-market (HML) and momentum (UMD). We further break the Asian equity factor into an Asia ex Japan factor and a Japan factor. We proxy these factors with Datastream market indexes. Our choice of factors is motivated by two simple facts: The funds in our sample invest mostly in Asian stocks and bonds. And they may also set aside a portion of their funds to invest in global stocks and bonds which are likely to have a high correlation with the US market. All our factors are constructed from their respective indexes by subtracting away the US treasury rate. Next for each month in our sample we sort the funds into deciles based on their past month returns. The difference between these portfolios and the US Treasury rate are then regressed on the four factors. We do so for post-fee and pre-fee returns. Our model for risk-adjustment follows very closely to Edwards and Liew (1999) and is in the same spirit as Agarwal and Naik (2003)[5].

Our regressions yield adjusted R squared numbers of about 0.45 which empirically validates our choice of factors. The regression coefficients displayed in Table IV show that risk as measured by our multi-factor model cannot account for all the persistence in returns. The alpha of the spread in post-fee returns between the highest return decile and the lowest return decile is statistically positive at 2.65 % per month or 31.8% per year. Since the mean excess return[6]of the spread is 2.01 % per month which is lower than its alpha, this suggests that systematic risk does little to explain the spread. We note that the spread's alpha is higher for the pre-fee returns than for the post-fee returns. This suggests either that less of the persistence in returns is passed on to investors due to performance fees which take away from returns when they exceed the hurdle rate, or that funds in the best return decile tend to have greater fees than funds in the worst return decile.

III. Principal components analysis of Asian hedge fund styles

It is well known that the typical hedge fund investor faces a bewildering array of fund styles from which to choose from. Mutual fund styles tend to only indicate what assets they invest in (e.g. large value, small growth, Emerging Asia, etc.). Hedge fund styles, on the other hand, give an indication of both what the funds invest in (e.g., fixed income instruments, equities, or convertibles) and how they invest (e.g., relative value, long/short, or multi-strategy). The situation is complicated by the fact that since the funds self declare their styles, there is ample room for strategic self-misclassification. For example, Brown and Goetzmann (1997) find that when mutual funds change their self reported style, it almost always results in them increasing their returns relative to the new benchmarks. Since the hedge fund industry is relatively less regulated than the mutual fund industry, such strategic self-misclassification may affect hedge funds styles more severely.

Fung and Hsieh (1997) and Brown and Goetzmann (2003) stress the need to benchmark and understand hedge fund managers who often engage in secretive, dynamic trading strategies, and vary their trading instruments. They use principal components analysis and a regression based style classification algorithm respectively to back out hedge fund style factors from fund return history.

Fung and Hsieh (1997) break down fund returns into five main components which explain about 43% of the cross-sectional deviation in fund returns. Brown and Goetzmann (2003) condense fund returns into eight classifications and find that they explain about 21% of the future out-of-sample cross-sectional variation in fund returns.

Such returns-based style analysis offers several benefits. By characterizing hedge funds through a multi-factor style model, one will be better able to identify the diversification benefits of investing in specific classes of hedge funds. Condensing the many, often ambiguous, and difficult to interpret hedge fund styles into a few orthogonal factors helps investors understand the bewildering array of hedge fund strategies. Moreover, the use of returns-based style analysis to back out the styles of hedge funds circumvents the possible self-misclassification problem in hedge fund databases.

In this section we follow the principal components methodology[7] of the Fung and Hsieh (1997) and back out from our Asian funds return data a set of principal components or styles. Our goals are two fold. First, we seek to further understand the multitude of style and geographical region combinations in the Asian funds dataset. Fung and Hsieh (2002a) note that a principal components analysis will most likely reduce the number of style factors to a more manageable and orthogonal set. Second, we hope to investigate the diversification benefits of different classes of hedge funds. Our investigations aim to shed light on the answers to questions like "Is there a diversification benefit from investing in Long/Short Equity Asia excluding Japan funds and Long/Short Equity Japan funds?"

To this end, we use principal components analysis to break the returns of the funds in the sample into orthogonal principal components. We are able to construct 42 principal components with non-zero eigenvalues, of which 18 have eigenvalues greater than one. These 18 principal components, their respective eigenvalues, and the proportion of cross-sectional return variance explained by each are displayed in Table V. Clearly, the first component, F1, dominates. It explains about 33% of the cross-sectional variation in returns. The next component, F2, only explains about 8% of the cross-sectional variation.

Next to help identify these principal components, we regress fund returns on the top 12 principal components component by component. Then we compute the mean R squared across the funds from each style / geographical region combination for which we have returns information. These mean R squared numbers are shown in the heat map of Figure 2.

Many of the principal components can be identified from the heat map in Figure 2. F1 is the common Asian component which is highly correlated with many of the styles which invest in Asia (e.g. Long/Short Asia including Japan, Fixed income Emerging Asia, Macro Asia including Japan, Distressed Debt Asia excluding Japan, etc.). F2 is the Emerging Asia multi-strategy component. F3 is the Asian macro component which is highly correlated with Macro Asia including Japan and less correlated with Macro Global. F4 is the Asian multi-strategy component while F5 is the global multi-strategy component. F6 is the global macro component. F9 is the Japanese CTA component. F7, F8, F10, F11, and F12 are less easily identifiable, and for this reason we will concentrate on the other seven components in the rest of the discussion.

Clearly both style and investment region matter to returns. But this depends on the specific style and investment region. Our roundup of seven identified components includes three Asian, one Emerging Asia, one Japanese, and two global components. There are also two macro, three multi-strategy, and one CTA component. Due to the high correlation with F1, the diversification benefits of investing in various Long/Short equities funds which target different investment regions are suspect. The heat map in Figure 2 suggests that the investor may reap greater diversification benefits by investing in macro, multi-strategy, and CTA funds as well.

To get a better sense of what drives F1, the common Asian hedge fund component, we perform a correlation analysis of F1 with various Asian market and US market indices. Not surprisingly, F1 is strongly correlated with the Datastream Asian equity index (correlation coefficient= 0.67), with the Datastream Asia excluding Japan equity index (correlation coefficient = 0.83), and with the Datastream Japan equity index (correlation coefficient = 0.48). All these correlations are significant at the 1% level. Hence Asian hedge funds have significant exposure to Asian equity markets, corroborating extant research by Asness, Krail, and Liew (2001) who show that contrary to popular beliefs, hedge funds possess significant market exposures. This finding also helps validate our use of Asian market factors in the previous section.

All in all, our results show that Asian funds co-move largely with a common Asian component. This common Asian component explains roughly 33% of the cross-sectional variation in fund returns. There are six other easily identified components which are differentiated by style (macro, multi-strategy, and CTA) and investment region (Asia, Emerging Asia, Japan, and global). The seven components in total are able to explain about 64% of the cross-sectional variation in Asian hedge fund returns. This compares favorably with the five main components that Fung and Hsieh (1997) construct which can explain 43% of US onshore and offshore funds.

IV. Asian hedge fund characteristics and their relationships to returns

Little is known about the relationship between hedge fund returns and hedge fund characteristics, such as fund size and fee structure. In the mutual fund arena, it is well-established that persistence in fund expenses contribute to persistence in fund returns (Carhart, 1997), that better managers on average do not make up for their higher expenses (Wermers, 2000), and that there is little evidence to suggest that large funds perform better than small funds. In the hedge fund arena, such studies are lacking, as data on fund characteristics were not available previously.

In this section, we take advantage of the detailed characteristics information embedded in our Asian fund dataset, and test the relationship between fund returns and fund characteristics, which include fund size, holding company size, management fee, performance fee, redemption period, and age. Our analysis is motivated by several issues: Do larger funds in larger holding companies perform better than smaller funds in smaller holding companies? Do funds with higher expenses perform better than funds with low expenses? Are older, more experienced funds better able to generate impressive returns than younger, less experienced funds? Clearly, the answers to these questions will have strong implications for potential investors of hedge funds.

We investigate the relationship between returns and fund characteristics in a cross-sectional Fama and MacBeth (1973) framework. The monthly fund returns are regressed on stock characteristics in a univariate and multivariate setting. The stock characteristics examined are fund fee structure characteristics like management fee, performance fee, minimum investment, and redemption period, as well as other fund characteristics such as fund size category, holding company size category, and fund age. The regressions are estimated for both post-fee and pre-fee returns. Both multivariate regressions and univariate regressions are conducted as some independent variables are likely to be strongly correlated. The multivariate regressions allow us to ascertain the incremental explanatory power of each fund characteristic on the cross-section of fund returns. Size category condenses size information into a number from 1 to 10. We use size categories as fund size data from AsiaHedge comes in ranges, and since the difference to returns between a 1 billion fund and a 1.05 billion fund is likely to be marginal. Details of the size categories are available in the Appendix.

Table VI reports the coefficient estimates from this simple exercise. The reported estimates are the time-series averages of monthly cross-sectional regression slope estimates as in Fama and MacBeth (1973). A number of interesting observations can be made from the results of the cross-sectional analysis. First, funds do not make up for their higher management fees and performance fees. In fact, the coefficient estimate on performance fee in the multivariate regression with post-fee returns as the dependent variable suggests that funds with higher performance fees have smaller post-fee returns than funds with lower performance fees controlling for all the other characteristics. Second, fund size is only weakly related to returns. Fund size seems to be positively correlated with post-fee returns, at least in a univariate setting. This may or may not due to the fact that larger funds have lower expenses than smaller funds. However this effect goes away in a multivariate setting. Third, the redemption period is strongly and positively correlated to fund returns. This could either be due to the fact that a longer redemption period allows a fund to unwind its positions in a timelier manner than would a shorter redemption period, or due to the fact that higher ability managers demand a higher redemption period. Fourth, the size of the holding company is positively related to the returns of the fund. This is consistent with the idea that funds benefit from the economies of scale provided by a larger holding company[8]. Instances of economies of scale at work may include managing companies employing highly skilled analysts who specialize in specific countries or sectors. Since employing these star analysts is costly, it only makes sense for the managing companies to employ these specialists if they manage a large group of hedge funds. Fifth, fund age and the size of the minimum investment do not appear to have any explanatory power on fund returns.

Next, to get a better understanding of the relationships between different fund characteristics and the underlying forces driving the regressions results discussed above, we compute the correlations between the fund characteristics. The matrix of correlation coefficients displayed in Table VII suggests that larger funds have higher management fees and higher minimum investment amounts. The reason why fund size loses its significance in the multivariate post-fee return regression is partly due to its high correlation with holding company size. Large funds are positively (but weakly) related to fund returns probably because large funds are usually operated by large holding companies which provide economies of scale for fund operations. There is no evidence to suggest that large funds have higher returns on an after-fee basis because the fees of large funds are lower than those of smaller funds.

Another notable observation from Table VII is that the redemption period is positively correlated with both management fee and performance fee. This explains why coefficients on the redemption period are smaller in the regressions with post-fee returns as the dependent variable than in regressions with pre-fee returns as the dependent variable. Finally, it is not surprising that funds with high management fees have lower performance fees on average. On one hand, funds with good track records can demand higher management fees from clients. On the other hand, funds with poor track records cannot demand high management fees from investors. They make up for this with higher performance fees. Investors do not mind the higher performance fees as much since they are contingent on good fund performance.

We further examine whether funds with high redemption periods have higher returns because a longer redemption period allows the manager to unwind positions in a more timely fashion, or because managers in funds with longer redemption periods possess greater asset selection skills. The transactions cost (first) story implies that funds with a longer redemption period should thrive in times of high redemption. One way of proxying for the degree of redemptions is to look at the returns of the US stock market. Insofar as the US stock market is a proxy for global wealth, redemptions should be greater when US stock market returns are low.

Hence we split the sample into two: months where the US stock returns are greater than the median US stock return month over the sample period, and months where the US stock returns are greater than the median US stock return month over the sample period. Then, we re-estimate the univariate cross-sectional return regressions with redemption period as the independent variable on both sub-samples separately. Consistent with the transactions cost explanation, the coefficient on redemption period is significantly positive for the low stock market return months but only insignificantly positive for the high stock market return months. This is true whether we use post-fee or pre-fee returns as the dependent variable.

V. Conclusions

The literature on hedge funds is still at its incipient stages. Little if any is known of fund characteristics in relation to fund returns. Even less is known of Asian hedge funds, an aggressively growing group of institutional investors. This study represents a first attempt to study these issues using a high resolution Asian hedge fund database.

First, we obtain evidence to support the results of Agarwal and Naik (2000) who find that US and global fund returns persist at quarterly frequencies. Using robust non-parametric methods, we find that Asian hedge fund returns persist at monthly to quarterly horizons. The strength of the persistence weakens considerably when we lengthen the measurement period beyond a quarter which echoes the findings of Brown, Goetzmann and Ibbotson (1999). Our results are robust to the adjustment for fund fees, and are unlikely the result of systematic risk, at least as measured by a simple 4-factor market model which captures 45% of the time-series variation in fund portfolio returns.

On Asian fund styles, we find that Asian funds co-move largely with a common Asian equity market component. This component explains most of the Long/Short Asian fund styles regardless of which Asian investment region (e.g. Korea, Japan, Asia excluding Japan) the fund invests in. Other major identified components include a CTA component, two macro components, and three global components. The seven components in total are able to explain up to 64% of the cross-sectional variation in Asian hedge fund returns.

Finally, we find strong evidence to suggest that Asian hedge fund returns are positively related to fund redemption (lockup) periods. This is mostly likely due to the fact that a longer redemption period allows funds to effect redemptions with lower transactions costs. There is also evidence to support the idea that economies of scale exist in the hedge fund universe. Funds managed by larger holding companies tend to perform better than funds managed by smaller holding companies. On fund expenses, we find no evidence to suggest that hedge funds with higher management or performance fees earn higher returns. This echoes the findings of Carhart (1997), Wermers (2000), and others who find that mutual funds do not make up for their expenses with better stock selection ability.

Much work remains to be done on Asian hedge funds, and on hedge funds in general. Promising avenues for further research include investigating the relationship between fund characteristics and fund returns for the funds which invest globally and/or in the United States, analyzing the return properties of European funds, comparing the risk of Asian hedge funds with that of the other hedge funds in the popular TASS and MAR databases, and examining the attributes of funds of hedge funds.

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VI. Appendix: Size category definitions

Size category	Size (in millions of USD)
1	0-25
2	25-100
3	100-250
4	250-500
5	500-750
6	750-1000
7	1000-2500
8	2500-5000
9	5000-10000
10	10000+

Figure 1: Returns of top 5 and bottom 5 funds in the asian hedge fund database. The sample period is from January 1999 to March 2003. Funds are ranked according to their average monthly return over the sample period. The cumulative monthly returns for the top 5 funds (solid lines) and the bottom 5 funds (dotted lines) are plotted.

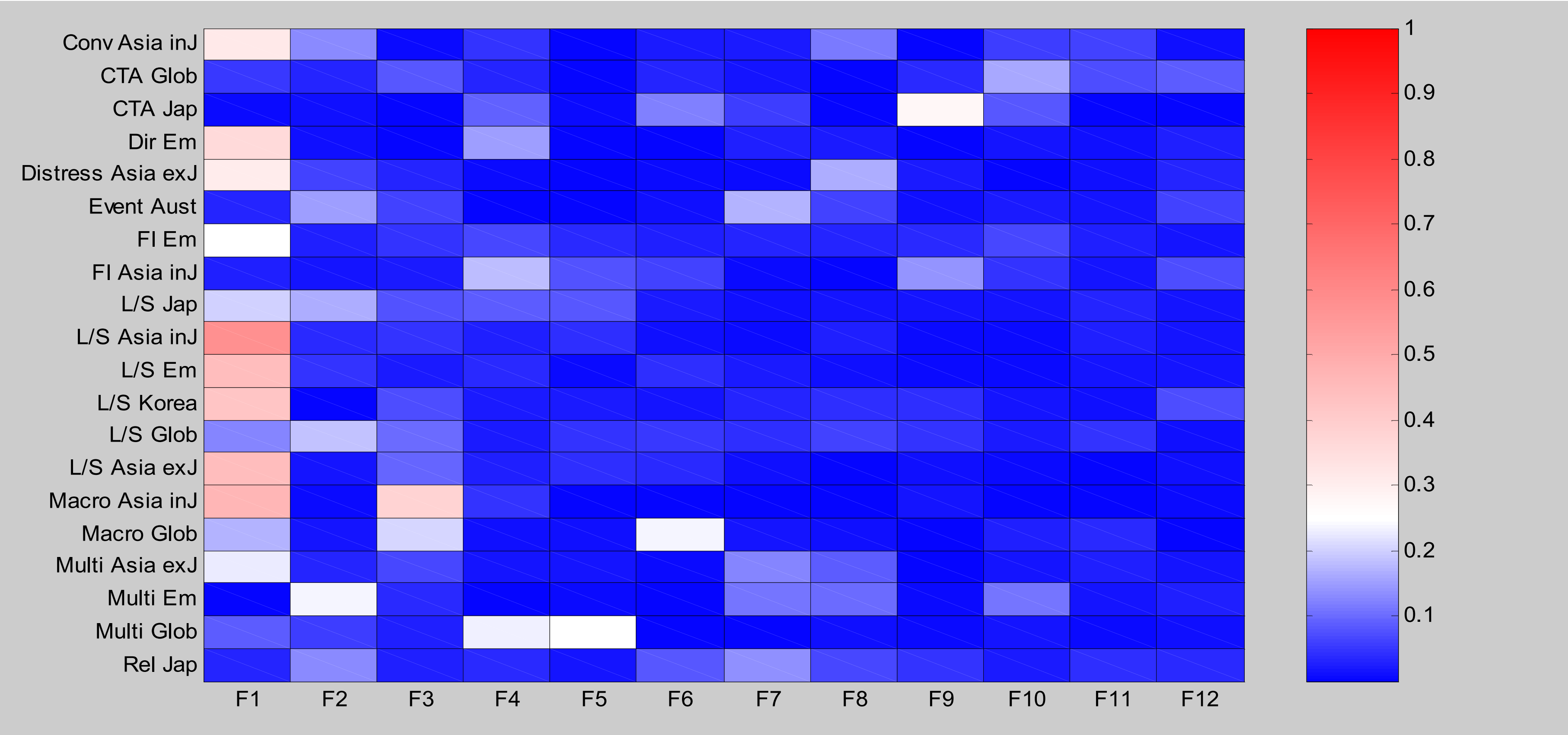

Figure 2. Average R square between principal components and hedge fund styles. The sample period is from January 1999 to March 2003. Principal components analysis is used to break the returns of the funds in the sample into orthogonal principal components. Funds are then regressed with each principal component individually component by component. Then the average R squared for each style / geographical region combination for the 12 principal components with the largest eigenvalues are displayed in the heatmap above. F1 is the principal component with the largest eigenvalue while F12 is the principal component with the 12th largest eigenvalue. The style classifications are Convertible Arbitrage (Conv), Commodities Trading Advisors (CTA), Directional (Dir), Distressed Debt (Distressed), Event Driven (Event), Fixed Income (FI), Long/Short Equities (L/S), Macro, Multi Strategy (Multi), and Relative Value (Rel). The geographical regions are Asia including Japan (Asia inJ), Global (Glob), Japan Only (Jap), Emerging Asia (Em), Asia excluding Japan (Asia exJ), Australia/New Zealand (Aust), and Korea.

Table I

EurekaHedge and AsiaHedge Combined Sample Description

The sample period is from January 1996 to March 2003. Funds are grouped according to their primary investment strategy (Panel A) or to their primary investment geographical region (Panel B). Funds without investment strategy or investment geographical region information are classfied as "unknown." The total number of funds is 417. The total number of dead funds is 27. And the total number of fund months with returns information from January 1999 to March 2003 is 3810. Some categories do not have fund return months as some funds do not have return information in either data bases.

Panel A

Investment Strategy	Total Funds	Dead Funds	Number of fund months with returns (Jan 1999 - Mar 2003)
Arbitrage	1	0	0
Convertible Arbitrage	10	1	51
Commodity Trading Advisors	14	1	153
Directional	1	0	51
Distressed Debt	9	0	51
Event Driven	6	1	51
Fixed Income	16	0	255
Long/Short Equities	260	21	2345
Macro	22	1	153
Multi-Strategy	37	0	204
Relative Value	24	0	292
Other	3	0	51
Unknown	14	4	153

Panel B

Geographical region	Total Funds	Dead Funds	Number of fund months with returns (Jan 1999 - Mar 2003)
Asia excluding Japan	55	2	459
Asia including Japan	75	8	910
Australia/New Zealand	30	1	51
Emerging Asia	34	0	866
Global	70	5	510
Japan only	125	12	912
Korea	7	0	102
Greater China	3	0	0
Taiwan	2	0	0
Unknown	16	4	0

Table II

Two period non-parametric cross-product ratio tests of return persistence

The sample period is from January 1999 to March 2003. For each formation/holding period, the sample is split into overlapping (to maximize power) periods of the required frequency. WW denotes funds that are winners in two consecutive periods; LL denotes funds that are losers in two consecutive periods; WL denotes funds that are winners in the first period and losers in the second period; and LW denotes the reverse. Each panel displays the number of occurrences of WW, WL, LW, and LL over the sample period, the chi-square statistic, and the cross-product ratio (CPR). The statistical significance of the CPR is tested with a Z-statistic, which measures the ratio of the natural log of CPR to its standard error. The chi-squared statistic is calculated as per Section 3. Panel A displays the persistence test results on post fee hedge fund returns, while Panel B displays the peristence test results pre fee hedge fund returns.

Panel A: Post fee returns

formation /holding period	WW	WL	LW	LL	CPR	Z-statistic of CPR	chi square statistic
1 months	2390	1885	1888	2445	1.642	11.414^^	130.947**
2 months	2262	1723	1725	2256	1.7169	11.951^^	143.722**
3 months	2066	1637	1634	2069	1.598	10.016^^	100.796**
6 months	1567	1352	1348	1575	1.3542	5.777^^	33.440**
9 months	1175	1074	1072	1176	1.2002	3.056^^	9.345**
12 months	854	820	821	852	1.0808	1.124	1.262

Panel B: Pre fee returns

formation /holding period	WW	WL	LW	LL	CPR	Z-statistic of CPR	chi square statistic
1 months	2438	1849	1849	2472	1.7628	13.018^^	170.616**
2 months	2317	1666	1671	2316	1.9276	14.452^^	210.743**
3 months	2138	1566	1569	2137	1.8595	13.190^^	175.385**
6 months	1662	1265	1258	1661	1.7347	10.430^^	109.479**
9 months	1223	1028	1024	1227	1.4255	5.924^^	35.185**
12 months	880	795	799	874	1.2108	2.764^^	7.646**

** Significant at the 1% level (chi-square critical value=6.63)

^^ Signifcant at the 1% level (Z-statistic critical value=2.58)

Table III
Multi-period Kolmogorov-Smirnov Normality Tests of Return Persistence

The sample period is January 1999 to March 2003. The Kolmogorov-Smirnov test is used to compare the observed frequency of wins and losses with that from a normal distribution. Observed frequencies of up to 30 consecutive wins and losses are recorded. This frequency distribution is compared with that generated from a normal distribution and the maximum difference in cumulative densities between the observed and the normal distribution is used to construct the Kolmogorov-Smirnov statistic.

Panel A: Post fee returns

formation/	Kolmogorov-Smirnov statistic	
holding period	**wins**	**losses**
1 months	3.5570**	3.2827**
2 months	3.3553**	3.1236**
3 months	2.6701**	2.3894**
6 months	1.3084*	1.1987
9 months	1.5091**	0.5011
12 months	0.66	0.5575

Panel B: Pre fee returns

formation/	Kolmogorov-Smirnov statistic	
holding period	**wins**	**losses**
1 months	4.3885**	3.8641**
2 months	4.4674**	3.865**
3 months	4.0074**	3.0014**
6 months	2.4605**	2.47**
9 months	1.4322*	1.0477
12 months	1.0445	1.0702

** distribution of wins/losses significantly different from the normal distribution at 5% level
* distribution of wins/losses significantly different from the normal distribution at 10% level

Table IV

Sorts On Past Performance

The sample period is from January 1999 to December 2002. Every month we form equal-weighted portfolios of funds based on their returns in the past month. The return series generated is regressed on the Asia ex Japan stock index (ASIA_EXJ), the Japan stock index (JAPAN), a proxy for the asian bond index (ASIA_BD), the US market factor (US_MKT), and the Fama and French (1993) factors for size (SMB), book-to-market (HML), and momentum (UMD). Alpha is the Jensen alpha from the multi-factor regression. The mean monthly return in excess of the risk free rate is also recorded.

Panel A: Post-fee returns

	Mean monthly excess returns	Std deviation	7-factor model								
			Alpha	ASIA_EXJ	JAPAN	ASIA_BD	US_MKT	SMB	HML	UMD	Adj R^2
decile1	0.87	5.64	0.11	0.51	0.04	-2.36	-0.02	-0.13	0.13	0.09	0.351
(lowest return)			(0.15)	(2.97)	(0.33)	(-2.54)	(-0.08)	(-0.85)	(0.66)	(0.99)	
decile2	0.14	3.02	0.45	0.11	0.08	0.56	0.21	0.04	0.03	0.01	0.326
			(1.09)	(1.13)	(1.3)	(1.1)	(1.61)	(0.54)	(0.28)	(0.17)	
decile3	0.17	2.55	0.11	0.25	0.07	-0.18	-0.03	0.02	0.01	0.05	0.469
			(0.36)	(3.55)	(1.45)	(-0.47)	(-0.28)	(0.25)	(0.15)	(1.44)	
decile4	0.50	2.24	0.42	0.18	0.04	-0.11	0.07	0.04	0.09	0.03	0.341
			(1.38)	(2.63)	(0.83)	(-0.28)	(0.69)	(0.69)	(1.13)	(0.99)	
decile5	0.41	2.36	0.39	0.18	0.04	0.18	0.10	0.10	0.07	0.08	0.501
			(1.39)	(2.92)	(0.83)	(0.54)	(1.18)	(1.82)	(1)	(2.51)	
decile6	0.87	2.86	0.86	0.25	0.10	0.08	0.04	0.04	0.08	0.04	0.457
			(2.46)	(3.09)	(1.94)	(0.18)	(0.36)	(0.62)	(0.92)	(0.94)	
decile7	1.32	2.64	1.32	0.22	0.06	0.03	0.10	-0.01	0.05	0.06	0.498
			(4.23)	(3.1)	(1.3)	(0.08)	(1.03)	(-0.16)	(0.64)	(1.77)	
decile8	1.47	3.73	1.25	0.42	-0.01	-0.27	-0.03	0.04	-0.01	0.15	0.538
			(2.96)	(4.43)	(-0.15)	(-0.51)	(-0.22)	(0.49)	(-0.09)	(3.08)	
decile9	2.18	3.96	2.01	0.47	0.05	-0.38	-0.11	0.12	0.09	0.00	0.533
			(4.46)	(4.57)	(0.75)	(-0.69)	(-0.78)	(1.38)	(0.78)	(0.02)	
decile10	2.88	5.35	2.76	0.49	0.11	-0.45	0.01	0.10	-0.03	0.17	0.549
(highest return)			(4.61)	(3.6)	(1.17)	(-0.62)	(0.07)	(0.84)	(-0.19)	(2.4)	
spread	2.01	6.18	2.65	-0.02	0.07	1.91	0.03	0.23	-0.16	0.08	-0.005
(decile 10-1)			(2.57)	(-0.09)	(0.43)	(1.5)	(0.1)	(1.11)	(-0.6)	(0.67)	

Table IV (continued)

Panel B: Pre-fee returns

	Mean monthly excess returns	Std deviation	7-factor model Alpha	ASIA_EXJ	JAPAN	ASIA_BD	US_MKT	SMB	HML	UMD	Adj R^2
decile1	0.70	4.41	0.26	0.29	0.02	-1.46	0.21	-0.10	0.15	0.07	0.349
(lowest return)			(0.45)	(2.13)	(0.2)	(-1.99)	(1.13)	(-0.86)	(1.01)	(0.95)	
decile2	0.49	3.53	0.70	0.23	0.09	0.12	0.06	-0.01	-0.06	0.02	0.357
			(1.49)	(2.17)	(1.23)	(0.2)	(0.4)	(-0.14)	(-0.46)	(0.39)	
decile3	0.47	2.96	0.32	0.31	0.09	-0.31	-0.08	0.03	0.04	0.06	0.484
			(0.91)	(3.91)	(1.7)	(-0.71)	(-0.69)	(0.5)	(0.45)	(1.37)	
decile4	0.66	2.18	0.59	0.17	0.03	-0.17	0.03	0.01	0.06	0.01	0.252
			(1.88)	(2.4)	(0.69)	(-0.43)	(0.34)	(0.23)	(0.76)	(0.4)	
decile5	0.87	2.99	0.87	0.23	0.05	0.35	0.13	0.10	0.06	0.13	0.544
			(2.59)	(3.02)	(0.95)	(0.84)	(1.29)	(1.5)	(0.68)	(3.38)	
decile6	1.04	2.43	0.94	0.26	0.07	-0.29	-0.03	0.01	0.05	0.02	0.495
			(3.28)	(3.99)	(1.53)	(-0.81)	(-0.38)	(0.24)	(0.71)	(0.59)	
decile7	1.43	3.22	1.44	0.30	0.09	0.24	0.05	0.01	0.08	0.05	0.434
			(3.57)	(3.23)	(1.43)	(0.48)	(0.38)	(0.13)	(0.81)	(0.99)	
decile8	2.09	4.07	1.83	0.47	0.00	-0.30	-0.05	0.08	0.02	0.15	0.531
			(3.94)	(4.45)	(0.01)	(-0.52)	(-0.35)	(0.85)	(0.15)	(2.88)	
decile9	2.85	4.19	2.74	0.48	0.09	-0.39	-0.10	0.05	0.02	0.04	0.565
			(5.96)	(4.59)	(1.24)	(-0.69)	(-0.69)	(0.57)	(0.17)	(0.78)	
decile10	3.62	5.44	3.53	0.50	0.15	-0.33	-0.04	0.13	-0.01	0.14	0.534
(highest return)			(5.7)	(3.55)	(1.54)	(-0.44)	(-0.19)	(1.06)	(-0.06)	(2.03)	
spread	2.93	6.12	3.26	0.21	0.13	1.12	-0.24	0.23	-0.16	0.08	0.085
(decile 10-1)			(3.35)	(0.96)	(0.86)	(0.94)	(-0.8)	(1.2)	(-0.65)	(0.71)	

Table V

Eigenvalues of Principal Components from Asian Hedge Fund Database

The sample period is from January 1999 to March 2003. Principal components analysis is used to break the returns of the funds in the sample into orthogonal principal components. There are 42 principal components with non-zero eigenvalues. The eigenvalues of the principal components with eigenvalues greater than one are displayed. The proportion of cross-sectional variance explained by each principal component is also shown.

Principal component	Eigenvalue	Proportion of variance explained	Cumulative proportion
F1	24.438	0.326	0.326
F2	5.645	0.075	0.401
F3	5.098	0.068	0.469
F4	3.852	0.051	0.520
F5	3.748	0.050	0.570
F6	3.046	0.041	0.611
F7	2.585	0.035	0.646
F8	2.267	0.030	0.676
F9	2.152	0.029	0.704
F10	2.045	0.027	0.732
F11	1.883	0.025	0.757
F12	1.706	0.023	0.780
F13	1.590	0.021	0.801
F14	1.382	0.018	0.819
F15	1.233	0.016	0.836
F16	1.210	0.016	0.852
F17	1.153	0.015	0.867
F18	1.003	0.013	0.881

Table VI

Fama MacBeth Cross-sectional Regressions With Fund Characteristics

Cross-sectional univariate and multivariate regressions are estimated for each month from January 1999 to March 2003 across all funds in the sample at that time. The dependent variable is the monthly fund return. The independent variables are fund characteristics such as management fee, performance fee, minimum investment, redemption period, fund size category, holding firm size category, and fund age. Minimum investment is in millions of USD. Redemption period is measured in days. Size category (cat) is a number from 1 - 10 that condenses fund size information. It is calculated from size according to the algorithm described in the Appendix. Fund age is measured in months since inception date. The reported estimates are the time-series averages of monthly cross-sectional regression slope estimates as in Fama and MacBeth (1973). The t-statistics, in parentheses, are on the time-series means of the coefficients.

	Dependent variable			
	Univariate regressions		**Multivariate regressions**	
Independent variable	**Post-fee returns**	**Pre-fee returns**	**Post-fee returns**	**Pre-fee returns**
Management fee	-0.111	-0.134	-0.130	-0.081
	(-0.45)	(-0.51)	(-0.56)	(-0.35)
Performance fee	0.008	**0.052****	**-0.047***	-0.037
	(0.367)	**(2.01)**	**(-1.96)**	(-1.51)
Minimum investment	-0.038	-0.019	-0.005	-0.016
	(-0.65)	(-0.31)	(-0.10)	(-0.31)
Redemption period	**0.008****	**0.012****	**0.011****	**0.014****
	(2.04)	**(2.71)**	**(2.39)**	**(2.76)**
Fund size category	**0.110****	0.070	-0.086	-0.117
	(2.32)	(1.51)	(-0.637)	(-0.819)
Holdings firm size category	0.098	**0.118***	**0.172***	**0.206****
	(1.50)	**(1.73)**	**(1.86)**	**(2.11)**
Age	-0.001	-0.0004	0.003	0.002
	(-0.37)	(-0.15)	(0.73)	(0.487)

** Significant at the 5% level

* Significant at the 10% level

Table VII

Correlations Between Fund Characteristics

The correlation between fund characteristics are computed for all funds for which we have the full set of characteristics data. Management fee and performance fee are measured in percentages. Redemption period is in days. Minimum investment is in USD. Size category is calculated from size according to the algorithm described in the Appendix.

	management fee	**performance fee**	**redemption period**	**minimum investment**	**fund size category**	**holding company size category**
management fee	1.000					
performance fee	-0.142*	1.000				
redemption period	0.180**	0.158**	1.000			
minimum investment	0.164	0.113	0.101	1.000		
fund size category	0.243***	-0.002	0.035	0.406***	1.000	
holding company size category	0.063	-0.110	-0.087	0.086	0.411***	1.000

*** Significant at the 1% level

** Significant at the 5% level

* Significant at the 10% level

[1]Wall Street Journal, September 23, 1997.

[2]1 JPY = 0.008 USD; 1 Euro = 1.175 USD; 1AUD = 0.645 USD.

[3]We take the high watermark and hurdle rate as the T-bill and assume that the returns accrue to a first-year investor in the fund.

[4]We use Fama and French's (1993) value-weighted market proxy RMRF as the US market factor.

[5]While some authors like Amin and Kat (2003) posit the existence of options-like factors for US-centric hedge funds, we believe that our multi-factor model provides a tractable first-order approximation of systematic risk of the Asian hedge fund returns portfolios we examine. This is because the derivatives markets in Asia is relatively less developed than those in the US and in Europe. Also, the less-developed nature of Asian markets implies that there are less opportunities to short stocks. The reasonably high adjusted R squared numbers in Table IV help justify our multi-factor model.

[6]We also perform Spearman rank correlation test on the decile rank and the mean excess return / alpha of the portfolios. We find that the Spearman tests reject the null hypothesis that the decile rank and the mean excess return are independent at the 1% level for both pre-fee returns and post-fee returns. These results hold when we test the alphas as well.

[7]We use principal components analysis instead the generalized least squares procedure of Brown and Goetzmann (2003) as our main aim is to explain contemporaneous variation in hedge fund returns.

[8]There may be concerns that since our fund characteristics are measured in 2002 and the returns are taken from Jan 1999 to December 2002, the causality may run from returns to holding company size category instead. The reason for this is that funds with good past

returns tend to grow bigger in light of greater net inflows. However, this effect from returns to size should affect fund size more than holding company size. The coefficient estimates from the multivariate regressions suggest that holding company size has a greater explanatory power than fund size and hence such concerns are likely to be second order.