# Essays on Institutional Investors

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ABSTRACT

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This dissertation analyzes the role of institutional investors in capital markets. The first essay studies what affect mutual fund decisions on hiring and firing sub-advisors and the ex-post effects. We show that deterioration in mutual fund performance or increase in outflows predicts a higher propensity of a fund to change its sub-advisors. However, mutual funds continue to underperform by about 1% in the 18-months after a change in sub-advisor, even after controlling for fund category, past returns and past flows. The continuing underperformance of mutual funds can be attributed to decreasing returns for sub-advisors in deploying their ability as suggested in Berk and Green (2004). The second essay provides empirical analysis on hedge fund exposures to overpriced real estate assets. Consistent with models in which delegated portfolio managers may want to invest in overpriced assets, I find that hedge funds were holding real estate stocks instead of selling short during the period of overpricing (2003Q1-2007Q2). The third essay finds that investor composition affect fund managers' portfolio choices. Specifically, I show that retail-oriented hedge funds invested more in overpriced real estate assets than institution-oriented hedge funds.

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My son, Regis, who has grown into a happy little young man despite that his mother spent so much time away from him working on this dissertation.

My parents, who emphasize the importance of independence and persistence.

# Hiring and Firing Mutual Fund Sub-Advisors*

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Abstract

Using a comprehensive database of mutual funds and monthly sub-advisor information from 2006 to 2012, we document several interesting empirical regularities of mutual funds and their sub-advisors around the event of an active sub-advisor change. First, deterioration in mutual fund performance or increase in outflows predicts a higher propensity of a fund to change its sub-advisors. Second, mutual funds chase past performance of sub-advisors. Third, mutual funds continue to underperform by about 1% in the 18-months after a change in sub-advisor, even after controlling for fund category, past returns and past flows. We show that the continuing underperformance of mutual funds can be attributed to decreasing returns for sub-advisors in deploying their ability as suggested in Berk and Green (2004).

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# I. Introduction

Certain mutual funds outsource their investment management function to an outside firm. These funds are generally known as sub-advised funds and their investment managers are referred as sub-advisors. The market share of sub-advised assets was quite stable over the past decade although mutual fund industry experienced extraordinary growth. In December 2001, sub-advised mutual fund assets (including underlying variable annuities) were $835 billion, representing 11% of assets in mutual fund industry[1]. As of December 2011, sub-advised assets were $1,489 Billion, or about 12% of the industry.

Why do certain mutual funds enter into outsourcing contracts with sub-advisors? Del Guercio, Reuter and Tkac (2007) suggest that these contracts must be beneficial to both parties. They argue that one of the benefits for mutual funds comes from cost efficiencies. When mutual funds want to expand their line of products in which they do not have expertise, the cost could be lower if they hire a sub-advisor who is already in place providing these products. The costs might be also lower for some mutual funds if they have geographic limitations to retain in-house talented portfolio managers. The other benefit is that mutual funds can increase demand for their services if sub-advisors provide high quality products and well recognized brand names. For sub-advisors, an obvious benefit is that

[1] 2012 Sub-advisory Study, Strategic Insight. The numbers are consistent with the report published by the Investment Company Institute http://www.idc.org/pdf/idc_10_subadvisors.pdf.

they get paid by providing sub-advisory services. A less obvious benefit is that mutual funds and sub-advisors may well be non-competitors if they differ in distribution channels. Sub-advisors may get access to a large pool of investors that they previously couldn't.

Despite these theories, there is empirical evidence that suggests the non-optimality of these outsourcing contracts. For instance, Chen, Hong and Kubik (2011) show that outsourced mutual funds underperform funds that ran internally by between 50 and 72 basis points a year. They attribute this phenomenon to contractual externalities due to firm boundaries, i.e., outsourced funds face steeper sensitivity of fund closures to past performance or excess risk taking, thus they take less risk in response.

In this paper, we study mutual funds and their sub-advisors around the event of a sub-advisor change and try to address the following specific questions. First, what affects the hiring and firing decisions of a mutual fund regarding its sub-advisors? Second, how does mutual fund performance change after a sub-advisor change? Third, what causes the change in mutual fund performance?

Answering these questions is important for the following reasons. First, sub-advisors are motivated to expand their businesses given capacity. On one hand, knowing what criteria mutual funds apply to filter sub-advisors is helpful for sub-advisors to expand their size; on the other hand, is it true that the bigger the size of sub-advisors the better?

Second, mutual funds are interested in knowing whether their decisions of hiring and firing sub-advisors are effective. Our study serves this need by providing empirical evidence on the ex-post effect of sub-advisor change on mutual funds and their investors. This would potentially help them making more sound hiring and firing decisions regarding sub-advisors.

Third, investors have been questioning who deliver mutual fund performance. They tend to attribute most of fund performance to portfolio managers rather than funds. Benefited from the fact that managers and funds are separated by construction in our paper, we are able to evaluate whether mutual funds add value by removing bad managers and picking better ones.

We hypothesize that in addition to past performance, there is also an inverse relation between mutual fund past flows and the propensity of changing a sub-advisor. We also hypothesize that there are decreasing returns for sub-advisors in deploying their ability, which causes the continuing underperformance of mutual funds who change sub-advisors.

This paper contributes to the literature as follows. First, flow-performance sensitivity has gained much attention in the literature. Different from previous literature that mainly study the impact of flows from retail investors on investment managers such as hedge funds and mutual funds, we analyze this question from a different and quite new angle, i.e., the impact of flows from institutional investors (mutual funds) on the performance of sub-advisors. We find that consistent with Berk and Green (2004), mutual funds chase sub-advisor performance and make rational use of information about sub-advisors' histories in doing so. To the best of our knowledge, our paper is the first to test Berk and Green (2004) using institutional flows. Second, our paper shows that there are decreasing returns to scale for sub-advisors, which explains the non-persistent performances in sub-advisors and mutual funds. Third, our analysis also distinguishes from the existing literature that focuses on the relationship of sub-advisor departure and mutual fund performance and flow (e.g., Kostovetsky and Warner (2011)).

## II. Background

A mutual fund, as defined in Tufano and Sevick (1997), is a legal entity with no employees to which investors allocate their portfolio decision rights. The fund, in turn, delegates all aspects of fund operation, including portfolio management, to an advisor. While it is true that the fund notionally "hires" the advisor, in practice it is the advisor who typically creates the fund in the first place. While the advisor may keep the portfolio decision rights to itself, it may also choose to allocate portfolio decision rights to an independent third party (i.e., sub-advisor).

In a typical outsourcing agreement, a mutual fund usually retains the marketing and distribution fees while the sub-advisor obtains the management fees. Chen, Hong and Kubik (2006) document that "Like for any of its funds, the family of an outsourced fund, through a board of directors, keeps track of its performance and monitors fund activities such as the fund's risk-taking behavior relative to its peers. The advisor retains the ability to replace the sub-advisor or close down the fund, while the sub-advisor can manage outsourced funds for other advisors as well as funds they market themselves (in-house funds)." Big names of mutual fund companies include Vanguard, John Hancock, Fidelity, etc.; and large sub-advisors include Wellington, Pimco, AllianceBernstein, etc.

Generally, investment companies ("funds") are required to file Form 497 (definitive materials) to the U.S. Securities and Exchange Commission (SEC) and report the names of their sub-advisors as well as sub-advisor changes, in accordance with Rule 497 of the Securities Exchange Act of 1933. However, according to Rule 15a-5 under the Investment Company Act of 1940, an investment company is permitted to hire and discharge sub-advisors without a shareholder vote in most cases. As a result, mutual fund investors are usually not aware of the existence of a sub-advisor or its change[2].

The departure of a sub-advisor is usually involuntary and often due to underperformance. Friction cost for mutual funds in moving portfolio may take 2%-5% of TNA (Proszek (2002), Bollen (2004) and Werner (2001)). As a result, in performance-based termination, funds would only be willing to incur the costs if their performances are expected to improve. For instance, in a recent filing to the SEC, AdvisorShares, an investment advisor announced a change in the sub-advisor for the Mars Hill Global Relative Value ETF. Noah Hamman, the CEO of AdvisorShares commented the following: "This change will bring an expert in global asset management to a product that has fallen short in performance relative to its peers. After reviewing the performance with the current sub-advisor, it was concluded that a change was in the best interest of shareholders."[3]

While performance is an important factor in determining a sub-advisor change, hiring and firing a sub-advisor usually involves both quantitative and qualitative

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[2] We show that investors are unaware of sub-advisor changes in Table 6 of this paper.

[3] For more detail, please refer to:
http://www.benzinga.com/pressreleases/11/11/n2141826/advisorshares-announces-change-in-sub-advisor-to-the-mars-hill-global-r

factors. According to a report by Strategic Insight[4], quantitative factors include: performance, tracking record; qualitative factors include: investment process, knowledge and skills, history, the assets of the firm overall, and within the strategy that needs to be outsourced, whether the firms are already near capacity for particular investment categories, how different managers work together, if the fund is multi-subadvised, prior experience with the fund, brand, reciprocal distribution, marketing and sales support, etc.

# III. Data

## A. Data Collection Process

We acquire a proprietary dataset from Strategic Insight, which includes monthly sub-advisor information for U.S. mutual funds from December 2006 to September 2012. The dataset covers 3622 unique mutual funds that are ever sub-advised during this period and 1112 unique sub-advisors. Since dead funds are not removed from the records after liquidation, our proprietary dataset is free of survivorship bias. Specifically, the dataset includes for each mutual fund in each month end, its sub-advisor names and their respective mandate assets with the fund. The dataset also includes a tag which indicates whether a sub-advisor is affiliated with the fund on a monthly basis (by affiliation we mean that the fund

[4] "Windows Into the Mutual Fund Industry: February 2006", Strategic Insight. http://www.sionline.com/Security/login.aspx?ReturnUrl=%2fresearch%2fsubscriber_windows%2f520.pdf

owns the sub-advisor or the fund and the sub-advisor have a common owner). This dataset allows us to identify 1871 active sub-advisor changes involving 1219 unique mutual funds and 842 unique sub-advisors during the period. Note that active sub-advisor changes refer to the situations when a fund fires, hires, or hires and fires at least one sub-advisor and excludes passive changes including liquidation, merger and new funds.

The proprietary dataset is then supplemented with monthly mutual fund information obtained from the Center for Research in Security Prices (CRSP), available through WRDS. CRSP provides mutual fund information at the share class level[5]. Given that our analysis is at the fund level, we aggregate share classes into a mutual fund by their CRSP Portfolio Number. Then, fund size is calculated as the sum of assets under management of all its share classes. We define fund age as the number of years since the inception of the most tenured share class within that fund. Fund return is calculated as the value weighted return of all its share classes.

We manually match the funds from our proprietary dataset with CRSP Mutual Funds database by name. We are able to match 3,214 mutual funds. However, there are 408 mutual funds that exist in our proprietary dataset but are not covered by CRSP Mutual Funds database. The main reason is that CRSP does not cover

[5] The labels are slightly different in CRSP. In CRSP, share class is labeled as fund and mutual fund is labeled as portfolio.

closed-end funds, such as Aberdeen Emerging Markets Telecommunications and Infrastructure Fund (live since 1992) and 40/86 Series Balanced (dead fund). The other reason is that although we can find a match in these two datasets, all other relevant information over the fund's history is missing on CRSP. An example is AZL AIM Basic Value Fund. We exclude such funds. Conversations with CRSP representatives suggest that such missing records seem to be random. In all, we believe our merged database remains free of survivorship bias.

The most salient feature of the combined dataset is that it allows us to analyze sub-advisor level performance change, rather than limited to fund level. Specifically, since we observe monthly mandate assets for each pair of fund and sub-advisor, we are able to estimate monthly performance of a sub-advisor as the value weighted average of performance of mutual funds that it sub-advises. Here we assume that fund performance gives a proper estimation on how each sub-advisor is doing with the fund. This assumption definitely holds for single-subadvised funds and their sub-advisors. But for multi-subadvised funds, our assumption may cloud the analysis if there is a remarkable difference in sub-advisor performances in the same fund and such difference is systematic. To address this issue, we further test our hypothesis by using the sample of sub-advisors served as the single mandate for a fund and compare the results with that of full sample.

Certainly, readers may raise two additional concerns about our estimation. First, some sub-advisors may well have in-house businesses and our estimation of these sub-advisor performances does not reflect their non-subadvisory businesses. This is not a problem because we are interested in knowing the sensitivity of sub-advisor performance to fund inflows and withdrawals. It is exactly the sub-advisory business that we want to evaluate. Second, what about a sub-advisor that serves funds with different styles (e.g., large growth and small blend) at the same time? Given that one of our measurements for mutual fund performance is its excess return relative to its Lipper Category, the performance of such sub-advisor will then be compared to a hypothetical sub-advisor who has the same portfolio allocation and delivers "average" returns.

A point worth noting is the definition of "date zero" (sub-advisor change date) used in this paper. For this, we provide a timeline of sub-advisor change in Figure 1. Throughout the paper, "date zero" is the effective date of sub-advisor change on file, or more accurately, the month end of effective date since we conduct all the analyses on a monthly basis. It is true that a decision date (on which a firing decision is made) or a "considering" date is more relevant, if the question is "how past poor performance is causing a firing decision". However, this date is unobservable. We may assume that in common cases, this date is about two months before the effective date. The effective date is more relevant, if the question is “how institutional flows are affecting sub-advisor performance”. This is because asset transition usually takes place around the effective date.

### B. Overview of Data

The definitions and summary statistics of the main variables are reported in Table 1. The average age of mutual fund in our sample is 7.8 years. The average fund sub-advisor change (expected probability of mutual fund sub-advisor change) is 1.06%. Following the standard practice in mutual fund literature, we measure the monthly mutual fund flow as the current month net flow of a fund as percentage of last month’s total net assets managed by the fund. The monthly average flow of mutual funds during the 6 months prior to a sub-advisor change is 1.01% and the median number is -0.23%. The average monthly mutual fund return in excess of its Lipper category 6 months prior to a sub-advisor change is -0.03% and the median number is -0.01%. The size of mutual funds in our sample is positively skewed: the average number is $932.7 million and the median number is $189.4 million.

Table 2 provides an overview of sub-advisor changes. Panel A shows that the merged dataset includes 1812 changes in sub-advisor from December 2006 to September 2012, among which 1534 are active. The total assets of sub-advisor changes exceed $1232 billion, among which $1129 billion are associated with active changes. Since passive changes are irrelevant for the purpose of our analysis, we will focus on active changes only in the rest of the paper.

Panel B of Table 2 presents the number of active sub-advisor changes in each year-performance category as a percentage of the number of sub-advised funds in that category. For instance, among sub-advised funds with negative past one year excess return relative to category in 2007, the number of active changes accounts for 13.7%. Notice that the numbers in 2006 and 2012 are much smaller than other years, because for 2006 we only have observations in December, and for 2012, we only have data from January to September.

Two patterns are noteworthy. First, the numbers in the left column are larger than the numbers in the right column. This suggests that funds with one-year poor performance (relative to category) tend to have more sub-advisor changes in the subsequent year. Second, the numbers in the right column are more or less stable while the numbers in the left column are not; indicating that besides underperformance, other reasons could also explain sub-advisor changes.

Panel C of Table 2 compares the composition of funds that have active sub-advisor changes and funds that are sub-advised. We classify funds by their structure, sub-advisor change type and size respectively. For instance, among funds that have active sub-advisor changes, 75.3% (24.7%) are multi-managed (single-managed) funds, while among funds that are sub-advised, 70.3% (29.7%)

are multi-managed (single-managed). An important message from this panel is that funds that have active sub-advisor changes are not biased towards a particular type of sub-advised funds.

## IV. Hypotheses

**Hypothesis 1**: *There is an inverse relation between fund past performance and the propensity of a mutual fund changing its sub-advisor, controlling for past flows. The inverse relationship should also hold between fund past outflows and the propensity of a mutual fund changing its sub-advisor, controlling for past performance.*

Our hypothesis is in the spirit of Khorana (1996), who documents that the probability of managerial change and the past performance of the fund is negatively correlated given internal and external monitoring. Intuitively, this relationship is due to the monitoring effects of board of directors. Fund outflows could be another factor for board of directors to monitor. Thus, when mutual fund performance is worsening, or when mutual funds experience more outflows, the probability that the board of directors changes mutual fund sub-advisors should increase.

**Hypothesis 2**: *There are decreasing returns for sub-advisors in deploying their superior ability.*

This hypothesis follows the seminal paper of Berk and Green (2004), which suggests that "there is differential ability to generate high average returns across managers, but due to decreasing returns for managers in deploying their superior ability, new money flows to the fund to the point at which expected excess returns going forward are competitive (page 1271)". Since mutual funds make their hiring and firing decisions based on sub-advisor past information, inefficiency may arise when the size of a sub-advisor exceeds it optimal level.

We develop three implications based on this hypothesis:

1. A Sub-advisor newly hired by a mutual fund (presumably because it performed relatively well before the hiring) gets more assets and delivers less attractive returns afterwards.

2. A Sub-advisor newly fired by a mutual fund (presumably because it performed relatively poor before the firing) gets less assets and delivers better returns afterwards.

3. A mutual fund with a sub-advisor change continues to underperform its peers.

# V. Empirical Evidence

## A. Hypothesis 1: the effect of performance and flows

### A.1. Overview

Our first hypothesis is that, when there is deterioration in fund performance or a decrease in fund flows, the probability of changing mutual fund sub-advisor increases, due to the monitoring effects of mutual fund board of directors. The hypothesis implies that as fund performance or fund flow decreases, the percentage of funds that have sub-advisor changes should increase accordingly.

In this section, we show that the percentage of funds with sub-advisor change decreases in mutual fund performance and fund flows. We start by calculating past 12 month excess return relative to category (*RetExCat[-12,-1]*) and past 12 month flow (*Flow[-12,-1]*) for each fund in each month during the sample period. Then we sort them into five quintiles respectively, with 1 being the bottom quintile and 5 being the top quintile. For each pair of return and flow quintile, we calculate the number of funds that have sub-advisor changes as a percentage of the total number of funds in each month. Table 3 presents the percentage of mutual funds with sub-advisor change averaged across all the months for each pair of return and flow quintile. The 5-1 differences in the numbers are tested and presented in the table as well.

Table 3 shows that when past 12 month flow quintile of mutual funds is controlled, the percentage of mutual funds changing sub-advisors decreases as past 12 month return quintile increases. For instance, for mutual funds in the bottom flow quintile (funds that experience most outflows), 1.66% have sub-advisor changes if they are in the bottom performance quintile and only 0.86% have sub-advisor changes if they are in the top performance quintile. The 5-1 differences are significant at less than 5% level for all flow quintiles. When past 12 month return quintile is controlled, the percentage of mutual funds with sub-advisor changes decreases in flow quintile. But the 5-1 differences are only significant when returns are in the 1$^{st}$, 2$^{nd}$ and 4$^{th}$ quintiles. The evidence suggests that when mutual fund past performance is mediocre or very good compared to its category, the likelihood of a fund changing its sub-advisor does not seem to vary much with whether the fund experience inflows or outflows.

### A.2. Semiparametric Analysis

In this subsection, we show that the relation between the probability of changing a sub-advisor and fund past performance is somewhat linear. We use a semiparametric approach, in which the relation between the probability of a sub-advisor change and performance is not restricted to be linear, to provide a diagnostic analysis of the change-to-performance sensitivity. This analysis is important as the relation between change and performance might be nonlinear, similar to the widely documented nonlinearity in flow-performance sensitivity.

Figure 2 shows the results of the semiparametric analysis. In the figure, the vertical axis is the probability of a mutual fund changing a sub-advisor in month *t* ($P(Change_{i,t} = 1)$) and the horizontal axis is the fund's past return performance, measured by the monthly excess return relative to benchmark averaged over months $t$-6 to $t$-1 ($RetExCat_{\mathrm{i,[t-6,t-1]}}$).

Figure 2 plots the change-to-performance sensitivity as estimated by the following equations:

$$P\left(Change_{i,t} = 1|X_{i,t}\right) = \frac{\exp\{f(X_{i,t})\}}{1 + \exp\{f(X_{i,t})\}} \qquad (1)$$

$$f\left(X_{i,t}\right) = f(RetExCat_{i,[t-6,t-1]}) + \beta Control_{i,t} + \varepsilon_{i,t} \qquad (2)$$

Note that in Equation (2) we have a semiparametric specification and *Control* is a vector of control variables that include fund size (*Size*, in log million dollars), fund age (*Age*, years since inception, in logs) and past flows ($Flow_{\mathrm{i,[t-k,t-k-5]}}$). The estimation of Equation (2) applies the method introduced by Robinson (1988) and used by Chevalier and Ellison (1997), Chen, Goldstein and Jiang (2010) in the study of flow-performance sensitivity.

The solid line in Figure 2 represents the plot of $P(Change_{i,t} = 1|X_{i,t})$ and the corresponding dotted lines represent the 90% confidence intervals. Figure 2 shows that there is a quite good linear relationship between the probability of changing a sub-advisor and past performance. Meanwhile, even for funds that outperform their peers by 2% per month, the probability of changing a sub-advisor is somewhere between 0.60% and 0.72%, indicating that (under)performance is not the only factor that affects sub-advisor change. In the next subsection, we move to a regression analysis that allows us to conduct proper tests of statistical significance.

### A.3. Regression Analysis

#### A.3.1. Effect of Performance

For a summary estimate of the effect of mutual fund past performance on changes in sub-advisors, we conduct the following probit regression at the fund-month level and report the results in Table 4:

$$\begin{aligned}\Pr(\mathrm{Change}_{i,t}) = \alpha + \beta \sum_{k} \mathrm{RetExCat}_{i,[t-k-5,t-k]} + \gamma \sum_{k} \mathrm{Poor}_{i,[t-k-5,t-k]} \\ + \delta \sum_{k} (\mathrm{RetExCat}_{i,[t-k-5,t-k]} \cdot \mathrm{Poor}_{i,[t-k-5,t-k]}) + \mathrm{Control}_{i,t} + \varepsilon_{i,t}\end{aligned} \tag{3}$$

In Equation (3), *Change* equals one if there is a sub-advisor change in mutual fund, and zero otherwise. $RetExCat_{i,[t1,t2]}$ is the monthly average excess return relative to category of the mutual fund during $[t1, t2]$ period. $Poor_{i,[t1,t2]}$ equals one if $RetExCat_{i,[t1,t2]}$ is negative and zero otherwise. The coefficient of $Poor_{i,[t1,t2]}$ captures the difference in the probability of changing a sub-advisor, when mutual fund past performance changes from slightly positive to slightly negative. The interaction term of $RetExCat_{i,[t1,t2]}$ and $Poor_{i,[t1,t2]}$ enters the model to test whether poorly performed funds have a different sensitivity of sub-advisor change to performance. Control variables (*Control*) include fund past flows (*Flow[t-k-5,t-k]*), an indicator of whether past flows are negative (*Out[t-k-5,t-k]*), the interaction of the two, as well as size of the fund in log million dollars (*Size*) and fund age in log years (*Age*). We also include time dummies in the regression to control for the variation over time in sub-advisor changes. Hence, if there is a special time that mutual funds tend to change their sub-advisors together, it will be captured by the time dummies. To compute the standard errors, we assume that the residuals are independent across different funds, but allow for correlation over time within a fund.

The evidence confirms our hypothesis: there is an inverse relation between fund performance in the past 2 years and the probability of changing a sub-advisor. Moreover, the sensitivity of sub-advisor change to performance exhibits quite good linearity, i.e., the change-to-performance sensitivities are quite similar in the positive performance region (*RetExCat*>0) and negative performance region (*RetExCat*<0).

Given that we estimate the effect in a probit regression, one needs to calculate the marginal effect of an explanatory variable on Pr(Y=1). For instance, to measure how one standard deviation decrease in *RetExCat[-6,-1]* (excess return during the previous 6 months) from its mean affects the likelihood of sub-advisor change, we can first compute $\Pr(Y=1)=\Phi(X\beta)$ with all independent variables evaluated at their means. Then we re-compute $\Pr(Y=1)=\Phi(X^{*}\beta)$, with *RetExCat[-6,-1]* evaluated at its mean minus standard deviation, and all other variables evaluated at their means. The difference in the two probabilities is the impact of a standard deviation decrease in *RetExCat[-6,-1]* from its mean when all other independent variables are held at their means.

The regression coefficients imply that, when *RetExCat[-6,-1]* decreases by one standard deviation from its mean of -0.03% to -0.81%, the probability of triggering a sub-advisor change increases by 33% (from 0.98% to 1.30%). This result is consistent with the evidence in Table 3.

Another interesting finding is the effect of fund size (*Size*) on the probability of changing a sub-advisor. Presumably, fund size could have effects that offset each other on the probability of sub-advisor change: on one hand, a large fund might be more structured and maintains a long-term relationship with its sub-advisor; therefore, it is less likely to change its sub-advisor. On the other hand, a large fund might be more aggressive in sub-advisor changes because it has more resources.

The regression estimate suggests that, when fund size increases one standard deviation from its mean, the probability of changing a sub-advisor increases by 13% (from 1.05% to 1.19%) and is significant. The result indicates that generally speaking, a large fund tends to be more aggressive in changing a sub-advisor.

### A.3.2. Effect of Flows

Following the previous section, we controll for fund past performances and estimate of the effect of mutual fund past flows on changes in sub-advisors. We use the following probit regression at the fund -month level and report the results in Table 5:

$$\begin{aligned} \mathrm{Pr}(\mathrm{Change}_{\mathrm{i,t}}) &= \alpha + \beta \sum_{\mathrm{k}} \mathrm{Flow}_{\mathrm{i,[t-k-5,t-k]}} + \gamma \sum_{\mathrm{k}} \mathrm{Out}_{\mathrm{i,[t-k-5,t-k]}} \\ &+ \delta \sum_{\mathrm{k}} (\mathrm{Flow}_{\mathrm{i,[t-k-5,t-k]}} \cdot \mathrm{Out}_{\mathrm{i,[t-k-5,t-k]}}) + \mathrm{Control}_{\mathrm{i,t}} + \varepsilon_{i,\mathrm{t}} \end{aligned} \tag{4}$$

In this equation, $Flow_{i,[t1,t2]}$ is the monthly average flow to the mutual fund during [t1,t2] period and that $Out_{i,[t1,t2]}$ is an indicator of fund outflows, which equals one if $Flow_{i,[t1,t2]}$ is negative and zero otherwise. Control variables

(*Control*) include fund past performance (*RetExCat[t-k-5, t-k]*), an indicator of whether the past performance is negative (*Poor[t-k-5, t-k])*, the interaction term, as well as fund size (Size) and fund age (Age). We also include time dummies in the regression to control for the variation over time in sub-advisor changes. To compute the standard errors, we assume that the residuals are independent across different funds, but allow for correlation over time within a fund.

Table 5 suggests that there is an inverse relation between fund past 6 month flow when flow is negative and the probability of changing a sub-advisor (-1.66 to -1.82). In other words, sub-advisors are more likely to be replaced if there is increasing outflows in the mutual fund. This can be attributed to the monitoring effect of board of directors in mutual funds. For example, if board of directors finds that the asset class or investment strategy that the sub-advisor specializes in starts to lose attractiveness among investors, it will tend to replace the sub-advisor. When flow is positive, the inverse relation is not significant. This indicates that the sensitivity of sub-advisor change to fund flow is convex. However, the inverse relation is insignificant when we consider longer term fund flows. Since the estimates for control variables are similar to those reported in Table 4, we do not report them here for the sake of space.

We now quantify the marginal effect of fund past 6 month flow on the probability of changing a sub-advisor. We find that when fund flow decreases by one standard deviation from its mean of 1.01% to -5.31%, the probability of changing a sub-advisor increases by 14% (from 0.94% to 1.07%). Recall that the probability of sub-advisor change increases by 33% when performance decrease by one standard deviation from its mean, this result shows that the effect of flow on sub-advisor change is relatively smaller compared to the effect of performance.

### A.3.3. Effect of Interaction of Performance and Flows

It could be possible that when performance and flows interact with each other, the effect on sub-advisor change becomes different and thus clouds our analysis on the effect of performance or flows on sub-advisor change. We estimate the following model and test this possibility in Table 6.

$$\begin{aligned}\Pr(\mathrm{Change}_{i,t}) = \alpha + \beta \sum_{k} \mathrm{RetExCat}_{i,[t-k-5,t-k]} + \gamma \sum_{k} \mathrm{Flow}_{i,[t-k-5,t-k]} \\ +\delta \sum_{k} (\mathrm{RetExCat}_{i,[t-k-5,t-k]} \cdot \mathrm{Flow}_{i,[t-k-5,t-k]}) + \mathrm{Control}_{i,t} + \varepsilon_{i,t}\end{aligned} \tag{5}$$

In all estimations, the coefficients on the interaction term of past excess returns and flows are insignificant. The results suggest that the effect of past performance on sub-advisor change does not change in past flows. By the same token, the effect of past flows on sub-advisor change does not change in past performance. The table also confirms our previous finding that past fund performance negatively predicts sub-advisor change.

### A.4. Investor Unawareness

In this section, we test investor awareness of sub-advisor changes. Since a mutual fund can hire or fire sub-advisors without a shareholder vote in most cases, the common view is that investors are unaware of sub-advisor changes. If this holds, fund flows should not respond to changes in sub-advisor. We test this prediction in the following regression at the fund-month level and present the results in Table 7:

$$\mathrm{Flow}_{\mathrm{i,t}} = \alpha + \beta\mathrm{Change}_{\mathrm{i,t}} + \gamma\mathrm{Control}_{\mathrm{i,t}} + \varepsilon_{i,\mathrm{t}} \tag{6}$$

In the equation, $Flow_{i,t}$ is mutual fund flow, $Change_{i,t}$ is a dummy variable that equals one if there is a sub-advisor change in the fund and zero otherwise. We use contemporaneous observations of the two variables because when sub-advisor changes take place, such information is immediately disclosed and is available to be viewed on the SEC website.

Control variables (*Control*) include average fund flow during the past 1 to 6 months (*Flow[-6,-1]*), average fund flow during the past 7 to 12 months (*Flow[-12,-7]*), average excess return during the past 1 to 6 months (*RetExCat[-6,-1]*), average excess return during the past 7 to 12 months (*RetExCat[-12,-7]*), fund size in log million dollars (*Size*), fund age in log years (*Age*) and fund expense ratio (ExpRatio). We control for fund past flows and returns as well as age because these variables are associated with sub-advisor changes, as shown in the previous section. We also control for fund expense ratio because presumably, an increase in expense ratio predicts a decrease in fund flows. We include time dummies in the regression to control for the variation over time in flows. To compute the standard errors, we assume that the residuals are independent across different funds, but allow for correlation over time within a fund.

Table 7 presents the results for all funds (equity funds, fixed income funds and mix, etc.) and for equity funds only. With all observations being included, Column (1) and (4) show that the sensitivity of flow to change in sub-advisor, captured by the coefficient of *Change*, is insignificant. This indicates that fund flows do not seem to respond to sub-advisor changes.

We now distinguish two possible rationales consistent with the previous findings. One potential rationale is that investors are unaware of a sub-advisor change; the other is that investors are actually aware of a sub-advisor change but simply decide not to respond to it. We argue that should investors be aware of a sub-advisor change, they are unlikely not to respond to it if the fund has been underperforming for a relatively long term. In other words, if investors do not to react to a sub-advisor change when fund past performance is poor, it’s very likely that they are unaware of the change.

To test this, we estimate the regression coefficients using a sub-sample of negative average excess returns during the past 6 months (*RetExCat[-6,-1]<0*), and a sub-sample of negative average excess returns during the past two consecutive half years (*RetExCat[-6,-1]<0 & RetExCat[-12,-7]<0*)). In Table 7, the results in Column (2), (3), (5) and (6) (obtained for the sub-samples of negative past performance) are very similar to those in Column (1) and (4) (obtained for the whole samples). This shows that even investors of poorly performed funds do not respond to a sub-advisor change, indicating that investor are probably unaware of it.

### B. Hypothesis 2: Decreasing Return of Sub-Advisors

So far, we analyze the factors that affect the probability of having an active sub-advisor change for mutual funds. Are these changes effective ex-post? Berk and Green (2004) suggest that there are decreasing returns for managers in deploying their superior ability. If this hypothesis holds for sub-advisors, mutual funds may well remain to underperform their peers. We test the hypothesis and its implications in this section.

#### B.1. Overview

If there are decreasing returns for sub-advisors in deploying their superior ability, new money flows to a sub-advisor to the point at which expected excess return going forward is competitive. Since mutual funds make rational use of sub-advisor past information, they hire sub-advisors that are past winners and fire those that are past losers. Inefficiency may arise when the size of a sub-advisor exceeds it optimal capacity.

Figure 3 presents the monthly average excess return of sub-advisors relative to their perspective categories around the hiring. Consistent with Prediction 1, the figure shows that sub-advisor excess return tends to decrease after it is hired by a mutual fund.

Figure 4 presents the monthly average excess return of sub-advisors relative to their perspective categories around the firing. The figure shows that before a sub-advisor is fired, its monthly excess return is negative and significant. The performance of the sub-advisor, however, improves after the firing. The evidence is consistent with Prediction 2.

Table 8 quantifies sub-advisor cumulative excess return around the hiring and firing events. Column (1) shows that when sub-advisor category is controlled, a newly hired sub-advisor significantly underperforms its category by 0.98% in the following 18 months after being hired. Before the hiring decision is made, the performance of the sub-advisor is comparative to its peers. Column (3) shows that a newly fired sub-advisor performed relatively well compared to its Lipper category in the following 18 months after being fired. This newly fired sub-advisor, however, significantly underperforms its peers by 2.00% before the firing decision is made. Column (2) and (4) show that, when sub-advisor category, past performance and flows are all controlled, a sub-advisor significantly underperforms its peers by 0.45% in the following 18 months after being hired, a sub-advisor performs relatively well with its peers in the following 18 months after being fired. We argue that the improvement in performance of fired sub-advisor is unlikely driven by mean reversion because Column (4) essentially serves as a placebo test.

### B.2. Regression Analysis

In this section, we directly test Hypothesis 2: there are decreasing returns for sub-advisors in deploying their superior abilities. For each sub-advisor, we calculate two measures to capture its size: the mandate assets in million dollars (*Assets*), and the mandate number of funds (*Counts*).

We test the hypothesis in the following model:

$$\mathrm{RetExCat}_{j,t} = \alpha + \beta \mathrm{Size}_{j,t-1} + \mathrm{Control}_{j,t} + \varepsilon_{j,t} \tag{7}$$

In the equation, control variables (*Control*) include sub-advisor return in excess of the category in the end of last month (*RetExCat(-1)*), the value weighted *Affiliation* score a sub-advisor gets from all of its mandated mutual funds (*Affiliation*), the value weighted *Index* score a sub-advisor gets from all of its mandated mutual funds (*Index*), the value weighted *FOF* score a sub-advisor gets from all of its mandated mutual funds (*FOF*), and the value weighted *Equity* score a sub-advisor gets from all of its mandated mutual funds (*Equity*). These variables (except for *RetExCat(-1)*) are sub-advisor characteristics that could potentially affect performance. All estimations include sub-advisor fixed effects. Standard errors adjust for heteroskedasticity. In Column (1) and (3), we include sub-advisor fixed effects to control for the unobserved heterogeneity across sub-advisors. In Column (2) and (4), we include both sub-advisor fixed effects and time effects so that we control for both the unobserved heterogeneity across sub-advisors as well as unexpected variation or special events (such as financial crisis) that may affect returns.

Our main prediction is that the sign of β should be negative. Table 9 presents results that are consistent with this prediction using two size measures, mandated assets and mandated counts respectively. Column (1) shows that, for a given sub-advisor, as its mandated assets increase across time by $2.7 million (so that the natural logarithm of the sub-advisor assets increases by $1 million), the sub-advisor excess return relative to its category decreases by 0.84% per year (-0.07%*12), controlling for other characteristics. The estimation is significant at less than 1% level. Column (3) shows that, for a given sub-advisor, as its mandated counts increases by 2.7 units (so that the natural logarithm of the sub-advisor counts increases by 1 unit), the sub-advisor excess return relative to its category decreases by 1.00% per year (-0.083%*12) and is significant at less than 1% level. In all estimations, sub-advisor past performance positively predicts its current performance and the coefficients are significant at less than 1% level. This is consistent with empirical findings in the mutual fund literature (see e.g., Chen, Goldstein and Jiang (2010)).

Table 10 replicates analyses from Table 9 on subsamples of equity sub-advisors. The effect of size on sub-advisor performance is stronger for equity sub-advisors. Specifically, for a given sub-advisor, as its mandated assets increase across time by $2.7 million, the sub-advisor excess return relative to its category decreases by 1.08% per year (-0.09%*12), controlling for other characteristics. The estimation is significant at less than 1% level. As its mandated counts increases by 2.7 units, the sub-advisor excess return relative to its category decreases by 1.44% per year (-0.12%*12) and is again significant at less than 1% level.

### B.3. Implication on Mutual Fund Performance

So far we analyze decreasing returns for sub-advisors in deploying their ability. The results show that for a given sub-advisor, its excess return decreases in its mandate assets or counts. How does this phenomenon affect the performance of mutual funds? This section addresses this issue.

Figure 5 Panel A plots mutual fund average excess return by time around an active sub-advisor change. The figure shows that mutual fund excess return relatively to its category seems to slightly increase after an active sub-advisor change. We test the significance in Table 11 and 12.

Table 11 presents the cumulative average return and the cumulative average expense ratio of mutual funds with a sub-advisor change (targets) in excess of the benchmarks, around the effective change date denoted as “date zero”. We calculate three benchmarks. Benchmark 1 in Column (1) and (4) is all funds in the same Lipper category as the target on “date zero”. Benchmark 2 in Column (2) and (5) is all sub-advised funds in the same Lipper category as the target on “date zero”. Benchmark 3 in Column (3) and (6) is all funds in the same Lipper category and in the same past return quintile as the target on “date zero”. For a detailed explanation of the calculation, please see Table 11. All standard errors adjust for cross-correlation and auto-correlation.

The most interesting finding in Table 11 is that mutual funds continue to significantly underperform their benchmarks by 0.60% to 0.93% in the 18-months after a sub-advisor change, depending on the benchmark measure. In particular, even when we control for last year's fund return and the fund category, mutual funds continue to significantly underperform by 0.93% in the following 18 months. This finding is consistent with our previous finding that after being hired by a mutual fund, sub-advisor performance decreases. The table also shows that before a sub-advisor change, mutual funds significantly underperform their benchmarks by 0.58% to 2.07%, depending on the benchmark measure. This result is not surprising since mutual funds that change their sub-advisors are likely to be poorly performing ones, as suggested in Table 3 and 4. Meanwhile, Column (4) to (6) suggest that mutual funds with sub-advisor change have higher expense ratio compared to their benchmarks and the magnitude is quite persistent over time.

Now we try to test whether the continued underperformance of mutual funds experiencing a sub-advisor change results from continued outflows from clients. Results in Coval and Stafford (2007) suggest that large outflows can cause poor fund performance because funds are forced to sell their stocks to meet client redemptions, putting downward pressure on prices. Evidence in Tables 3 and 5 suggests that outflows predict sub-advisor changes, but it's also likely that outflows continue even after the sub-advisor is changed because outflows are persistent. If so, the later outflows could help explain the underperformance after a sub-advisor change. We test this by controlling for past flow quintiles, in addition to fund category and past return quintiles.

In Table 12, Column (1) control for fund past 12 month flows, in addition to fund category and past 12 month returns. Column (2) control for fund past 6 month flows, in addition to fund category and past 6 month returns. Column (3) control for fund past 1 month flows, in addition to fund category and past 1 month returns. All standard errors adjust for cross-correlation and auto-correlation.

The table shows that sub-advised mutual funds continue to significantly underperform by about 0.8% to 1.0% in the 18-months after a change in sub-advisor, even when we control for last year's fund flows, fund returns and fund category. Thus, we believe that the continuing underperformance of mutual funds with sub-advisor change is unlikely to be resulted from continuing outflows from clients. Rather, it is reasonable for us to believe that the underperformance of mutual funds can be attributed to decreasing returns for sub-advisors in deploying their ability. The table also suggests that for mutual funds with sub-advisor changes, their performance is not improved in the 18 months following the change, compared to the performance in the 18 months before the change. These funds, however, have 0.28% (0.14%*2) higher expense ratios per year, compared to their benchmarks.

## VI. Conclusion

This paper provides an empirical analysis of mutual funds and their sub-advisors around the event of a sub-advisor change. We test two hypotheses. First, there is an inverse relation between mutual fund past performance and the probability of changing a sub-advisor. There is also an inverse relation between mutual fund past outflows and the probability of changing a sub-advisor. This is because of the monitoring effects of mutual fund board of directors. Second, there are decreasing returns for sub-advisors in deploying their ability. We present evidence that is consistent with these views.

The contribution of our paper is threefold. First, our paper sheds new light on the factors that affect mutual fund decisions in sub-advisor change. We find that in addition to fund performance, fund outflows and fund size affect the propensity of mutual funds changing their sub-advisors. Second, our paper is the first in the literature to provide evidence on decreasing returns for money managers in deploying their ability in the context of sub-advisors. While previous literature provides analysis from the perspective of mutual funds and hedge funds, data used in our paper allows us to address this issue from the perspective of sub-advisors. We show that after being hired by a mutual fund, the size of the sub-advisor increases and its subsequent performance decreases. Third, our paper shows that although mutual funds make rational decisions in changing a sub-advisor, their performance is not improved due to decreasing returns for sub-advisors in deploying their ability.

# Hedge Fund Equity Holdings in the Real Estate Boom and Bust*

Abstract

This paper provides empirical evidence on the exposure of hedge funds to overpriced real estate assets. First, I show that the Real Estate Investment Trusts (REITs) were overpriced from 2003Q1 to 2007Q2. Second, using a comprehensive sample of 434 hedge funds, I find that these funds were holding RETIs instead of selling short during the overpriced period, consistent with models in which delegated portfolio managers may want to invest in overpriced assets.

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# I. Introduction

Hedge fund managers are sometimes faced with a dilemma: whether to invest in overpriced assets or not. Holding overpriced assets could be disastrous if prices start to fall. At the same time, selling short could result in losses if managers are forced to close out positions if prices keep rising. Avoiding the market could also be risky if fund managers' returns are not competitive. For instance, John Paulson, the hedge fund manager who started to trade against the housing market in mid-2006, endured one of the most difficult periods in his life in the latter half of 2006 as housing prices continued to rise. Yet he managed to fend off skepticism and hostility from investors and meet their redemptions. He finally made $15 billion for his firm in 2007[6].

How managers make choices when faced with this dilemma is not well studied since data on hedge funds is difficult to obtain. This paper investigates their behavior. Specifically, I ask whether hedge funds were holding or short selling overpriced real estate stocks.

Before addressing these questions, a critical question is whether and when the real estate sector was overpriced. Although there were differing views in academia and in the public media before the financial crisis, this paper provides evidence on real estate overpricing using information before the market collapsed.

[6] More details are available in "*The Greatest Trade Ever*" (Zuckerman, 2009).

Following Ofek and Richardson (2002), I find that, at the peak, the Real Estate Investment Trust (REIT) sector that consisted of 268 stocks, was priced as if the average future earnings growth rate across all these entities would exceed the growth rates experienced by some of the fastest growing individual firms in the past, and meanwhile, the required rate of return would be zero for the next five years. Other valuations also suggest that REITs were overpriced beginning in 2003.

Having documented the overpricing in real estate, I analyze hedge fund reactions using a comprehensive sample of 434 hedge funds. The data cover the period 2003Q1 to 2009Q1 and are compiled from various sources. Specifically, I start by estimating the exposure of hedge funds to REITs based on the long positions reported in their 13F filings. I find that the proportion of hedge funds' overall stock holdings devoted to REITs was higher than the corresponding weight of REITs in the market portfolio during the overpricing period from 2003Q1 to 2007Q2.

To test how potential short positions affect this analysis, I regress returns on various aggregate hedge fund indexes on the market return and the real estate excess return. I find that for most aggregate hedge fund returns, loadings on the real estate sector were not significant. The insignificance indicates that hedge funds' net exposures to REITs were comparable to the market portfolio.

Moreover, dynamic analysis that allows for time-varying regression coefficients also supports this result. To conclude, hedge funds were holding real estate stocks rather than selling short during the overpricing period.

The above empirical finding is consistent with two main insights in the literature on limits of arbitrage. First, professional investors may be reluctant to trade aggressively against mispricing. In DeLong, Shleifer, Summers and Waldman (1990a), an arbitrageur with a short time horizon will limit her willingness to trade against mispricing because of "noise trader risk", which is the risk of a further change in the opinion of noise traders away from its mean. Abreu and Brunnermeier (2002) show that a rational trader may delay an arbitrage trade because of synchronization risk, which is the uncertainty about the timing of other arbitrageurs' actions, and her desire to minimize holding costs. Shleifer and Vishny (1997) argue that delegated portfolio managers can become most constrained when they have the best opportunities (i.e., when mispricing widens). The fear of forced redemption would stop them from trading aggressively to eradicate mispricing. Consistent with this view, Sirri and Tufano (1998), Chevalier and Ellison (1997), and Chen, Goldstein and Jiang (2010) find that mutual funds experience outflows when their performance is poor. Others document similar flow-performance sensitivity for hedge funds: Goetzmann, Ingersoll, and Ross (2003); Agarwal, Daniel, and Naik (2004); Baquero and Verbeek (2005); Ding, Getmansky, Liang, and Wermers (2009).

Second, under certain circumstances, rational investors may find it optimal to invest in overpriced assets. In DeLong, Shleifer, Summers and Waldman (1990b), rational investors will buy overpriced assets and raise prices. This is because positive feedback investors, who buy when prices rise and sell when prices fall, are expected to react to today's price rise by buying, which will raise prices even further. In Abreu and Brunnermeier (2003), arbitrageurs will invest in overpriced assets if they believe their peers are unlikely to trade against them yet. Arbitrageurs will sell those assets only when their subjective probability that the bubble will burst is sufficiently high. In all, my findings are consistent with these theoretical results.

The empirical finding in this paper is also consistent with Brunnermeier and Nagel (2004). In their seminal paper, the authors find that hedge funds were heavily invested in technology stocks from 1998 to 2000 and gained from this strategy. Furthermore, they find that different exposures to the technology segment during the overpricing period coincided with quite different flow patterns, which indicates that hedge fund investment strategies and fund flows are closely related.

The rest of the paper is organized as follows. In Section II, I outline the hypothesis and discuss the underlying premise. Section III describes the data collection process and presents the summary statistics. In Section IV, I define the overpriced sector and provide evidence on overpricing. In Section V, I test my hypothesis. Finally, Section VI concludes.

## II. Hypothesis

*Hedge funds are holding overpriced assets before the market collapses.*

Shleifer and Vishny (1997) suggest that trading against mispricing is risky because mispricing may deepen in the short run, even though there is no long run fundamental risk in the trade. Since fund flows are sensitive to past performance, the fear of forced redemption would stop delegated portfolio managers from trading aggressively to eradicate mispricing.

Furthermore, managers may have incentive to invest in overpriced assets if they believe they can predict other investors' behavior. DeLong, Shleifer, Summers and Waldman (1990b) show that in anticipation of the demand from positive feedback investors who chase the price trend, rational investors will buy today and drive prices up because positive feedback investors are expected to buy tomorrow and raise future prices even further. In Abreu and Brunnermeier (2003), arbitrageurs will invest in the overpriced assets if their subjective probability that their peers will trade against overpricing is low. They will only sell or short the overpriced assets when their subjective probability that the bubble will burst is sufficiently high. In both models, rational investors believe that they can get out of the market before it collapses.

In this section, I present the hypothesis that is analyzed in this paper. To conduct my study, I compile several data sources since virtually no single dataset is eligible to test the hypothesis. In the next section, I discuss the data collection process and present the summary statistics.

# III. Data Description

In subsection 1, I discuss the data collection process and describe how each dataset serves my analysis. In subsection 2, I provide an overview of hedge fund stock holdings.

## A. Collection of the Data

My first dataset is comprised of monthly stock prices, shares outstanding, and share codes that are obtained from CRSP. The sample ranges from January 1998 to March 2009 so that both the technology overpricing and the real estate overpricing, and their consequent collapsing periods are covered. I then link this dataset to stock accounting information such as earnings and debts from

COMPUSTAT (Both CRSP and COMPUSTAT are available through WRDS). I use this combined dataset to provide evidence on overpricing.

The second dataset includes quarterly institutional holdings from 1998Q1 to 2009Q1 from the Thomson Reuters Ownership Database (formerly known as the CDA/Spectrum database). The holdings are based on institutional 13F filings with the U.S. Securities and Exchange Commission (SEC) and are available through WRDS. Prior to the Dodd-Frank Act[7], a 1978 amendment to the Securities and Exchange Act of 1934 required all institutional investment managers that exercise investment discretion over $100 million or more in securities to file Form 13F to the SEC. Such securities include common stock, put/call option, class A shares, and certain convertible debentures. However, the Thomson Reuters Ownership Database only reports institutional stock holdings. Holdings are reported quarterly with a maximum of 45-day delay, where all common-stock positions greater than 10,000 shares or $200,000 must be disclosed. I merge this dataset with the third one to study hedge fund investment strategies.

The third dataset consists of a list of hedge funds[8]. Although the term "hedge fund" is not statutorily defined, it refers generally to any pooled investment

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[7] On July 21, 2010, the Dodd-Frank Act requires that advisers to hedge funds and other private funds with assets under managing of more than $150 million register with the SEC. This change in criterion does not affect my analysis since my sample period ends in 2009.

[8] I thank Prof. Wei Jiang for providing the list of hedge funds and their clientele information.

vehicle that is privately organized, administered by professional money managers, and not widely available to the public[9]. In practice, Agarwal, Fos and Jiang (2010) classify an institution that files a 13F as a hedge fund company if it satisfies one of the following: " (i) It matches the name of one or multiple funds from the Union Hedge Fund Database which includes CISDM, Eureka, HFR, MSCI, and TASS. (ii) It is listed by industry publications (Hedge Fund Group (HFG), Barron's, Alpha Magazine, and Institutional Investors) as one of the top hedge funds. (iii) The company's own website claims itself as a hedge fund management company or lists hedge fund management as a major line of business. (iv) The company is featured by news articles in Factiva as a hedge fund manager/sponsor. (v) Some 13F filer names are those of individuals, for example, Soros Fund Management." The list consists of relatively "pure-play" hedge funds, since full-service banks that engage in hedge fund business (such as Goldman Sachs Asset Management and UBS Dillon Read), fund management companies that enter both the mutual fund (or sub-advisors of mutual fund) and hedge fund business are excluded from the list. The reason for exclusion is that 13F holdings of these full service companies may not be informative of their hedge fund business.

The last database consists of a variety of monthly hedge fund indices available from the Hedge Fund Research (HFR). Each index reflects the aggregate

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[9] A list of discussions on the definition of "hedge fund" is available at: http://www.sec.gov/spotlight/hedgefunds/hedge-vaughn.htm

historical performance of a group of hedge funds with the same investment style. These indices are net of fees and rebalanced quarterly. For a hedge fund to be included in the index, a minimum asset size of $50 million and 24-month track record are required. I back out hedge fund net investments in the real estate sector from these indices.

### B. Summary Statistics

Definitions of the main variables are reported in Table 1.

[Insert Table 1]

Table 2 presents the summary statistics of hedge funds quarterly holdings in the sample of real estate overpricing. Column (3) suggests that the fast growth in the number of managers with a valid 13F filing from 2003Q1 to 2007Q1 coincides with the stock market boom. Column (5) shows that the median number of stocks per manager is around 90, indicating that hedge fund holdings were concentrated to a certain extent. In the paper, I use the total stock holdings of the fund as a proxy for hedge fund size. Column (7) and Column (8) show that the sizes of hedge funds in my sample are positively skewed, i.e., a few hedge funds are much larger than the majority of funds. Column (13) reveals that the aggregate size of all the hedge funds in my sample increased sharply until 2007 and slumped to 374 billion dollars as of 2009Q1, when the stock market reached the trough.

[Insert Table 2]

Column (10) to (12) report the annual portfolio turnover that measures hedge funds' trading unrelated to flows. Following Chen, Jegadeesh and Wermers (2000), quarterly portfolio turnover is denoted as the minimum of the absolute values of buys and sells of a manager over the quarter scaled by the last quarter end total holdings. Then, the quarterly turnover is multiplied by four so that it is annualized and comparable to the literature. The annual (quarterly) portfolio turnover in my sample is around 100% (25%), consistent with Brunnermeier and Nagel (2004). This relatively small number indicates that a substantial part of hedge funds' holdings survives from one quarter to the next, and it is exactly this low frequency part that is relevant — I am interested in the long-term overall allocation to the real estate sector rather than the high frequency trades.

In this section, I describe the data collection process and present summary statistics on hedge funds holdings. Before analyzing the data, a critical question is whether and when the real estate sector was overpriced. In the next section, I address this issue.

# IV. Evidence on Overpricing

In this section, I provide evidence on real estate overpricing using information before the market collapsed. Clarity on this point is important since based on the analysis, my conjecture is that hedge fund managers were aware of the overpricing. The following section is organized as follows. In subsection 1, I present controversial views on whether the real estate sector was overpriced. In subsection 2, I examine the Real Estate Investment Trusts and provide evidence on overpricing.

### A. Controversial Views

There were differing views on whether the real estate sector was overpriced before the market started to collapse in 2007. On one hand, Himmelberg, Mayer, and Sinai (2005) argue that it was impossible to state definitively whether or not a housing bubble existed. They find that most housing markets did not look much more expensive in 2004 than they had looked over the previous 10 years, and in most major cities their valuation measures were nowhere near their historic highs.

On the other hand, there was a popular perception of overpricing in the U.S. housing market as early as in the year of 2002. For instance, articles in the *Economist* repeatedly warned of overpricing not only in the U.S. but also in the U.K. and other countries. From 2002 to 2003, the *Economist* published a series of articles with titles like "Bubble Trouble" (05/16/2002), "Betting the House" (03/06/2003), "Castles in Hot Air" (05/29/2003), and "House of Cards" (05/29/2003). Baker (2002) identifies the bubble and argues that the increase in home prices cannot be grounded in fundamental economic factors, based on the house price datasets produced by the US government. Case and Shiller (2003) conclude that the general indicators of the defining characteristics of bubbles were fairly strong in 2003 by looking at survey data. Robert Shiller further emphasized this point in February 2005 in his best-selling book *Irrational Exuberance*, by showing that the U.S. residential real estate prices rose by 52% between 1997 and 2004, or 6.2% per year, while the prices rose by only 66% between 1890 and 2004, or by just 0.4% a year. In addition, some expressed their doubts on housing privately. In mid-2004, David Andrukonis, the then Chief Risk Officer of Freddie Mac, warned Richard F. Syron, the then CEO that Freddie Mac was financing risk-laden loans that threatened its financial stability. However, Syron simply decided to ignore the warnings[10].

### B. Evidence from REITs

A real estate investment trust is a company that owns and typically operates income producing real estate or real estate-related assets. An entity that qualifies as a REIT can avoid most entity-level federal tax by complying with detailed restrictions on its ownership structure and operations[11]. An important restriction is that a REIT must distribute at least 90 percent of its taxable income to shareholders annually in the form of dividends. Hence, to fund the growth of its business, a REIT usually relies heavily on external financing, i.e., shareholder

[10] Read more details at http://www.nytimes.com/2008/08/05/business/05freddie.html

[11] See more details at: http://www.sec.gov/answers/reits.htm

equity capital or debt borrowed from other lenders (see discussion in Wu and Riddiough, 2005).

Real Estate Investment Trusts (REITs) are usually considered as the closest substitute for real estate business in the stock market. With the fast growth in the real estate market, the MSCI U.S. REITs Index more than tripled from early 2003 onwards till early 2007; during the same time, the S&P 500 Index increased only about 80% (see Figure 1).

[Insert Figure 1]

To evaluate the individual real estate stocks, I identify 268 REITs that are publicly traded in the U.S. stock market[12]. As a first check, I compare the median Enterprise Value to EBITDA (EV/EBITDA) ratios of the REITs sector with NYSE stocks[13]. Enterprise Value is denoted as a firm's market capital plus debt minus cash and equivalent. EBITDA is equivalent to earnings before interest, tax, depreciation and amortization. Like the Price to Earnings (P/E) ratio, EV/EBITDA ratio is a valuation multiple that measures the value of a firm; however, the latter is more appropriate for valuations of REITs and comparisons

[12] A stock is classified as a Real Estate Investment Trust (REIT) if its share code is 18 on CRSP. I provide the list of 268 REITs in Appendix.

[13] I use median instead of mean so that my results are not driven by outliers. The results look similar when I aggregate the Enterprise Value and EBITDA for each sector and take the ratios. The results also look similar when I compare the EV/EBITDA ratios of REITs with NYSE/NASDAQ/AMEX stocks.

across companies. The reason is twofold. First, different from most fixed-plant or equipment investment, real estate rarely loses value. Therefore, EBITDA is a superior gauge of REITs' performance since it excludes depreciation. Second, P/E ratio fails to consider various levels of leverage across the companies, while EV/EBITDA ratio maintains capital structure neutrality. Hence, for each stock, I calculate its enterprise value and relate it to EBITDA that is lagged at least six months, following the accounting convention.

Figure 2 presents the evolution of the median EV/EBITDA ratios of REITs and NYSE stocks from January 2000 to March 2009. Two observations immediately follow. First, the EV/EBITDA ratio of REITs increased dramatically from 13 to 32 during early 2002 and early 2007, followed by substantial declines thereafter. Second, this extraordinary rise in EV/EBITDA ratio is not pervasive among the NYSE stocks. In fact, the median EV/EBITDA ratio of the NYSE stocks was around 10 before 2007. Hence, the substantial increase in EV/EBITDA ratio before early 2007 and the subsequent decrease was largely confined to the real estate sector.

[Insert Figure 2]

To formalize the analysis, I follow Ofek and Richardson (2002) that built on Miller and Modigliani (1961) model for stock valuation. I show that despite the controversial views, REIT prices reached levels that could not be supported by their fundamentals. Specifically, I find that at the peak, the entire REITs sector, comprised of 268 stocks, was priced as if the average future earnings growth rate across all these firms would be in the top decile of all existing individual firms in the past, and meanwhile, the required rate of return would be 0% over the years. The derivation is as follows:

Miller and Modigliani (1961) show, that for a firm with supernormal return opportunities $r^*$ over $T$ periods,

$$\frac{V}{E} = \frac{1}{r}\left\{1 + \frac{\mathrm{k}(r^* - r)}{r - \mathrm{k}r^*}\left[1 - \left(\frac{1 + \mathrm{k}r^*}{1 + r}\right)^{\mathrm{T}}\right]\right\} \tag{1}$$

where $V$ denotes the total market value of the firm, debt plus equity, $E$ represents earnings, $r$ is the market rate of return and $k$ denotes the investment to earnings ratio.

Note that the "pass through" nature of REITs does not invalidate the model because the current value of a firm is determined by the value of the earning power of the currently held assets as well as the special earning opportunity and is independent of dividend policy. Alternatively, one can think of the investment to earnings ratio $k$, as $k = k_i + k_e$, where $k_i$ denotes the fraction of total profits retained in the firm, and $k_e$ represents the amount of external capital raised as a fraction of profits.

Following Ofek and Richardson (2002), assume that for the first $T$ periods these firms earn supernormal return $r^*$ with a fraction $k$ invested; after this initial period, these firms act like their "old economy" counterparts and achieve similar V/E ratios. In addition, assume a cost of capital of 0%, that is, investors require no return on the firm. Then, Equation (1) can be rewritten as:

$$\left(\frac{V}{E}\right)^{\text{Super Normal}} = (1 + \mathrm{k}r^*)^{\mathrm{T}} \left(\frac{V}{E}\right)^{\text{Old}} \tag{2}$$

The aggregate investment to earnings ratio ($k$ in the equation) of the REIT sector during the overpricing period is 86%, and the median value of individual REITs is 72%[14]. This implies that the annual earnings growth would have to reach 27.7% (13.1%) for 5 (10) years for the EV/EBITDA ratio to drop from the peak of 32 to the target of 11. How large is 27.7% for 5 years? Chan, Karceski and Lakonishok (2001) report that over a 5-year period from 1951-1998, the 90th percentile of the growth rates are 26.7% and 19.3% respectively for all firms and the two largest deciles[15]. This suggests that the required growth rate of the entire real estate sector is higher than the highest 10% of existing individual firms.

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[14] I estimate the investment of a REIT by the difference in the values of total real estate property in two consecutive years, adjusted for housing appreciation using the Case-Shiller Home Price Index.

[15] As Chan, Karceski and Lakonishok (2001) point out, their sample is subject to survivorship bias. Specifically, their numbers are biased upwards since their sample reflects more successful firms.

To conclude, my conjecture is that, if hedge fund managers performed similar back-of-the-envelope calculation as I discussed above, they should be aware of the overpricing in REITs beginning in 2003.

In this section, I provide evidence on real estate overpricing. In the next section, I examine hedge fund investment in overpriced sector.

# V. Empirical Evidence

In this section, I empirically test the hypothesis described in Section 2.

## A. Overview

My hypothesis is that hedge funds are willing to invest in overpriced sector. I start by computing the weight of REITs in the aggregate hedge fund portfolio, defined as the total market value of all hedge funds holdings in REITs scaled by the total market value of their entire stock holdings. For comparison, I also compute the weight of REITs in the market portfolio, defined as the total market value of REITs scaled by the total market value of all stocks on CRSP. The hedge fund portfolio weights are compared to market portfolio weights rather than be judged by their absolute levels because price movements change portfolio weights over time.

Figure 3 Panel A compares the weight of REITs in the aggregate hedge fund portfolio with the market portfolio. A few points are worth noting. First, hedge fund holdings in REITs were relatively small—less than 2.5% in the sample period. Second, hedge fund holdings in REITs increased from 1.7% to 2.3% from early 2003 to late 2006, exceeding the market portfolio by about 50% to 70%. Third, the weight of REITs in the aggregate hedge fund portfolio peaked in 2006Q3, at least one quarter before the REIT prices peaked; and it declined sharply after 2006Q4, about one quarter before the market portfolio started to decline. The gap between the weights narrows gradually over the subsequent quarters. By mid-2007, the weight of REITs in the aggregate hedge fund portfolio is very close to the market portfolio.

[Insert Figure 3]

However, one cannot tell whether the earlier decline of hedge fund investment in REITs is because hedge funds unwound their long positions earlier than the market or not. It could be the case that the prices of REITs held by hedge funds dropped earlier. To rule out this situation, I compute the weight of REITs in the aggregate hedge fund portfolio by percentage of shares, denoted as the total shares of all hedge funds holdings in REITs scaled by the total shares of hedge funds holdings in entire stocks. For comparison, I also compute the weight of REITs in market portfolio by percentage of shares, denoted as the total outstanding shares of REITs scaled by the total outstanding shares of entire stocks on CRSP. Figure 3 Panel B presents the results. In Panel B, the weight of REITs in hedge funds portfolio (by percentage of shares) dropped heavily from its peak after 2006Q4, indicating that hedge funds were unwinding their long positions. This implies that hedge funds reacted to the real estate collapse earlier than the market.

In summary, the preliminary analysis of long positions suggests that instead of attacking the real estate overpricing, hedge funds held more REITs than the market portfolio until early 2007. However, two further questions remain open after this initial analysis. First, hedge fund holdings in the real estate sector seem to be small in magnitude. Are they economically important? Second, data on hedge fund long positions may not be quite informative about their true portfolio allocations. This is because hedge funds could have several short positions or derivative contracts that alter the direction of their long exposures. How would the potential short positions affect the analysis? I address these issues in the next subsection.

### B. Return Regressions

In this subsection, I back out hedge fund net exposures to REITs from a variety of hedge fund indexes. Similar to Brunnermeier and Nagel (2004), I consider hedge funds that focus on stock trading. Assume that hedge fund returns can be written as the weighted average of the returns on the market portfolio with return $R_M$ and a portfolio of REITs with return $R_{REITs}$, plus some idiosyncratic return. Also, assume that $\varepsilon_t$ is orthogonal to $R_{M,t}$ and $R_{REITs,t}$[16]. Without loss of generality, one can think of hedge fund managers allocating their assets through two steps. First, allocate a fraction $b$ (by value) of the total portfolio to the market portfolio. Second, to achieve the desired exposure to the real estate sector, reallocate a fraction $g$ (by value) of the total portfolio from their market investment to the REITs portfolio. Then, the hedge fund return can be written as:

$$R_t = (b - g)R_{M,t} + gR_{REITs,t} + \varepsilon_t \tag{3}$$

where $\varepsilon_t$ is the idiosyncratic return.

In previous subsection, I compare the weight of REITs in the hedge fund portfolio with $m_{REITs}$, the weight of REITs in the market portfolio. Here I want to take into account the short positions. In my model above, the net investment in REITs as a proportion of the total portfolio is $(b - g)m_{REITs} + g$. Hence, the net investment in REITs as a proportion of hedge fund net investment in stocks $b$ is:

$$w_{REITs} = \frac{(b - g)}{b} m_{REITs} + \frac{g}{b} = m_{REITs} + \frac{g}{b}(1 - m_{REITs}) \tag{4}$$

To calculate $w_{REITs}$, I estimate $g$ and $b$ from the following regression:

$$R_t = \alpha + \beta R_{M,t} + \gamma\left(R_{REITs,t} - R_{M,t}\right) + \varepsilon_t \tag{5}$$

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[16] This assumption is realistic since I exclude hedge funds that mainly invest in other asset classes (e.g., currencies, bonds).

Given my assumptions, it is easy to demonstrate that β=$b$, and γ=$g$.

My hedge fund return data is comprised mainly of monthly hedge fund style indexes from Hedge Fund Research (HFR). HFR groups hedge funds according to their investment style and calculates performance indexes for each category. I choose styles that are likely to have significant exposure to stocks[17]. These hedge fund returns would reveal the potential offsetting effects of short sales on the long positions. My hedge fund return data also includes monthly return series on long-only "copycat" funds, denoted 13F. I construct the series by adding up quarterly hedge fund holdings retrieved from 13F reports across all hedge funds.

The monthly REIT returns are constructed from the MSCI U.S. REITs index available through the MSCI website[18]. The market factor $R_{M,t}$ is the NYSE/NASDAQ/AMEX composite return available through CRSP. For ease of reference, I denote the second factor, $R_{REITs,t} - R_{M,t}$, the excess REITs factor.

I run the time-series regression from January 2003 to June 2007, denoted as the overpricing period in this paper. The crisis period ranges from the "Quant meltdown" in the summer of 2007 to the trough of the stock market in March 2009, following the practice of Ben-David, Franzoni, and Moussawi (2010). I

[17] For example, I exclude fixed income styles, distressed debt styles, etc.

[18] The results are similar when I use the NAREIT Real Estate 50 Index that tracks the performance of larger and more frequently traded Equity REITs in the U.S.

check two issues in the regression. First, the correlation between the market factor and the excess REITs factor is -0.09 in the sample. This relatively small number suggests that the estimated regression coefficients are unbiased. Second, standard errors are adjusted for heteroskedasticity. In all, if hedge funds were over (under) weighted in REITs compared to the market portfolio, the loadings of returns on REITs should be significantly positive (negative)[19].

Table 3 presents the loadings of hedge fund returns on REITs and the implied net weights of REITs in hedge funds' portfolios. Panel A reports the results for different HFR style categories. The results show that the coefficients on the market factor have the signs and magnitude as I expected given the investment styles. For example, market-neutral funds have $\beta \approx 0$, and short-bias hedge funds have $\beta \approx -1$. Meanwhile, loadings on REITs are statistically insignificantly different from zero, except for the real estate funds. This indicates that the weight of REITs in most styles of hedge funds is similar to the market, which reflects that most hedge funds chose to invest in REITs only through their market portfolio. The loading on the excess REITs factor is negative and insignificant for short-selling specialists, indicating that these funds were not trading against the real estate either. Since $W_{RE}$ has a different meaning when $\beta < 0$, I do not report it here. Not surprisingly, due to the artifact of sector focus, the real estate funds

[19] The only exception is real estate fund, and I'll discuss the interpretation separately.

have positive exposure to the excess REITs factor (0.214), and the coefficient is significant at the 1% statistical level. This indicates an implied weight of 0.34. However, according to the HFR index description[20], the real estate style typically contains greater than 50% of portfolio exposure to real estate positions. This reflects the fact that these real estate expertise funds were not optimistic about the real estate segment during the overpricing period, and they invested less than the default level by either reducing their long positions in the sector or by having short positions that offset their long positions.

[Insert Table 3]

Panel B repeats the same exercises for the long-only "copycat" portfolios. Consistent with Panel A, the exposure to the excess REITs factor for the aggregate 13F hedge fund portfolio (13F) is negligible and insignificant, implying that hedge fund exposure to REITs is at the same level as the market. The results from Panel A and Panel B suggest that the 13F holdings data do a reasonable job in uncovering hedge fund exposure because short positions were not used by hedge funds to offset real estate exposure (except the real estate expertise). However, the results imply that the relatively higher weight of hedge funds compared to the market shown in Figure 3 Panel A is economically insignificant. In this sense, my conclusion in this paper is slightly different from Brunnermeier

[20] https://www.hedgefundresearch.com/pdf/HFRX/_formulaic/_methodology.pdf

and Nagel (2004), who find that hedge funds invested more in the technology stocks than the market portfolio.

To sum up, my results are consistent with the hypothesis that hedge funds overall were holding REITs rather than selling short during the overpricing period.

### C. Time Pattern of Exposures

A drawback of Equation (5) is that the regression estimate only yields the average fund exposure in the overpricing period. It could be possible that hedge funds' short positions were concentrated in a short period and were not reflected in the static analysis. Hence, it would be interesting to see how the exposures estimated from returns evolve over time and how they match the pattern found in holdings. For this purpose, I extend the regression with time-varying coefficients, using the Kalman filter approach. Specifically I estimate the following state space model:

$$R_t = \alpha_t + \beta_t R_{M,t} + \gamma_t\left(R_{REITs,t} - R_{M,t}\right) + \varepsilon_t \qquad (6)$$

Here the regression coefficients are assumed to evolve over time according to

$$\begin{pmatrix} \alpha_{t+1} - \bar{\alpha} \\ \beta_{t+1} - \bar{\beta} \\ \gamma_{t+1} - \bar{\gamma} \end{pmatrix} = \begin{pmatrix} 0 & 0 & 0 \\ 0 & \emptyset & 0 \\ 0 & 0 & \emptyset \end{pmatrix} \begin{pmatrix} \alpha_t - \bar{\alpha} \\ \beta_t - \bar{\beta} \\ \gamma_t - \bar{\gamma} \end{pmatrix} + \begin{pmatrix} v_{1,t+1} \\ v_{2,t+1} \\ v_{3,t+1} \end{pmatrix} \tag{7}$$

where the disturbances $\varepsilon_t$ and $v_t$ are normally distributed, mutually uncorrelated conditional on currently available information, and uncorrelated over time. I assume that shocks to alphas are completely transitory and shocks to factor loadings are persistent with parameter φ. These assumptions are necessary to keep the number for unknown parameters low enough given my relatively short sample. One can interpret $\bar{\alpha}$, $\bar{\beta}$ and $\bar{\gamma}$ as the steady-state coefficients. I run the Kalman filter iterations to find the maximum likelihood estimates for the parameters of the model. The values of the coefficients at date *t* are based on information up to that date. I then calculate the smoothed coefficients by using information through the end of the sample to improve the inference about the historical values that the coefficients took in the middle of the sample.

Figure 4 presents the parameter estimates. Since my main interest lies in the hedge fund exposures to real estate stocks, I only report the time-varying coefficients on the excess REITs factor. In the interest of parsimony, I calculate the equal-weighted average of all HFR index returns except *Short Bias* and *Real Estate* and denote it as *HFR*. *13F* is the same as defined in Table 3.

[Insert Figure 4]

The loadings estimated from hedge fund returns (*HFR*) and 13F returns (*13F*) are alligned with each other, indicating that my 13F holdings data are reasonable in revealing hedge fund exposures to the real estate sector. Moreover, the loadings estimated from hedge fund returns (*HFR*) vary around zero during the overpricing period, suggesting that hedge funds did not concentrate their short positions in a short period of time.

## VI. Conclusion

Using a comprehensive sample of 434 hedge funds from 2003Q1 to 2009Q1, this paper investigates how hedge funds reacted to the recent real estate overpricing. I find that instead of selling short, hedge funds were holding overpriced real estate stocks. The findings are consistent with models in which rational investors believe that they can get out of the overpriced market before it collapses.

# Investor Composition and Hedge Fund Portfolio Allocation*

Abstract

Using a comprehensive sample of 434 hedge funds and their clientele informaiton, I study the effect of investor composition on hedge fund portfolio alloction. I find that retail-oriented hedge funds tend to invest more in overpriced real estate assets during the period of 2003Q1 to 2007Q2, even after controlling for industry-specific effects and fund-specific effects.

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# I. Introduction

There has been a growing literature on the difference between retail-oriented and institution-oriented funds. But whether and how did investor composition potentially affect the delegated portfolio managers' investment strategies is less studied. We address this question in the paper.

Building on earlier studies of how hedge funds invested in overpriced assets, this paper shows that the composition of a hedge fund's investors affected money manager's propensity to invest in overpriced stocks. My main finding is that retail-oriented hedge funds invested more in overpriced assets than their institutional counterparts.

Specifically, I find that at different quantiles, the proportion of stock holdings devoted to REITs was higher for retail-oriented funds than for institution-oriented funds when overpricing persisted. However, this result does not necessarily indicate that investor composition affects hedge fund investment in overpriced assets. In fact, the result may be driven by retail-oriented hedge funds' industry-specific preference, which has nothing to do with investment in overpriced assets. To rule out this possibility, I examine the proportion of stock holdings devoted to REITs when overpricing collapsed. The previous result does not apply to this sample, indicating that the industry-specific effect is not driving my results.

To quantify the effects of investor composition on managers' investment strategies, I employ a Tobit difference-in-difference regression. The first difference is the difference between retail-oriented and institution-oriented hedge funds; the second difference is the difference between the overpricing period (2003Q1-2007Q2) and the crisis period (2007Q3-2009Q1). The results imply that the difference in the weight of REITs in retail-oriented hedge fund portfolio and in institution-oriented hedge fund portfolio was 20% higher when the assets were overpriced. The difference is significant at less than the 10% statistical level.

Alternatively, my results might well be driven by fund characteristics, which have nothing to do with investor composition. For instance, frequently traded hedge funds could be more likely to chase short-term performance; thus, they might be more willing to invest in overpriced stocks. Similarly, large funds might be more willing to invest in overpriced stocks because they have more funds available when asset prices go against them; and concentrated funds might be more willing to do so because they have more specialized information.

I address this point by including fund level control variables such as the fund turnover ratio, size, the Herfindahl Index to measure portfolio concentration, and their respective interactions with a dummy variable for whether the real estate stocks were overpriced. My results remain significant after controlling for these fund characteristics. More generally, I include fund dummies to control for any unobserved fund fixed effect and find similar results.

Since this paper is built on Brunnermeier and Nagel (2004), which analyzes hedge fund investment in the technology bubble, it would be interesting to see if the investor composition effect also applies to that sample. Using data on the holdings of retail-oriented and institution-oriented hedge funds from 1998Q1 to 2002Q4, I find that the difference in the weight of technology stocks in the two types of hedge funds was 20% higher when these stocks were overpriced. In particular, the difference is statistically significant at less than the 5% level.

The empirical findings can be explained by two pieces of literature. First, in funds where flows are more sensitive to past performance, delegated portfolio managers are more likely to engage in strategies that will deliver better performance in the short run (Shleifer and Vishny, 1997; Jin and Kogan, 2007). They tend to invest in overpriced assets that have not crashed yet because failure to include these assets in their portfolios will hurt performance relative to their peers and trigger outflows. Following substantial outflows, funds need to readjust their portfolios and conduct costly and unprofitable trades, which further damage future returns (Edelen, 1999; Coval and Stafford, 2005).

Second, flows are more sensitive to past performance in retail-oriented funds than in institution-oriented funds. For instance, James and Karceski (2002) find that retail mutual fund flows are significantly more sensitive to past fund performance than institutional mutual fund flows. Similarly, Dahlquist and Martinez (2012) show that inflows and outflows are strongly correlated with measures of past performance in mutual funds but not in pension funds whose investors are large institutions[21]. The intuition is that retail investors are less sophisticated and have less information than institutional investors. Moreover, an individual investor usually holds only a small proportion of the fund shares and is thus more affected by others. When a fund's performance is poor, the expectation that other investors will withdraw their money reduces the expected return from staying in the fund and increases the incentive for each individual investor to withdraw as well (Chen, Goldstein, and Jiang, 2010).

I test these explanations using my sample data. First, my story relies on the premise that retail-oriented hedge funds face steeper flow-performance sensitivity. I confirm this premise in the data. Second, given that flows are more reactive in retail-oriented hedge funds, one would expect that these funds have higher flow volatility. I find evidence that is consistent with this view.

My paper contributes to the hedge fund literature. To date, much of the research on hedge funds focuses on manager skills and risk-return tradeoffs (e.g., Edwards and Caglayan, 2001; Liang, 2001; Jagannathan, Malakhov and Novikov,

[21] This is different from Del Guercio and Tkac (2002), who find that pension clients punish poorly performing managers by withdrawing assets under management.

2010). Others have focused on the real impact of hedge fund activism (Brav, Jiang, Partnoy and Thomas, 2008; Klein and Zur, 2009). To the best of my knowledge, this paper is the first to test the effect of investor composition on hedge fund investment strategies.

The rest of the paper is organized as follows. In Section II, I outline the hypothesis and discuss the underlying premise. In Section III, I discuss the data collection process. In Section IV, I test my hypothesis on the effect of investor composition on the investment strategies. Section V provides evidence that supports the premise of my hypothesis. Finally, Section VI concludes.

## II. Hypothesis

*The pattern that hedge funds are holding overpriced assets before the market collapses is more prominent in retail-oriented hedge funds than in institution-oriented funds.*

In delegated portfolio management, managers are concerned about short-term performances because flows are subject to run (Shleifer and Vishny, 1997). In funds where flows are more sensitive to past performance, managers are more likely to invest in overpriced assets because failure to include these assets in their portfolios will hurt their performance relative to peers and trigger outflows. Following substantial outflows, funds need to re-adjust their portfolios and conduct costly and unprofitable trades, which further damage the future returns (e.g., Edelen, 1999; Coval and Stafford, 2005).

The premise that underlies my hypothesis is that flows are more sensitive to past performance in retail-oriented funds, i.e., retail-oriented funds face steeper flow-performance sensitivity than institution-oriented funds. James and Karceski (2002) document this effect using mutual funds data from 1995 to 2001. Similarly, Dahlquist and Martinez (2012) compare mutual funds with pension funds and find that the flow-performance sensitivity only exists in mutual funds. Moreover, Chen, Goldstein and Jiang (2010) suggest that an individual investor, who holds only a small proportion of the fund‘s shares, is more affected by others; in contrast, an institutional investor, who typically owns a larger percent of the fund, knows that by not withdrawing she guarantees that her shares will not contribute to the overall damage caused by withdrawals of the fund's assets.

While this effect is mainly documented among mutual funds, I conjecture that the same effect is in place within hedge funds. This is realistic because hedge funds investors are observed to react to funds' past performance despite various restrictions such as lock-up periods (e.g., Goetzmann, Ingersoll and Ross, 2003; Agarwal, Daniel, and Naik, 2004; Baquero and Verbeek, 2005; Ding, Getmansky, Liang, and Wermers, 2009). For example, consider two prominent hedge funds—Tiger Management and Soros Fund Management—during the technology bubble.

In 1999, Tiger shorted the technology segment and lost about 25% of its assets through withdrawals in the final quarter. Later, Tiger announced its liquidation just when prices of technology stocks started to tumble. In contrast, during the third quarter of 1999, Soros benefited from the run-up of the bubble by increasing the proportion invested in the technology segment and attracted new capital[22].

## III. Data Collection

My database contains hedge funds' clientele information based on Form ADV filings in 2006 and will be combined with my database on institutional holdings to analyze the effect of investor composition. The SEC requires that all registered investment advisers file their Form ADVs within 90 days of the adviser's fiscal year-end and disclose information on their businesses, clients, employees on the Investment Adviser Registration Depository (IARD) system. On Form ADV Item 5 Question D, a filing investment adviser is required to report the approximate percentage that each type of client comprises of its total number of clients. These clients include individuals, high net worth individuals, banking or thrift institutions, investment companies, pension and profit sharing plans, pooled investment vehicles, charitable organizations, corporations, state or municipal government entities, foundations, etc. In this paper, a hedge fund is classified as retail-oriented if individuals and wealthy individuals represent over 50% of its

[22] http://www.investopedia.com/articles/mutualfund/05/HedgeFundFailure.asp

clients, and it is classified as institution-oriented if the rest of investors compose over 50% of its clients.

I observe a snapshot of the clientele information rather than a time-series because once an investment adviser files the most recent Form ADV to the SEC through the IARD system, information from the previous year is replaced. To test my hypothesis, I assume that these funds do not switch between retail-oriented and institution-oriented during the sample period. This assumption is realistic. Anecdotally, hedge funds understand the difference in the needs of individual investors and institutional investors; therefore, they target specific clients based on their own advantages[23]. Furthermore, by retrieving a random sample of 50 hedge funds and comparing their clientele information in my dataset and their most recent records on the SEC website, I find that only one out of the 50 funds switched its type, or more specifically, from retail-oriented to institution-oriented fund. Based on disclosed information, this change is likely due to an acquisition transaction in 2010.

The final list consists of 434 hedge funds, among which 111 are retail-oriented, and 323 are institution-oriented. Notable funds such as Citadel Investment Group and Private Capital Management are classified as retail, and D.E.Shaw and Paulson are classified as institutional. My unique hedge fund

[23] See "*How to create and manage a hedge fund : a professional's guide*" (McCrary, 2002).

dataset is free of selection biases, while commercial hedge fund databases such as CISDM, Eureka, HFR, MSCI, and TASS all suffer from the self-reporting problems (see Malkiel and Saha (2005), Ang, Rhodes-Kropf and Zhao (2008), and Agarwal, Fos and Jiang (2010)). Since my hedge fund data are collected at the manager level, I use "hedge fund" and "hedge fund manager" interchangeably throughout this paper.

# IV. Empirical Evidence

## A. Overview

My hypothesis predicts that retail-oriented hedge funds are more likely to invest in the overpriced sector than institution-oriented funds. The intuition is that in retail funds where flows are more sensitive to past performance, if managers fail to capture the upturn of the overpricing, their poor performance relative to the peers will trigger more outflows, which further dampen the performance.

The time-varying regression results in Essay 2 suggest that my 13F holdings data do not paint a misleading picture of hedge fund exposure to real estate stocks. Therefore, in the rest of the paper, I return to the 13F holdings data to address questions at the fund level. Specifically, I compute for each hedge fund the weight of REITs in its portfolio at the end of each quarter. The weight of REITs in a hedge fund's portfolio is defined as the market value of REITs held by the hedge fund scaled by the market value of the fund's entire stock holdings.

Then, for each quarter end, I rank the weights within each group of hedge funds, namely, the retail-oriented funds and the institution-oriented funds. A hedge fund is classified as retail-oriented (or institution-oriented) if individuals or high net worth individuals represent over (under) 50% of its total clients.

Figure 1 plots the 90th, 80th, 60th, and 40th percentiles of weights for retail and institution-oriented funds at the end of each quarter from 2003Q1-2009Q1. An interesting pattern is that, for the 80th, 60th, and 40th percentiles of weights shown in the figure, retail-oriented hedge funds allocated more of their stock holdings to REITs than institutional funds prior to mid-2007[24]. The gap between the weights in retail funds and institutional funds reduces significantly thereafter. Overall, the figure seems to suggest that retail-oriented hedge funds were over-invested in REITs compared to their institutional counterparts during the overpricing period.

### B. Regression

A simple way to evaluate how investor composition affects hedge funds' reaction to overpricing is to compare the holdings of REITs in retail funds' portfolios and institutional funds' portfolios during the overpricing period and estimate the difference. However, the problem with this pure cross section approach is that there might be systematic, unmeasured differences in retail hedge

[24] Similar results prevail when I measure the weight by percentage of shares rather than by percentage of capital.

funds and institutional hedge funds that have nothing to do with investor composition. As a result, attributing the difference in weights in the overpricing period to investor composition might be misleading.

A common solution to this problem is the difference-in-difference methodology. By adding a comparison period, this methodology compares the cross-sectional variation (the first difference) in the overpricing period and a non-overpricing period (the second difference). Here I include the crisis period (2007Q3-2009Q1) rather than the pre-2003 period as a comparison. This is because certain REITs may have started to see their stock prices shooting up prior to 2003, while by 2009Q1 the gains on the REITs Index had been wiped out. Hence, my way of selecting the sample period is parsimonious.

The difference-in-difference methodology allows for both the investor composition effect and the time effect. Nevertheless, unbiasedness of the estimator still requires that investor composition is not systematically related to other factors that affect weights and are hidden in residuals. To this end, I estimate the following specification from 2003Q1 to 2009Q1 using quarterly data at the fund level.

$$Weight_{j,t} = \beta Overprice_t + \gamma Retail_j + \delta Retail_j Overprice_t + Controls_{j,t} + \varepsilon_{j,t} \quad (1)$$

where *Weight* is a fund's portfolio allocation to REITs as defined above. *Overprice* is a dummy variable that equals one if the data observation is between 2003Q1 to 2007Q2 and zero otherwise. *Retail* is a dummy variable that equals one if the fund is retail-oriented and zero otherwise.

Control variables (*Controls*) include fund size (*Size*, in log million dollars), fund turnover ratio (*Turnover*, in percentage points) and fund herfindahl index (*Herfindahl*, in percentage points) that measures the concentration of a fund's investment. All variables are lagged with one quarter. These variables are fund characteristics that may affect weights. For example, funds that trade more frequently are more likely to chase short-term performance, thus, they might be more willing to invest in the overpriced stocks. Similarly, large funds might be more willing to do so because they have more funds available when asset prices go against them; concentrated funds might be more willing to do so because they have more specialized information. The control variables enter both directly and interactively with the overpricing dummy. In selected specifications, fund dummies are included to control for any unobserved fund fixed effect. There are 8216 fund-quarter level observations in each of the regression.

I use a censored regression (i.e., Tobit) model to estimate the coefficients because the dependent variable *Weight* in the regression is non-negative and has a spike in the histogram at zero. In addition, standard errors in the estimation adjust for heteroskedasticity and within-cluster correlations at the fund level.

The coefficient of interest, δ, measures how the difference in the weight of REITs in retail-oriented funds and the weight of REITs in institutional funds varies when the real estate sector is overpriced. If investor composition does not affect hedge fund investment strategies in the overpriced sector, δ is expected to be zero. Under my hypothesis, δ is expected to be positive because retail hedge funds are more likely to invest in overpriced assets.

Table 1 shows how investor composition affects hedge fund investment in the overpriced real estate stocks. Column (1) controls for fund characteristics except for fund size and indicates that the difference in the weight between retail-oriented funds and institution-oriented funds is 0.489% higher when REITs are overpriced and is statistically significant at the 10% level. Column (2) adds the fund dummies and the effect drops to 0.454%. Column (4) shows that this pattern is repeated even when fund size and fund fixed dummies are all included. Since a representative hedge fund invests about 2% in REITs during the overpricing period, this translates into about 21% (0.43% divided by 2%) more investment in REITs in retail-oriented hedge funds' portfolio than in institutional funds' portfolio. The estimates in Table 1 are therefore consistent with the hypothesis that retail-oriented hedge funds are more likely to invest in the overpriced assets.

[Insert Table 1]

### C. Technology Sample

In previous subsection, I test my hypothesis in the real estate sample. One potential concern is that the effect of investor composition on hedge fund investment in REITs may be caused by fund preference to this particular sector. While this is unlikely since I employed the difference-in-difference methodology which is aimed at eliminating this explanation, a direct way to address this concern is to test my hypothesis in another episode of overpricing: the technology bubble period.

Following Brunnermeier and Nagel (2004), for each month from January 1998 to December 2002, I rank the P/S (price to sales) ratios of all stocks in the Nasdaq market into five quintiles. Then I form five portfolios based on their P/S quintiles. These portfolios are rebalanced every month. The top quintile portfolio is defined as the Tech sector (or high P/S portfolio).

Figure 2 presents the cumulative return of three portfolios: High, Median and Low P/S portfolios. Similar to the literature, the Tech sector (high P/S) experienced extraordinary returns: the cumulative return of the high P/S portfolio increased dramatically after early 1998 until August 2000, when it peaks at 10. The cumulative return fell thereafter. In contrast, the mid P/S and Low P/S portfolios did not exhibit such a pattern. The figure suggests that this parsimonious P/S grouping seems valid in picking up the overpriced stocks. Since the previous literature has conducted thorough analyses on the overall hedge fund investment in the overpriced sector, my focus here is to examine how investor composition affects their strategies.

[Insert Figure 2]

I repeat the analysis of Table 1 in the sample of the technology overpricing. The sample consists of an overpricing period from 1998Q1 to 2000Q4 and a comparison period that ranges from 2001Q1 to 2002Q4. The overpricing period ends in 2000Q4 rather than 2000Q1 when the Nasdaq index reached its peak because Brunnermeier and Nagel (2004) show that individual stocks may reach their price peaks before or after the overall peak, and hedge funds were picking stocks that have not yet crashed until the end of 2002. As before, I choose the collapsing period rather than pre-1998 period as a comparison.

In the estimation, the dependent variable *Weight* is the weight of high P/S stocks in a hedge fund portfolio, defined as the market value of high P/S stocks held by a hedge fund scaled by the market value of the fund's entire stock holdings. *Overpricing* is a dummy variable that equals one if the data observation is between 1998Q1 and 2000Q4, and zero otherwise. Other explanatory variables are the same as before. There are 3598 fund-quarter level observations in each of the regressions.

Table 2 shows that the results are consistent with those in Table 1. In detail, Column (1) shows that by controlling for fund Herfindahl index and turnover ratio, the difference in the weight between retail-oriented funds and institution-oriented funds is 2.39% higher when the technology sector is overpriced and the difference is statistically significant at the 5% level. Column (2) adds fund fixed dummies and the difference increases to 3.20% and is statistically significant at the 1% level. Column (4) finds similar pattern when adding fund size and fund dummies as controls. Since the average weight of technology stocks in a hedge fund portfolio is 15.6% in the overpricing period, this implies that retail-oriented hedge funds invested about 19% (e.g., 3% divided by 15.6%) more in the overpriced technology stocks than their institutional counterparts. Again, the results support my hypothesis that investor composition affects hedge fund investment in overpriced assets.

[Insert Table 2]

In this section, I show that retail-oriented hedge funds tend to invest more in overpriced assets. In the next section, I provide additional evidence that support the mechanism of the story.

# V. Mechanism

My story that retail-oriented hedge funds are more likely to invest in overpriced assets relies on the assumption that they face steeper flow-performance sensitivity. I test this premise in Subsection 1. Furthermore, if flows react more to performance in retail-oriented hedge funds, one would expect that they have higher flow volatility. I examine this view in Subsection 2.

## A. Flow-Performance Sensitivity

As elaborated in Section 2, the underlying assumption of my hypothesis is that retail-oriented hedge funds face steeper flow-performance sensitivity than their institutional counterparts when performance is poor. An ideal dataset to test this premise should include individual hedge fund flows, returns, assets under management and other relevant fund level information. Unfortunately, I do not have access to such databases. However, following the standard practice in the fund literature, I can still estimate these variables based on hedge fund holdings. Specifically, following Agarwal, Fos and Jiang (2010), I construct the quarterly flows for each hedge fund as below:

$$Flow_{j,t} = \frac{Size_{j,t} - Size_{j,t-1}(1 + Ret_{j,t})}{Size_{j,t-1}} \tag{2}$$

where *Size* is the total value of the fund's quarter-end equity portfolio, using reported shares and corresponding quarter-end stock prices reported in CRSP, and

*Ret* is the value-weighted return of all stocks in the hedge fund's portfolio over the quarter. *Flow* measures the change in the value of the fund's equity portfolio due to changes in investment by the fund's investors and not due to the changes in the stock prices; therefore, it is a proxy for the net fund flows.

To estimate the performance of a fund relative to its peers, I apply a modification of the methodology used by Sirri and Tufano (1998) in their study of the mutual fund flow-performance relation, which involves two steps. First, for each hedge fund, I calculate the fractional rank, $Perct_{j,t}$ , from 0 to 1, based on the return on the fund's portfolio (*Ret*) during quarter t. Second, I calculate the bottom rank $Perf_{j,t}^{L}$, and the top rank $Perf_{j,t}^{H}$ as follows:

$$Perf_{j,t}^{L} = Min\ (\frac{1}{2}, Perct_{j,t}) \tag{3}$$

$$Perf_{j,t}^{H} = Min\left(\frac{1}{2}, Perct_{j,t} - Perf_{j,t}^{L}\right) \tag{4}$$

Then, the following regression is specified to test the effect of investor composition on flow-performance sensitivity.

$$Flow_{j,t} = \beta_L Perf_{j,t-1}^{L} + \beta_H Perf_{j,t-1}^{H} + \gamma_L Retail_j \cdot Perf_{j,t-1}^{L} + \gamma_H Retail_j \cdot Perf_{j,t-1}^{H} + Retail_j + Controls_{j,t-1} + \varepsilon_{j,t} \tag{5}$$

In Equation (12), $Perf_{j,t-1}^{L}$ and $Perf_{j,t-1}^{H}$ are lagged by one quarter to capture the fund's past relative performance. The dummy variable for whether the hedge fund is retail-oriented (*Retail*) enters both directly and interactively with the performance measures. Control variables (*Controls*) include fund size (*Size*, in log million dollars), fund Herfindahl index (*Herfindahl*, in percentage points), fund age (*Age*, in log years) and fund turnover ratio (*Turnover*, in percentage points), all lagged with one quarter. Control variables also include fund's lagged flows (*Flow*(−1)). These variables are shown in the prior literature to affect hedge fund flows. If retail-oriented hedge funds have higher flow-performance sensitivity than institution-oriented hedge funds when performance is poor, the coefficient $\gamma_L$ is expected to be positive.

Table 3 presents how investor composition affects hedge funds' flow-performance sensitivity. Column (4) shows that the coefficient of interest, the cross-term of retail dummy and the bottom rank of performance, is 0.07 and statistically significant at the 10% level. This suggests that for a 1% increase in the fractional rank of returns in the poor performance region, flows of retail-oriented hedge funds increase roughly 0.07% more than their institutional counterparts, consistent with my hypothesis. However, flows seem rather insensitive to past poor performance in institution-oriented funds in my sample. In general, the magnitude of the flow-performance sensitivity is lower than that in previous literature. For example, Chen, Goldstein and Jiang (2010) find the relation is between 0.27% and 0.70% depending on the measure. The fact that these variables are constructed from 13F holdings data might have clouded the analysis.

[Insert Table 3]

### B. Flow Volatility

So far I have shown that retail-oriented hedge funds face steeper flow-performance sensitivity. If flows react to fund's performance to a greater extent, they are expected to be more volatile as well. Another way of interpreting this is investor's patience (e.g., Jin and Kogan, 2007; Greene, Hodges, and Rakowski, 2007). If flows are more sensitive to past performance, then these investors must be less patient and be more likely to move their flows in and out of the funds; therefore, flows are more volatile.

For a summary estimate of the effect of investor composition on flow volatility, I conduct the following cross-sectional regression and report the results in Table 4.

$$Vol_{Flow_j} = \gamma Retail_j + Controls_j + \varepsilon_j \tag{6}$$

In Column (1) to (3), the dependent variable is the standard deviation of a fund's flow from 2003Q1 to 2009Q1. In Column (4) to (6), the dependent variable is the standard deviation of a fund's absolute flow during the sample. Greene, Hodges, and Rakowski (2007) suggest that this measure is more relevant when considering the overall response of investors to share restrictions. In all regressions, *Retail* is a dummy variable for whether a fund is retail-oriented. Control variables (*Controls*) include the sample averages of a fund's turnover ratio (*Turnover*, in percentage points), fund Herfindahl index (*Herfindahl*, in percentage points) and fund size (*Size*, in log million dollars). I also control for fund age (*Age*, in log years). All observations are collected at the fund level. The coefficient of interest, $\gamma$, is expected to be positive if retail-oriented hedge funds have higher flow volatility.

[Insert Table 4]

Table 4 shows that consistent with my prediction, retail-oriented hedge funds have higher flow volatility. This is indicated by the positive coefficient estimates on *Retail* in all specifications. Meanwhile, all coefficients are statistically significant at less than the 5% level. Specifically, the estimated coefficient for *Retail* is 0.016 in Column (3), indicating that the sample average of flow volatility in retail-oriented hedge funds is 40% (0.016 versus 0.04) higher than that in institutional funds, everything else being equal. When we take the absolute value of flows, flow volatility is 20% (0.008/0.04) higher for the retail funds. The decrease in magnitude is expected since by taking the absolute value of flows, the standard deviation is reduced. The results provide support for my prediction that flows in retail-oriented hedge funds are more volatile.

In sum, empirical evidence suggests that retail-oriented hedge funds have steeper flow-performance sensitivity and more volatile fund flows. These findings support the mechanism of my story that retail funds are more likely to invest in overpriced assets. As a caveat, though, I want to point out that my data on hedge fund flows and returns are calculated from the 13F holdings and are therefore proxies. In this respect, one should view this section as a study of the premise, rather than as a formal test on the theory.

## VI. Conclusion

In this paper, I investigate how investor composition affected hedge fund exposure to overpriced assets. I find that the difference in the proportion of REITs in retail-oriented hedge fund portfolio and institution-oriented hedge fund portfolio was 20% more when the assets were overpriced. I further show that this difference in hedge fund exposures could stem from the difference in flow-performance sensitivities in the two types of funds.

There are a number of avenues for future work. For example, fund flows and performance analyzed in this paper are indirectly estimated through hedge fund 13F holdings. Comprehensive database that covers hedge fund flows and returns (such as TASS) combined with the clientele information would serve better to test the effect of investor composition on flow-performance sensitivity. It would also be interesting to examine how risk-adjusted performance and risk-taking behaviors differ in retail-oriented and institution-oriented hedge funds.

# Figures and Tables

## I. Figures

### A. Essay 1

**Figure 1. Sub-Advisor Change Timeline**

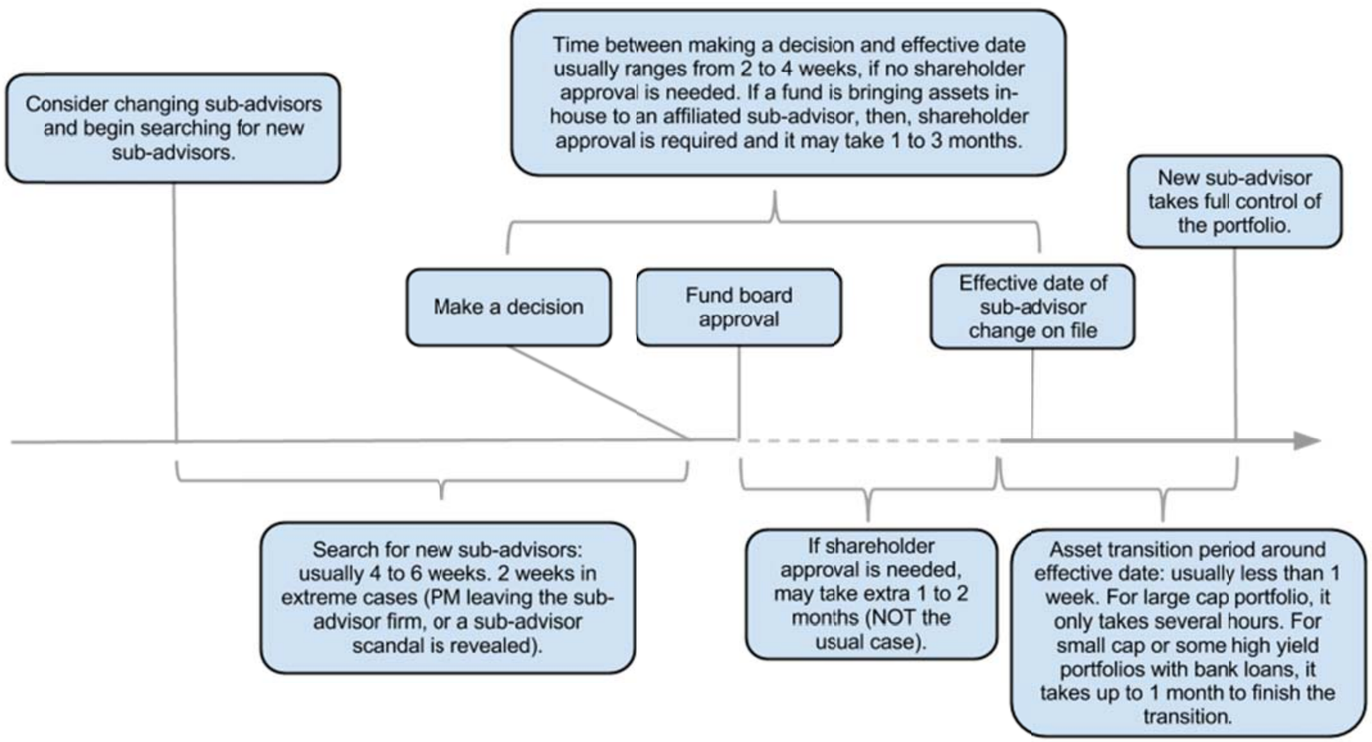


**Figure 2. Effects of Past Performance on Sub-advisor Change: A Semiparametric Analysis**

The figure plots the probability of changing a sub-advisor, estimated from the following equations:

$$P(Change_{i,t} = 1|X_{i,t}) = \frac{\exp\{f(X_{i,t})\}}{1 + \exp\{f(X_{i,t})\}}$$

$$f(X_{i,t}) = f(RetExCat_{i,[t-6,t-1]}) + \beta Control_{i,t} + \varepsilon_{i,t}$$

The vertical axis is the probability of a mutual fund changing a sub-advisor in month $t$ ($P(Change_{i,t} = 1)$) and the horizontal axis is the fund's past return performance, measured by the monthly excess return relative to benchmark averaged over months $t$-6 to $t$-1 ($RetExCat_{\mathrm{i,[t-6,t-1]}}$). $Control$ is a vector of control variables that include fund size, fund age and past flows. The estimation of $f(\cdot)$ applies the method introduced by Robinson (1988) and used by Chevalier and Ellison (1997), Chen, Goldstein and Jiang (2010) in the study of flow-performance sensitivity.

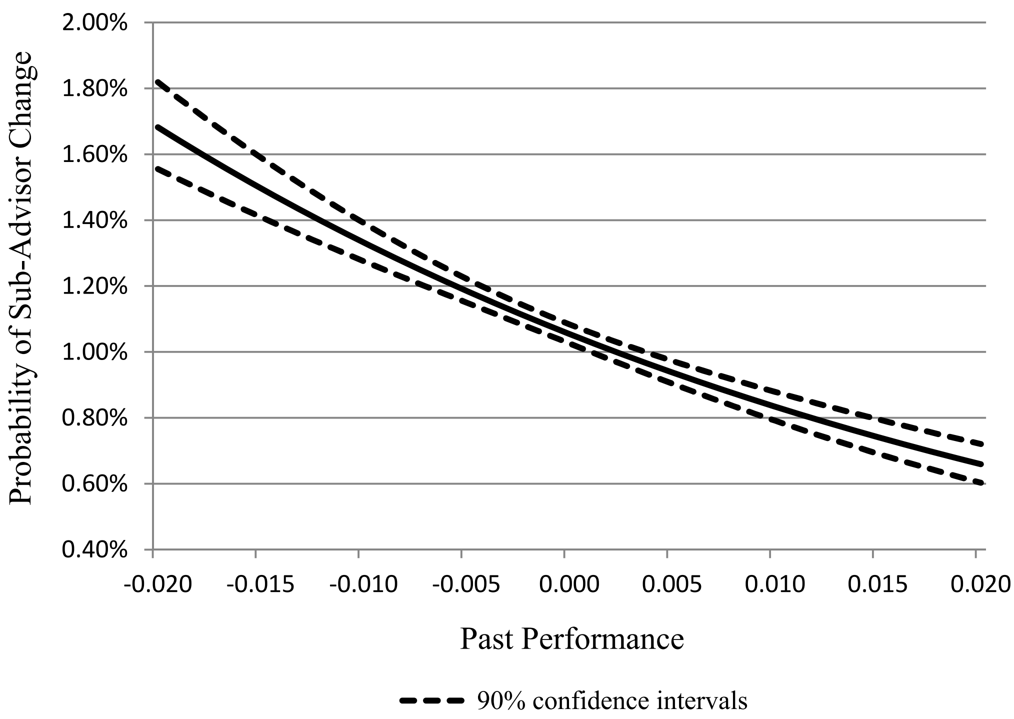


**Figure 3. Sub-Advisor Average Excess Return by Time around Hiring**

The horizontal axis measures time, in months, around a sub-advisor is **hired** by a mutual fund. The vertical axis measures the monthly average *RetExCat* across all targeted sub-advisors. Sub-advisor *RetExCat* is the monthly excess return of a sub-advisor, estimated as the value weighted average of excess returns of mutual funds that it sub-advises to. The dashed lines indicate the 95% confidence interval of the mean by month. To correct for cross correlation, sub-advisors that are hired during the same month are aggregated into one portfolio.

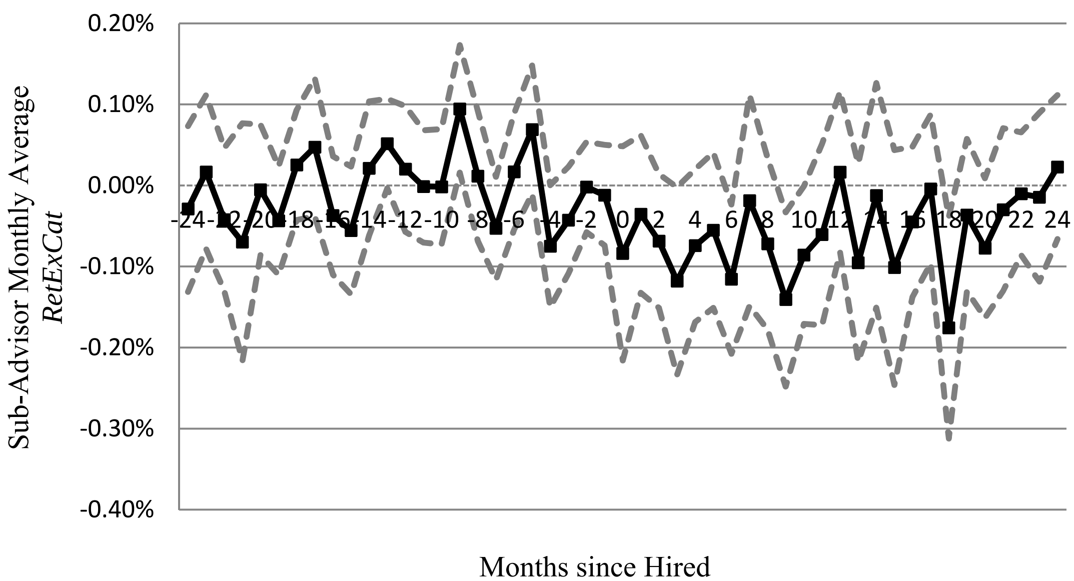


**Figure 4. Sub-Advisor Average Excess Return by Time around Firing**

The horizontal axis measures time, in months, around a sub-advisor is **fired** by a mutual fund. The vertical axis measures the monthly average *RetExCat* across all targeted sub-advisors. Sub-advisor *RetExCat* is the monthly excess return of a sub-advisor, estimated as the value weighted average of excess returns of mutual funds that it sub-advises to. The dashed lines indicate the 95% confidence interval of the mean by month. To correct for cross correlation, sub-advisors that are hired during the same month are aggregated into one portfolio.

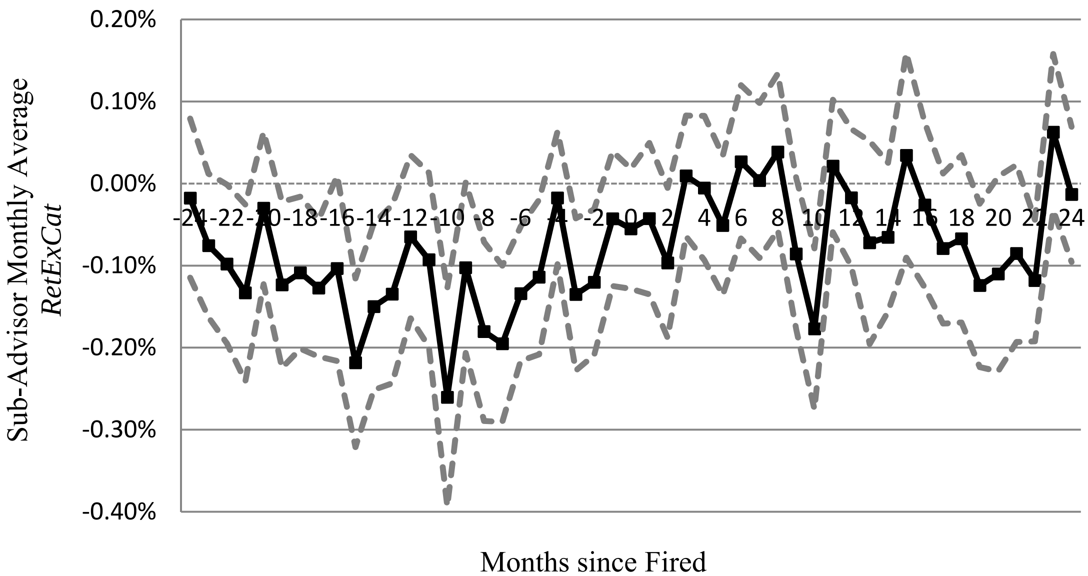
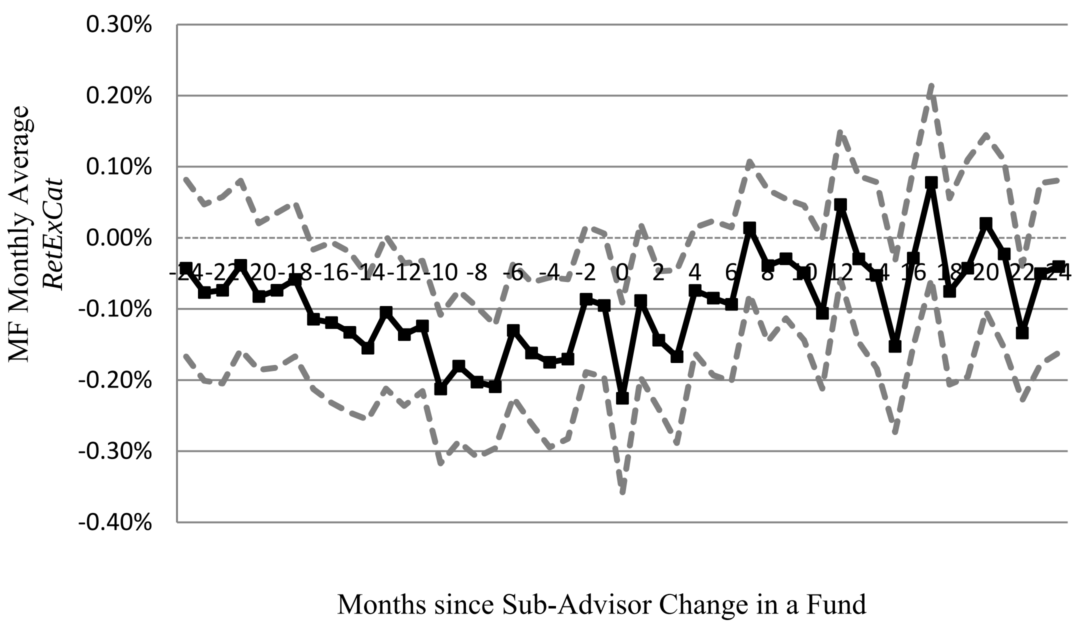


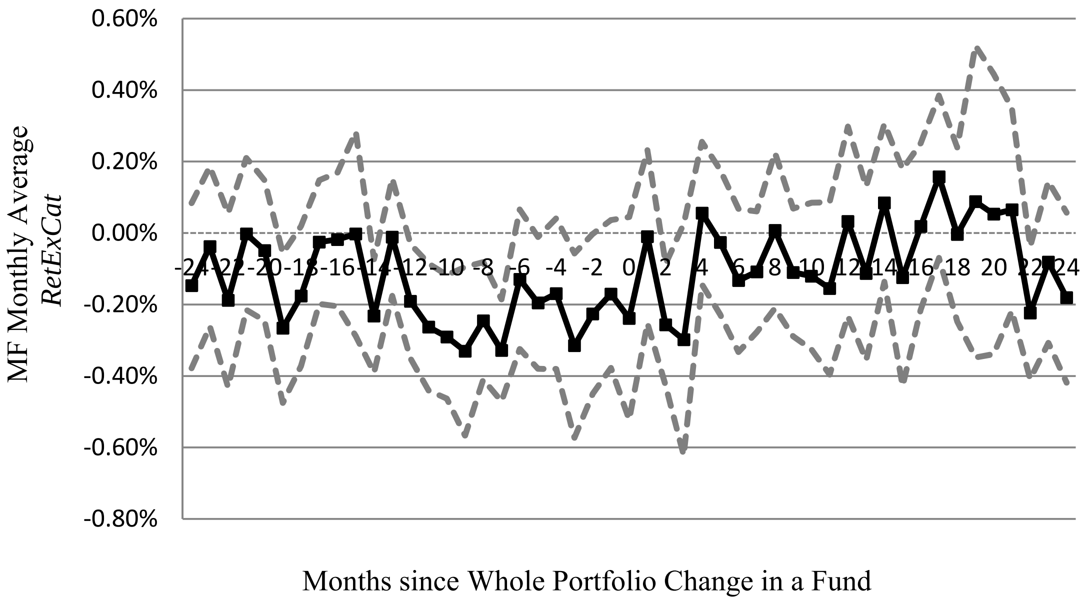
**Figure 5. Mutual Fund Average Excess Return by Time around Sub-Advisor Change**

In Panel A, the horizontal axis measures time, in months, around the event when a mutual fund actively changes its sub-advisors. In Panel B, the horizontal axis measures time, in months, around the event when a mutual fund fires all of its sub-advisor(s) and hires completely different new ones (referred as Whole Portfolio Change in this paper). The vertical axis measures the monthly average *RetExCat* across all targeted mutual funds, where *RetExCat* is the monthly return of the fund (before fees) in excess of that of the category. The dashed lines indicate the 95% confidence interval of the mean by month. To correct for cross correlation, funds in which sub-advisor change takes place during the same month are aggregated into one portfolio.

**Panel A: Mutual Funds with Active Sub-advisor Changes**



**Panel B: Mutual Funds with Whole Portfolio Changes**



## B. Essay 2

### Figure 1. Returns on REITs and S&P 500 Indexes

The figure plots the cumulative returns on the MSCI U.S. REITs Index and S&P 500 Index. The series includes monthly data ranging from January 2003 to March 2009.

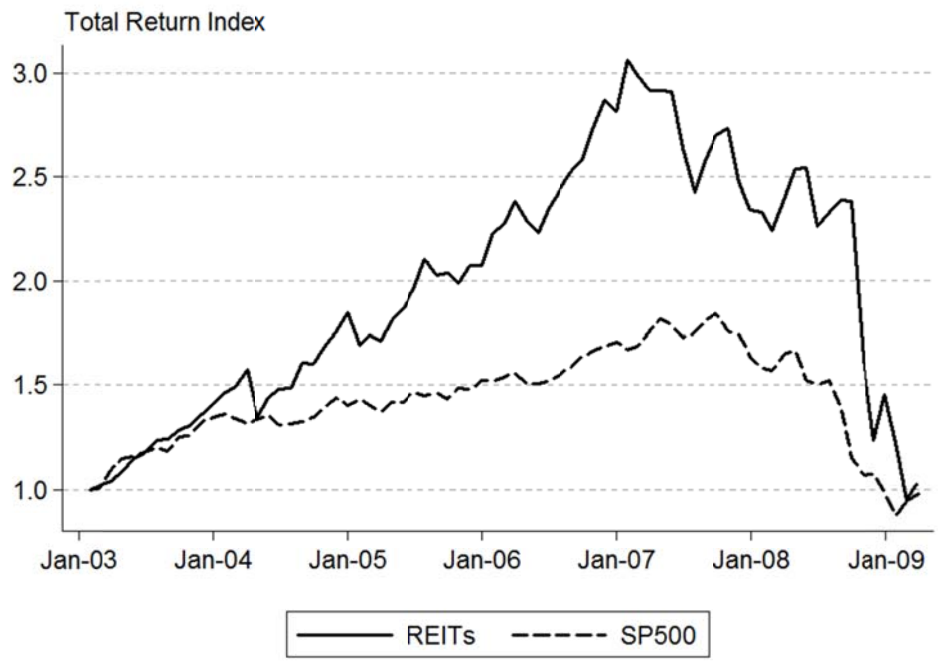


**Figure 2. EV/EBITDA Ratio of REITs and NYSE Stocks**

The figure plots the median EV/EBITDA (Enterprise Value to EBITDA) ratios of REITs and NYSE stocks. Enterprise Value is defined as the firm's market capital plus debt minus cash and equivalent. EBITDA is the earnings before interest, tax, depreciation and amortization. I use EBITDA that is lagged six months in the calculation. The series ranges from January 2000 to March 2009.

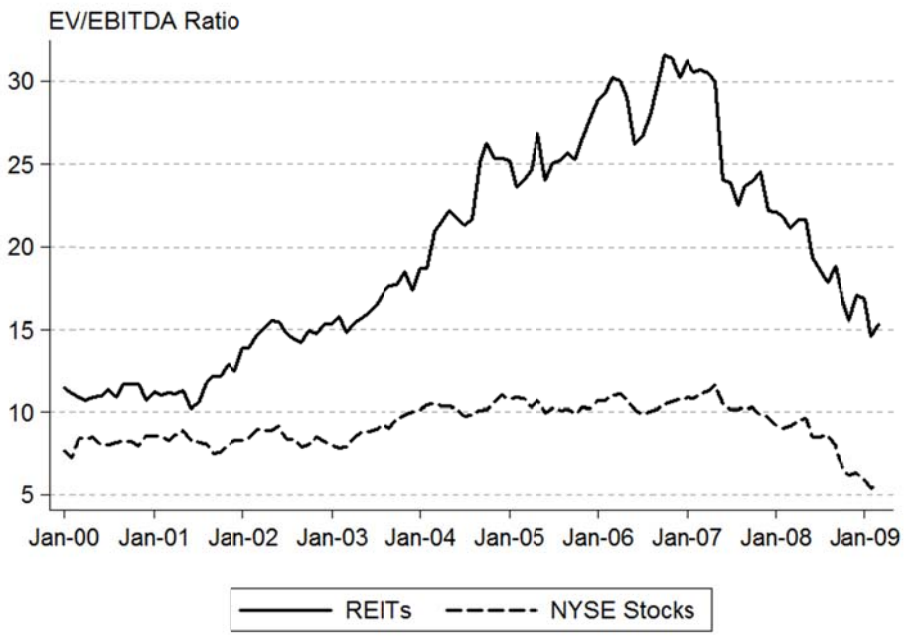
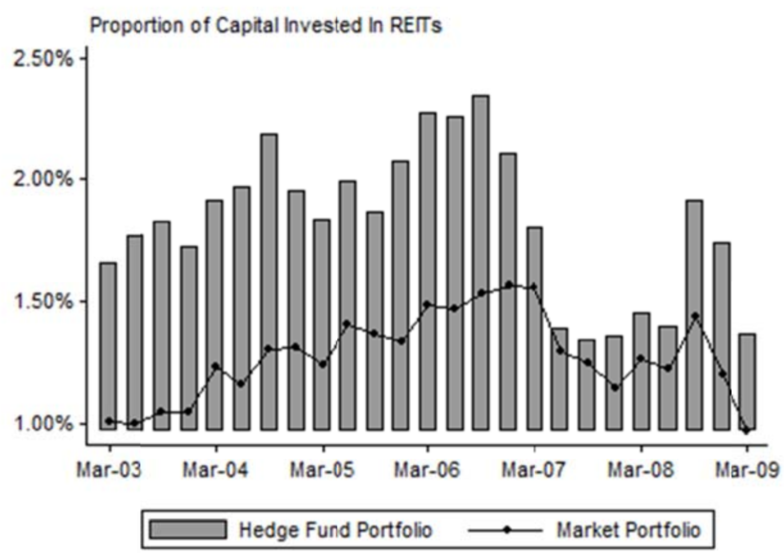


**Figure 3. Aggregate Weight of REITs in Hedge Fund Portfolio and Market Portfolio**

The figures plot the weight of REITs in the aggregate hedge fund portfolio and the market portfolio. In Panel A, the weight of REITs in the aggregate hedge fund portfolio is defined as the total market value of all hedge funds holdings in REITs scaled by the total market value of their entire stock holdings. The weight of REITs in the market portfolio is defined as the total market value of REITs scaled by the total market value of all stocks on CRSP. In Panel B, the weight of REITs in the aggregate hedge fund portfolio by percentage of shares is defined as the total shares of all hedge funds holdings in REITs scaled by the total shares of hedge funds holdings in entire stocks. The weight of REITs in the market portfolio by percentage of shares is defined as the total outstanding shares of REITs scaled by the total outstanding shares of entire stocks on CRSP. The series includes quarterly data ranging from 2003Q1 to 2009Q1.

Panel A: The Proportion of Capital Invested in REITs




Panel B: The Proportion of Shares Invested in REITs

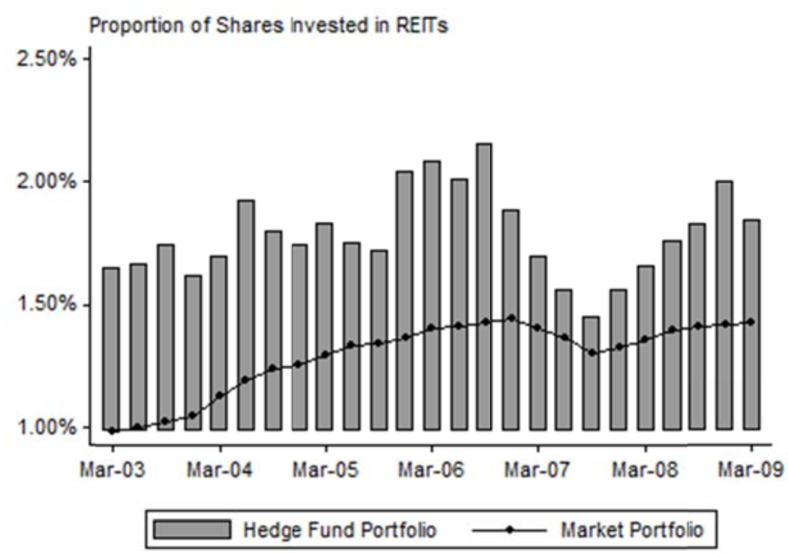
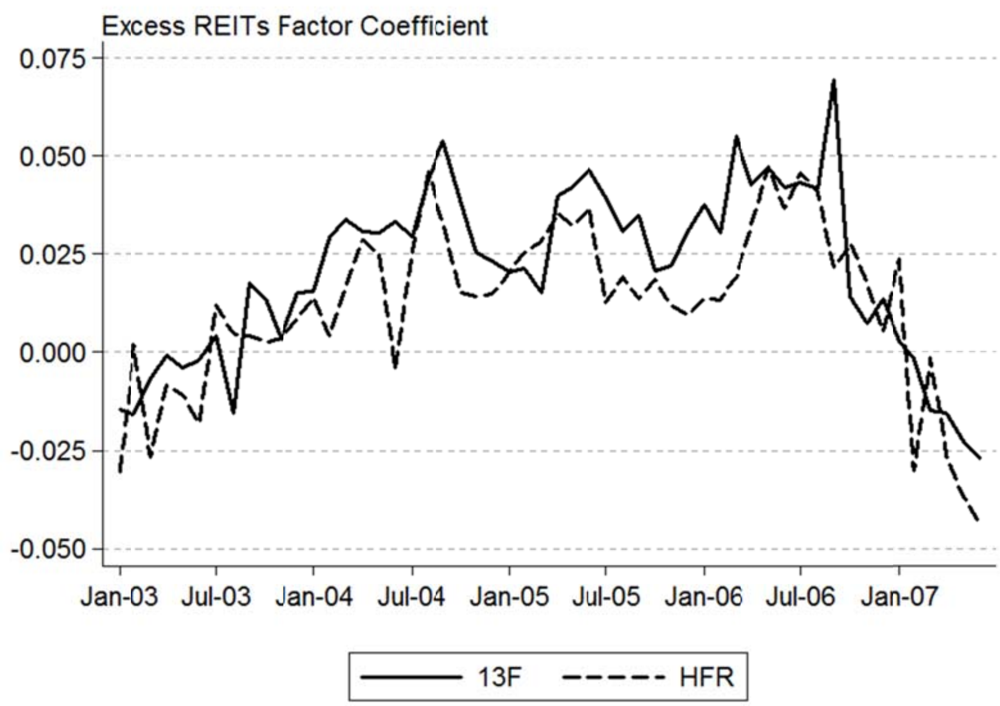


**Figure 4. Exposure of Hedge Funds to the Real Estate Sector: Smoothed Kalman Filter Estimates**

This figure presents the results of time-series regressions of monthly hedge fund index returns on $R_{M,t}$, the CRSP value-weighted NYSE/AMEX/Nasdaq market index, and $R_{REITs,t} - R_{M,t}$, the REITs return in excess of the market return (the excess REITs factor), as in Table 3, but allowing for stochastic time-varying regression coefficients, estimated by Kalman filter approach with smoothing. Dependent variables are *13F*, the monthly return on the aggregate long positions of hedge funds; and *HFR*, the equal-weighted average across all HFR style indexes examined in Table 3, with the exception of short-selling specialists (*Short Bias*) and real estate specialists (*Real Estate*). The sample period is January 2003 to June 2007.



## C. Essay 3

**Figure 1. Percentiles of Weights**

**Retail-Oriented Funds V.S. Institution-Oriented Funds**

This figure plots the 90th, 80th, 60th, and 40th percentiles of the weight of REITs in retail-oriented hedge fund portfolio and institution-oriented hedge fund portfolio at the end of each quarter from 2003Q1 to 2009Q1. For each hedge fund at the end of each quarter, I compute the weight of REITs in its portfolio. The weight of REITs in a hedge fund's portfolio is defined as the market value of the hedge fund's holdings in REITs scaled by the market value of its entire stock holdings. Then, for each quarter end, I rank these weights within each group of hedge funds, namely, the retail-oriented hedge funds and the institution-oriented hedge funds.

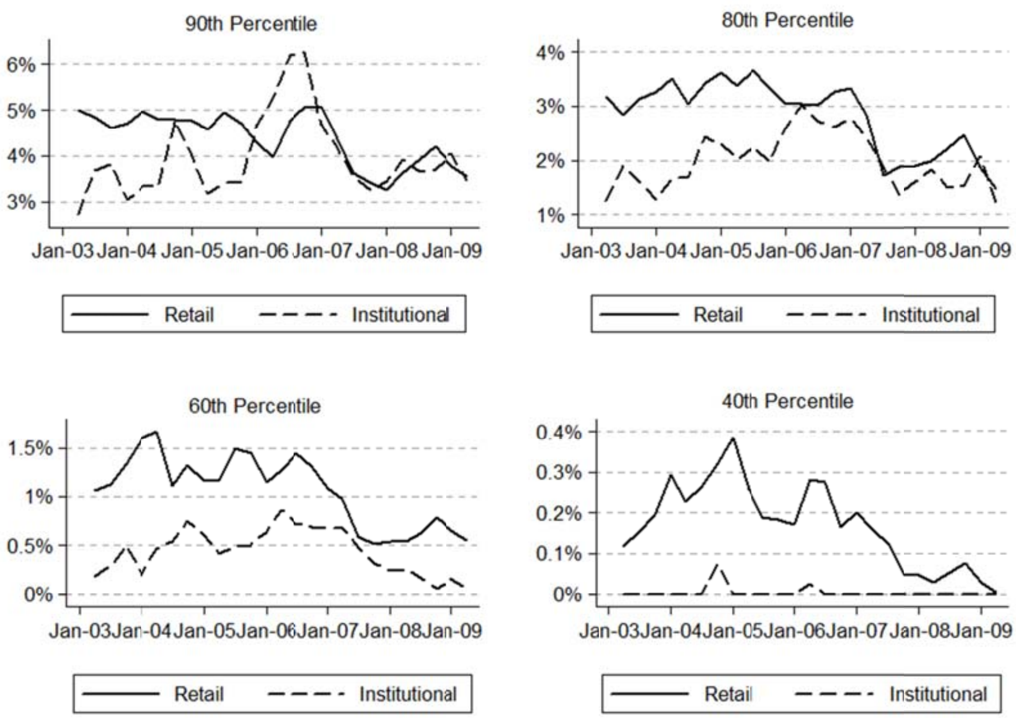
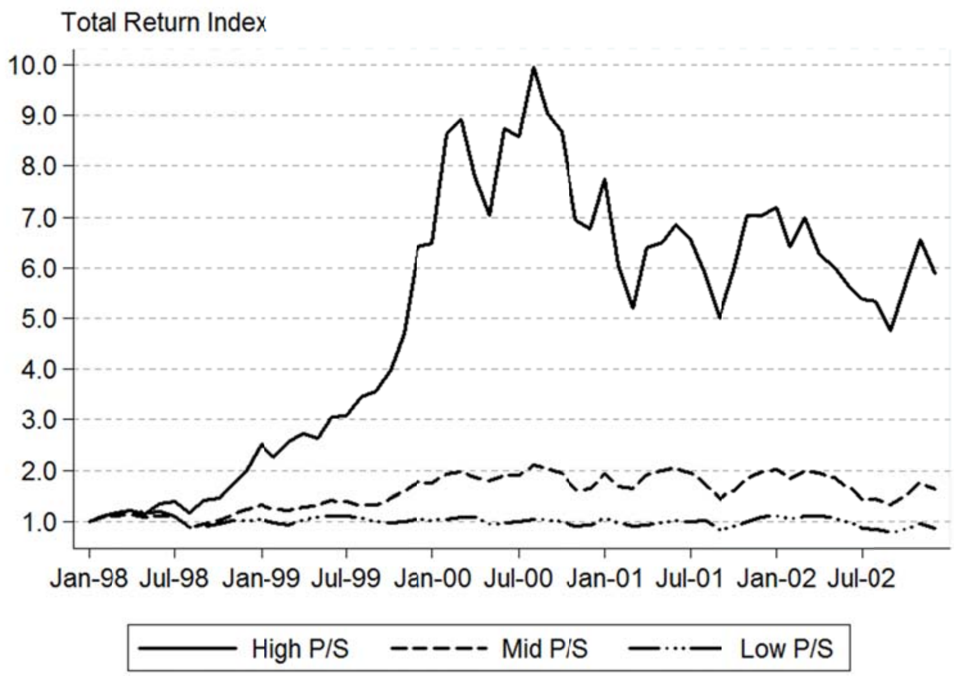


**Figure 2. Returns on Nasdaq by Price/Sales Quintile, 1998-2002**

At the end of each month, I rank all stocks on Nasdaq by their Price/Sales (P/S) ratios and form five portfolios based on quintile breakpoints. Portfolios are rebalanced each month. The figure shows value-weighted indexes of total returns for the high P/S, median P/S, and low P/S portfolios.



# II. Tables

## A. Essay 1

### Table 1. Variable Definitions and Summary Statistics

The sample contains 145,024 fund-month observations of 3,214 sub-advised funds from December 2006 to September 2012. Data are obtained from the Center for Research in Security Prices (CRSP) mutual fund database. Panel A defines all variables. Panel B provide summary statistics of these variables.

**Panel A. Variable Definitions**

| Variable | Definition |
|---|---|
| Mutual Fund Level | |
| *Age* | Number of years since the fund's inception. |
| *Change* | Dummy=1 if an active change in sub-advisor takes place in fund. |
| *Equity* | Dummy=1 if fund is an equity fund. |
| *ExpRatio* | Expenses of a fund as a percentage of total assets. |
| *ExpExCat* | Monthly expense ratio of a fund in excess of that of all funds in the same category. |
| *ExpExSub* | Monthly expense ratio of a fund in excess of that of sub-advised funds in the same category. |
| *ExpExQtl* | Monthly expense ratio of a fund in excess of that of funds in the same quintile (based on past 12 month return before fees). |
| *Flow* | Monthly percentage net flow into the fund. |
| *Flow[t1,t2]* | Monthly percentage net flow into the fund, averaged over the months [t1,t2]. |
| *FOF* | Dummy=1 if fund is a fund of fund. |
| *Index* | Dummy=1 if fund is an index fund. |
| *Out[t1,t2]* | Equals one if *Flow[t1,t2]* is negative, otherwise equals zero. |
| *RetExCat* | Monthly return of a fund (before fees) in excess of that of the category. |
| *RetExCat[t1,t2]* | Monthly return of a fund (before fees) in excess of that of all funds in the same category, averaged over the months [t1,t2]. |
| *Poor[t1,t2]* | Equals one if *RetExCat[t1,t2]* is negative, otherwise equals zero. |
| *RetExSub* | Monthly return of a fund (before fees) in excess of that of sub-advised funds in the same category. |
| *RetExQtl* | Monthly return of a fund (before fees) in excess of that of funds in the same quintile (based on past 12 month return before fees). |
| *Size* | Total asset value of a fund, in millions. |
| Sub-Advisor Level | |
| *RetExCat* | Monthly excess return of a sub-advisor, estimated by the value weighted average of *RetExCat* of mutual funds that it sub-advises to. |
| Fund - Sub-Advisor Level | |
| *Affiliation* | Dummy=1 if a fund is affiliated with a sub-advisor. |

**Panel B. Summary Statistics of Key Variables**

| Variable | Mean | Std. Dev. | p1 | p50 | p99 |
|---|---|---|---|---|---|
| *Age* | 7.8 | 7.8 | 0.1 | 4.8 | 38.9 |
| *Change* | 1.06% | 10.24% | 0.00 | 0.00 | 1.00 |
| *ExpRatio* | 1.10% | 0.56% | 0.14% | 1.05% | 2.68% |
| *Flow* | 0.77% | 7.87% | -17.38% | -0.22% | 37.03% |
| *Flow[-6,-1]* | 1.01% | 6.32% | -8.69% | -0.23% | 31.56% |
| *Flow[-12,-7]* | 1.12% | 6.43% | -8.31% | -0.17% | 31.52% |
| *Flow[-24,-13]* | 1.49% | 6.48% | -6.03% | -0.02% | 31.27% |
| *Flow[-36,-25]* | 1.77% | 7.23% | -5.77% | 0.09% | 35.79% |
| *RetExCat* | -0.04% | 2.07% | -5.22% | -0.02% | 4.98% |
| *RetExCat[-6,-1]* | -0.03% | 0.78% | -2.35% | -0.01% | 2.12% |
| *RetExCat[-12,-7]* | -0.02% | 0.78% | -2.31% | -0.01% | 2.15% |
| *RetExCat[-24,-13]* | -0.01% | 0.54% | -1.52% | -0.01% | 1.54% |
| *RetExCat[-36,-25]* | -0.01% | 0.54% | -1.48% | -0.01% | 1.58% |
| *Size* | 932.7 | 7654.8 | 0.9 | 189.4 | 11460.6 |

## Table 2. Overview of Sub-advisor Changes

### Panel A. Sub-Advisor Change by Category

In this Panel, Column (1) presents the number of sub-advisor changes in each category. Column (2) presents the total assets (in millions) of sub-advisor changes in each category. Sample period ranges from December 2006 to September 2012. Passive Change refers to a sub-advisor change when a fund liquidates, merges, or establishes. Active Change refers to the situations when a fund fires, hires, or hires and fires at least one sub-advisor at the same time.

| | (1) Number of Occurrence | (2) Assets (in Millions) |
|---|---|---|
| Passive Change | | |
| Liquidation | 57 | $3,031.50 |
| Merge | 102 | $93,088.75 |
| New Fund | 119 | $7,556.73 |
| Total | 278 | $103,676.97 |
| Active Change | | |
| Fire | 274 | $222,529.43 |
| Hire | 320 | $433,047.90 |
| Hire and Fire | 940 | $473,221.09 |
| Total | 1534 | $1,128,798.42 |

### Panel B. Percentage of Sub-Advisor Active Change by Year and Performance

This Panel presents the number of active sub-advisor changes in each year-performance category as a percentage of the number of all sub-advised funds in that category. *RetExCat[-12,-1]* is the monthly return of a fund (before fees) in excess of that of all funds in the same category, averaged over the 12 months before sub-advisor change.

| | (1) *RetExCat[-12,-1]*<=0 | (2) *RetExCat[-12,-1]*>0 |
|---|---|---|
| 2006 | 2.2% | 0.9% |
| 2007 | 13.7% | 10.7% |
| 2008 | 20.1% | 10.1% |
| 2009 | 16.2% | 10.6% |
| 2010 | 15.2% | 7.2% |
| 2011 | 12.7% | 11.3% |
| 2012 | 9.3% | 6.9% |

(Note: sub-advisor change in 2006 only includes data in December; sub-advisor change in 2012 only includes data from January to September.)

**Panel C. Comparing Composition of Funds:**
**Funds with Active Sub-Advisor Changes v.s. Sub-Advised Funds**

Panel C compares the composition of funds that have active sub-advisor changes and funds that are sub-advised. Funds can be classified into different groups by their structure, sub-advisor change type and size. Column (1) presents the number of funds that have active sub-advisor changes in each group, as a percentage of the total number of funds that have active sub-advisor changes. Column (2) presents the number of sub-advised funds in each group as a percentage of the total number of sub-advised funds.

| | Active Change | Sub-Advised |
|---|---|---|
| By Structure | | |
| Multi-managed | 75.3% | 70.3% |
| Single-managed | 24.7% | 29.7% |
| By Change Type | | |
| Whole Portfolio Change* | 40.9% | NA |
| Partial Portfolio Change** | 59.1% | NA |
| By Size | | |
| <10MM | 5.7% | 5.2% |
| 10MM-100MM | 26.5% | 24.9% |
| 100MM-1000MM | 48.2% | 51.4% |
| >1000MM | 19.6% | 18.5% |

* Whole Portfolio Change refers to the situation that a mutual fund fires all of its sub-advisor(s) and hires completely different new sub-advisor(s).
** Partial Portfolio Change refers to all other situations.

**Table 3. Percentage of Mutual Funds with Sub-Advisor Change: Double Sorted by Past Performance and Flow**

The table presents the monthly average of the percentage of mutual funds with sub-advisor changes, double sorted by their past 1 year *RetExCat* (relative return to Lipper category) and past 1 year flow.

Past 1 year Flow Quintile

| Past 1 year RetExCat Quintile | 1 | 2 | 3 | 4 | 5 | 5-1 |
|---|---|---|---|---|---|---|
| 1 | 1.66% | 1.74% | 1.46% | 1.24% | 1.02% | -0.64%** (-2.28) |
| 2 | 1.62% | 1.51% | 1.37% | 0.96% | 0.82% | -0.80%*** (-3.43) |
| 3 | 1.08% | 1.20% | 1.10% | 0.75% | 0.92% | -0.17% (-0.82) |
| 4 | 1.46% | 1.39% | 0.83% | 0.85% | 0.93% | -0.53%** (-2.11) |
| 5 | 0.86% | 0.98% | 0.48% | 0.63% | 0.61% | -0.25% (-1.37) |
| 5-1 | -0.80%*** (-3.16) | -0.77%** (-2.58) | -0.98%*** (-3.70) | -0.61%** (-2.52) | -0.41%** (-2.04) | -1.05%*** (-4.65) |

**Table 4. Effects of Fund Prior Performance on Sub-advisor Change**

This table presents estimated coefficients from probit regressions. The dependent variable is the dummy variable that equals one if the fund changed its sub-advisor in month t and zero otherwise (*Change*). RetExCat[t1,t2] equals the monthly average return of a fund (before fees) in excess of that of all funds in the same category in months [t1, t2]. Poor[t1,t2] is a dummy variable that equals one if RetExCat[t1,t2] is negative and zero otherwise. Table 1 lists the detailed definitions and calculations of all variables in the regression. All estimations include controls for past flows and year–month fixed effects. Observations are at the fund -month level. Standard errors adjust for heteroskedasticity and within-cluster correlation clustered at the fund level, and therefore the effective number of observations is on the order of number of funds. *, ** and *** indicate statistical significant at less than the 10%, 5% and 1% level, respectively.

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| *RetExCat[-6,-1]* | -16.121*** | -16.117*** | -15.247*** | -15.809*** |
| | (4.872) | (4.982) | (5.007) | (5.074) |
| *Poor[-6,-1]* | 0.021 | 0.015 | 0.013 | 0.011 |
| | (0.033) | (0.033) | (0.033) | (0.033) |
| *RetExCat[-6,-1]* Poor[-6,-1]* | 12.381** | 11.332* | 9.489 | 10.155 |
| | (6.077) | (6.330) | (6.483) | (6.567) |
| *RetExCat[-12,-7]* | | -19.206*** | -18.039*** | -19.412*** |
| | | (5.250) | (5.198) | (5.255) |
| *Poor[-12,-7]* | | 0.007 | 0.004 | 0.001 |
| | | (0.035) | (0.035) | (0.035) |
| *RetExCat[-12,-7]* Poor[-12,-7]* | | 12.348* | 9.642 | 11.146* |
| | | (6.495) | (6.474) | (6.500) |
| *RetExCat[-24,-13]* | | | -21.650*** | -24.318*** |
| | | | (7.297) | (7.309) |
| *Poor[-24,-13]* | | | -0.014 | -0.022 |
| | | | (0.034) | (0.034) |
| *RetExCat[-24,-13]* Poor[-24,-13]* | | | 17.852* | 21.383** |
| | | | (10.362) | (10.297) |
| *RetExCat[-36,-25]* | | | | 1.822 |
| | | | | (6.003) |
| *Poor[-36,-25]* | | | | 0.026 |
| | | | | (0.036) |
| *RetExCat[-36,-25]* Poor[-36,-25]* | | | | -13.645 |
| | | | | (8.488) |
| *Size(Ln)* | 0.021** | 0.021** | 0.021** | 0.022** |
| | (0.010) | (0.010) | (0.010) | (0.010) |
| *Age(Ln)* | 0.023 | 0.024 | 0.025 | 0.028 |
| | (0.025) | (0.025) | (0.025) | (0.025) |
| Time Dummies | Yes | Yes | Yes | Yes |
| Controls for Past Flows | Yes | Yes | Yes | Yes |
| Observations | 89,215 | 89,215 | 89,215 | 89,215 |
| $R^2$ | 0.025 | 0.028 | 0.030 | 0.031 |

**Table 5. Effects of Prior Flows on Sub-advisor Change**

This table presents estimated coefficients from Probit regressions. The dependent variable is the dummy variable that equals one if the fund changed its sub-advisor in month t and zero otherwise (*Change*). *Flow[t1, t2]* equals the monthly average percentage net flow into the fund in months [t1, t2]. *Out[t1, t2]* equals one if *Flow[t1, t2]* is negative and zero otherwise. Table 1 lists the detailed definitions and calculations of all variables in the regression. Observations are at the fund -month level. All estimations include controls for past performance and year-month fixed effects. Standard errors adjust for heteroskedasticity and within-cluster correlation clustered at the fund level, and therefore the effective number of observations is on the order of number of funds. *, ** and *** indicate statistical significant at less than the 10%, 5% and 1% level, respectively.

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| *Flow[-6, -1]* | -0.375 | -0.330 | -0.323 | -0.326 |
| | (0.336) | (0.310) | (0.321) | (0.318) |
| *Out[-6, -1]* | 0.032 | -0.008 | -0.017 | -0.016 |
| | (0.034) | (0.034) | (0.034) | (0.034) |
| *Flow[-6, -1]* Out[-6, -1]* | -1.655** | -1.778** | -1.818** | -1.820*** |
| | (0.682) | (0.704) | (0.710) | (0.705) |
| *Flow[-12, -7]* | | -0.353 | -0.340 | -0.330 |
| | | (0.351) | (0.345) | (0.337) |
| *Out[-12, -7]* | | 0.113*** | 0.099*** | 0.099*** |
| | | (0.032) | (0.032) | (0.032) |
| *Flow[-12, -7]* Out[-12, -7]* | | 0.604 | 0.651 | 0.609 |
| | | (0.780) | (0.785) | (0.777) |
| *Flow[-24, -13]* | | | -0.129 | -0.125 |
| | | | (0.132) | (0.128) |
| *Out[-24, -13]* | | | 0.045 | 0.046 |
| | | | (0.033) | (0.033) |
| *Flow[-24, -13]* Out[-24, -13]* | | | -0.306 | -0.514 |
| | | | (1.012) | (1.005) |
| *Flow[-36,-25]* | | | | 0.004 |
| | | | | (0.004) |
| *Out[-36,-25]* | | | | 0.007 |
| | | | | (0.033) |
| *Flow[-36,-25]* Out[-36,-25]* | | | | 1.338 |
| | | | | (1.105) |
| *Size(Ln)* | 0.018* | 0.021** | 0.023** | 0.022** |
| | (0.010) | (0.010) | (0.010) | (0.010) |
| *Age(Ln)* | 0.044* | 0.030 | 0.020 | 0.023 |
| | (0.024) | (0.024) | (0.024) | (0.024) |
| Time Dummies | Yes | Yes | Yes | Yes |
| Controls for Past Performance | Yes | Yes | Yes | Yes |
| Observations | 89,215 | 89,215 | 89,215 | 89,215 |
| $R^2$ | 0.028 | 0.030 | 0.031 | 0.031 |

**Table 6. Effects of Interaction of Past Performance and Flow on Sub-advisor Change**

This table presents estimated coefficients from Probit regressions. The dependent variable is the dummy variable that equals one if the fund changed its sub-advisor in month t and zero otherwise (*Change*). *RetExCat[t1,t2]* equals the monthly average return of a fund (before fees) in excess of that of all funds in the same category in months [t1, t2]. *Flow[t1, t2]* equals the monthly average percentage net flow into the fund in months [t1, t2]. Table 1 lists the detailed definitions and calculations of all variables in the regression. Observations are at the fund -month level. All estimations include year-month fixed effects. Standard errors adjust for heteroskedasticity and within-cluster correlation clustered at the fund level, and therefore the effective number of observations is on the order of number of funds. *, ** and *** indicate statistical significant at less than the 10%, 5% and 1% level, respectively.

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| *RetExCat[-6,-1]* | -6.352*** | -7.455*** | -7.098*** | -7.207*** |
| | (1.216) | (1.295) | (1.385) | (1.423) |
| *Flow[-6,-1]* | -0.260 | -0.404 | -0.325 | -1.200*** |
| | (0.196) | (0.330) | (0.346) | (0.420) |
| *RetExCat[-6,-1]* Flow[-6,-1]* | -10.358* | -18.158 | -16.701 | -15.959 |
| | (5.731) | (11.076) | (12.092) | (15.742) |
| *RetExCat[-12,-7]* | | -8.775*** | -9.121*** | -9.456*** |
| | | (1.273) | (1.325) | (1.394) |
| *Flow[-12, -7]* | | -0.003 | 0.029 | -0.792** |
| | | (0.027) | (0.026) | (0.363) |
| *RetExCat[-12,-7]* Flow[-12,-7]* | | 1.398 | 1.436 | 15.694 |
| | | (4.187) | (2.976) | (22.823) |
| *RetExCat[-24,-13]* | | | -8.665*** | -8.612*** |
| | | | (2.345) | (2.469) |
| *Flow[-24,-13]* | | | -0.227** | -0.345 |
| | | | (0.109) | (0.346) |
| *RetExCat[-24,-13]* Flow[-24,-13]* | | | 17.565 | 15.972 |
| | | | (17.266) | (32.061) |
| *RetExCat[-36,-25]* | | | | -7.169*** |
| | | | | (2.465) |
| *Flow[-36,-25]* | | | | 0.041*** |
| | | | | (0.013) |
| *RetExCat[-36,-25]* Flow[-36,-25]* | | | | 11.531*** |
| | | | | (3.518) |
| *Size(Ln)* | 0.014* | 0.013 | 0.014 | 0.022** |
| | (0.008) | (0.008) | (0.009) | (0.010) |
| *Age(Ln)* | 0.031** | 0.050*** | 0.045** | 0.042* |
| | (0.015) | (0.018) | (0.020) | (0.024) |
| Time Dummies | Yes | Yes | Yes | Yes |
| Observations | 127,625 | 115,238 | 105,781 | 89,215 |
| $R^2$ | 0.013 | 0.017 | 0.020 | 0.027 |

## Table 7. Investor Unawareness of Sub-Advisor Change

This table presents the sensitivity of fund flows to changes in sub-advisor for all funds and equity funds. The dependent variable is mutual fund flow in the current month (*Flow*). *Flow[t1,t2]* is the monthly percentage net flow into the fund, averaged over the months [t1,t2]. *RetExCat[t1,t2]* is the monthly average return of a fund (before fees) in excess of that of all funds in the same category in months [t1, t2]. Table 1 lists the detailed definitions and calculations of all variables in the regression. Observations are at the fund -month level. Column (1) and (4) include all observations. Column (2) and (5) include observations with *RetExCat[-6,-1]*<0. Column (3) and (6) include observations with both *RetExCat[-6,-1]*<0 and *RetExCat[-12,-7]*<0. All estimations include year–month fixed effects. Standard errors adjust for heteroskedasticity and within-cluster correlation clustered at the fund level, therefore the effective number of observations is on the order of number of funds. *, ** and *** indicate statistical significant at less than the 10%, 5% and 1% level, respectively.

| | All Funds | | | Equity Funds Only | | |
|---|---|---|---|---|---|---|
| | All Observations | RetExCat [-6,-1]<0 | RetExCat[-6,-1]<0 & RetExCat[-12,-7]<0 | All Observations | RetExCat [-6,-1]<0 | RetExCat[-6,-1]<0 & RetExCat[-12,-7]<0 |
| *Change* | 0.005 | 0.011 | 0.005 | 0.011 | 0.005 | 0.009 |
| | (0.009) | (0.012) | (0.015) | (0.010) | (0.013) | (0.017) |
| *Flow[-6,-1]* | 0.235*** | 0.199*** | 0.179*** | 0.253*** | 0.223*** | 0.237*** |
| | (0.015) | (0.018) | (0.024) | (0.013) | (0.017) | (0.023) |
| *Flow[-12,-7]* | 0.073*** | 0.070*** | 0.096*** | 0.078*** | 0.071*** | 0.083*** |
| | (0.007) | (0.010) | (0.013) | (0.008) | (0.010) | (0.013) |
| *RetExCat[-6,-1]* | 0.710*** | 0.546*** | 0.402*** | 0.794*** | 0.615*** | 0.424*** |
| | (0.049) | (0.087) | (0.121) | (0.052) | (0.089) | (0.124) |
| *RetExCat[-12,-7]* | 0.316*** | 0.350*** | 0.391*** | 0.318*** | 0.316*** | 0.356*** |
| | (0.041) | (0.055) | (0.103) | (0.046) | (0.058) | (0.110) |
| *Size (Ln)* | 0.001*** | 0.002*** | 0.001*** | 0.001*** | 0.001*** | 0.001*** |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| *Age (Ln)* | -0.006*** | -0.006*** | -0.006*** | -0.005*** | -0.006*** | -0.006*** |
| | (0.000) | (0.001) | (0.001) | (0.000) | (0.001) | (0.001) |
| *ExpRatio* | -0.302*** | -0.400*** | -0.416*** | -0.256*** | -0.300*** | -0.301** |
| | (0.060) | (0.083) | (0.114) | (0.068) | (0.091) | (0.124) |
| Time Dummies | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 95,510 | 47,814 | 25,409 | 74,279 | 37,266 | 19,391 |
| $R^2$ | 0.084 | 0.072 | 0.069 | 0.104 | 0.093 | 0.097 |

**Table 8. Sub-Advisor Cumulative Excess Return around Hiring and Firing Events**

This table presents the average cumulative return of sub-advisors that are being hired or fired in excess of that of benchmarks. In Column (1) and (3), sub-advisor *RetExCat* is the value weighted *RetExCat* (return in excess of Lipper Category) of all the funds that the sub-advisor sub-advises. In Column (2) and (4), *RetExDD6* is the sub-advisor return (*RetExCat*) in excess of the return (*RetExCat*) of all sub-advisors that are in the same past 6 month return quintile and in the same past flow category. It is calculated as follows. Step 1, for each sub-advisor that is ever hired or fired in our sample (target), we calculate its *RetExCat* around "date zero". Step 2, for each target, we calculate its benchmark return during the same period. To calculate the benchmark return, for each month, we first assign each sub-advisor a return quintile number (1 through 5) based on its past 6 month *RetExCat* and assign a flow category (+, -, 0) based on its past 6 month flow sign. Then, for each potential "date zero", a portfolio is formed with all sub-advisors in the same return quintile and flow category as the target. We are then able to track the monthly performance of the portfolio around "date zero". Step3, we calculate the return of each target in excess of that of the benchmark around "date zero". Step 4, for sub-advisors that are being hired or fired in the same calendar month, we aggregate them into a single observation to overcome cross correlation. Step 5, for each calendar month, we sum up excess returns over the windows for different "date zeros". Step 6, we take the average cumulative excess return across different calendar months. The last two steps follow the methodology used in Jegadeesh and Titman (1993). t-statistics are presented in the parenthesis. *, ** and *** indicate statistical significant at less than the 10%, 5% and 1% level, respectively.

| | Hired Sub-Advisor | | Fired Sub-Advisor | |
|---|---|---|---|---|
| | (1) Cumulative *RetExCat* | (2) Cumulative *RetExDD6* | (3) Cumulative *RetExCat* | (4) Cumulative *RetExDD6* |
| [-18,-13] | 0.05% | 0.12% | -0.81%*** | -0.43%*** |
| | (0.45) | (1.17) | (-5.27) | (-4.10) |
| [-12,-7] | 0.07% | 0.19%* | -0.99%*** | -0.32%*** |
| | (0.63) | (1.79) | (-6.31) | (-3.38) |
| [-6,-1] | -0.05% | 0.01% | -0.54%*** | -0.09% |
| | (-0.49) | (0.20) | (-4.12) | (-1.18) |
| [-18,-1] | 0.06% | 0.29% | -2.00%*** | -0.73%*** |
| | (0.25) | (1.55) | (-6.05) | (-4.10) |
| [1,6] | -0.42%*** | -0.18%** | -0.14% | 0.09% |
| | (-3.00) | (-2.12) | (-1.06) | (0.80) |
| [7,12] | -0.30%** | -0.17%** | -0.19% | -0.02% |
| | (-2.12) | (-2.14) | (-1.55) | (-0.18) |
| [13,18] | -0.39%** | -0.07%* | -0.24% | -0.21% |
| | (-2.01) | (-1.70) | (-1.26) | (-1.04) |
| [1,18] | -0.98%*** | -0.45%*** | -0.40% | -0.04% |
| | (-3.25) | (-2.54) | (-1.56) | (-0.15) |
| [1,18] – [-18,-1] | -1.03%*** | -0.73%*** | 1.60%*** | 0.69%*** |
| | (-2.76) | (-2.76) | (3.80) | (2.72) |

**Table 9. Effects of Size on Sub-advisor Performance**

This table presents estimated coefficients from baseline regression model. Observations are at the sub-advisor-month level. Dependent variable is sub-advisor return in excess of the category in the end of the month (*RetExCat*), in percentage. We calculate two measures to capture the size of a sub-advisor: the mandated assets in million dollars (*Assets*), and the mandated number of funds (*Counts*). *RetExCat[-1]* is sub-advisor return in excess of the category in the end of last month. *Affiliation* is the value weighted *Affiliation* score a sub-advisor gets from all of its mandated mutual funds. *Index* is the value weighted *Index* score a sub-advisor gets from all of its mandated mutual funds. *FOF* is the value weighted *FOF* score a sub-advisor gets from all of its mandated mutual funds. *Equity* is the value weighted *Equity* score a sub-advisor gets from all of its mandated mutual funds. Standard errors adjust for heteroskedasticity. *, ** and *** indicate statistical significant at less than the 10%, 5% and 1% level, respectively.

| *Size Measure* | *Assets* | | *Counts* | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| *Size* | -0.072*** | -0.077*** | -0.083*** | -0.080*** |
| | (0.017) | (0.017) | (0.023) | (0.023) |
| *RetExCat[-1]* | 0.080*** | 0.082*** | 0.080*** | 0.082*** |
| | (0.016) | (0.016) | (0.016) | (0.016) |
| *Affiliation* | 0.192* | 0.193** | 0.215** | 0.221** |
| | (0.099) | (0.098) | (0.098) | (0.098) |
| *Index* | -0.096 | -0.104 | -0.117 | -0.132 |
| | (0.212) | (0.212) | (0.211) | (0.211) |
| *FoF* | -0.043 | -0.026 | -0.067 | -0.051 |
| | (0.095) | (0.095) | (0.095) | (0.095) |
| *Equity* | -0.103 | -0.106 | -0.060 | -0.064 |
| | (0.083) | (0.082) | (0.083) | (0.083) |
| Observations | 41,454 | 41,454 | 41,454 | 41,454 |
| Sub-advisor FE | Yes | Yes | Yes | Yes |
| Time FE | No | Yes | No | Yes |
| $R^2$ | 0.046 | 0.055 | 0.045 | 0.055 |

**Table 10. Effects of Size on Sub-advisor Performance:**
**Equity Sub-advisor Only**

This table replicates the analyses of Table 8, except that the sample includes equity sub-advisor only. Observations are at the sub-advisor-month level. Dependent variable is sub-advisor return in excess of the category in the end of the month (*RetExCat*), in percentage. We calculate two measures to capture the size of a sub-advisor: the mandated assets in million dollars (*Assets*), and the mandated number of funds (*Counts*). *RetExCat[-1]* is sub-advisor return in excess of the category in the end of last month. *Affiliation* is the value weighted *Affiliation* score a sub-advisor gets from all of its mandated mutual funds. *Index* is the value weighted *Index* score a sub-advisor gets from all of its mandated mutual funds. *FOF* is the value weighted *FOF* score a sub-advisor gets from all of its mandated mutual funds. Standard errors adjust for heteroskedasticity. *, ** and *** indicate statistical significant at less than the 10%, 5% and 1% level, respectively.

| *Size Measure* | *Assets* | | *Counts* | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| *Size* | -0.092*** | -0.103*** | -0.124*** | -0.122*** |
| | (0.021) | (0.022) | (0.031) | (0.031) |
| *RetExCat[-1]* | 0.063*** | 0.065*** | 0.062*** | 0.065*** |
| | (0.018) | (0.018) | (0.018) | (0.018) |
| *Affiliation* | 0.128 | 0.126 | 0.163 | 0.174 |
| | (0.124) | (0.124) | (0.122) | (0.123) |
| *Index* | -0.318 | -0.332 | -0.335 | -0.364 |
| | (0.281) | (0.281) | (0.278) | (0.277) |
| *FoF* | -0.005 | 0.024 | -0.040 | -0.018 |
| | (0.117) | (0.116) | (0.115) | (0.115) |
| Observations | 30,451 | 30,451 | 30,451 | 30,451 |
| Sub-advisor FE | Yes | Yes | Yes | Yes |
| Time FE | No | Yes | No | Yes |
| $R^2$ | 0.046 | 0.059 | 0.045 | 0.058 |

## Table 11. Mutual Fund Performance and Expense Ratio around Sub-Advisor Change

This table presents the average return and the average expense ratio of funds with a sub-advisor change in excess of the benchmarks. It is calculated as follows. Step 1, for each mutual fund that ever has a sub-advisor change in our sample (target), we calculate its raw return (before fees) and expense ratio around “date zero”. Step 2, for each target, we calculate its benchmark raw return and expense ratio during the same period. We use three types of benchmarks: Benchmark 1 used in Column (1) and (4) is all funds in the same Lipper category as the target on “date zero”; Benchmark 2 used in Column (2) and (5) is all sub-advised funds in the same Lipper category as the target on “date zero”; Benchmark 3 used in Column (3) and (6) is all funds in the same Lipper category and in the same past return quintile as the target on “date zero”. To calculate Benchmark 3, for each month, we first assign each fund a quintile number (1 through 5) based on its past 12 month raw return within the same category. Then, for each potential “date zero”, a portfolio is formed with all funds in the same category and quintile as the target. We are then able to track the monthly performance and expense ratio of the portfolio around “date zero”. Step3, we calculate the return and expense ratio of each target in excess of that of the benchmark around “date zero”. Step 4, for funds that have sub-advisor changes in the same calendar month, we aggregate them into a single observation to overcome cross correlation. Step 5, for each calendar month, we sum up excess returns over the windows for different “date zeros”. Step 6, we take the average cumulative excess return across different calendar months. The last two steps follow the methodology used in Jegadeesh and Titman (1993). t-statistics are presented in the parenthesis. *, ** and *** indicate statistical significant at less than the 10%, 5% and 1% level, respectively.

| | Cumulative Excess Return | | | Cumulative Excess Expense Ratio | | |
|---|---|---|---|---|---|---|
| | (1) RetExCat | (2) RetExSub | (3) RetExQtl | (4) ExpExCat | (5) ExpExSub | (6) ExpExQtl |
| [-18,-13] | -0.64%*** | -0.51%*** | -0.66%*** | 0.19%*** | 0.18%*** | 0.16%*** |
| | (-3.79) | (-3.03) | (-4.51) | (35.42) | (26.12) | (34.49) |
| [-12,-7] | -0.99%*** | -0.79%*** | -0.02% | 0.19%*** | 0.19%*** | 0.16%*** |
| | (-6.71) | (-5.02) | (-0.14) | (32.93) | (25.10) | (35.38) |
| [-6,-1] | -0.76%*** | -0.57%*** | 0.00% | 0.21%*** | 0.21%*** | 0.17%*** |
| | (-5.16) | (-3.41) | (0.00) | (32.00) | (28.26) | (36.21) |
| [-18,-1] | -2.07%*** | -1.61%*** | -0.58%** | 0.51%*** | 0.50%*** | 0.43%*** |
| | (-6.19) | (-4.64) | (-2.24) | (24.38) | (21.44) | (24.91) |
| [1,6] | -0.60%*** | -0.47%** | -0.46%** | 0.21%*** | 0.22%*** | 0.18%*** |
| | (-3.56) | (-2.52) | (-2.32) | (27.33) | (23.75) | (31.30) |
| [7,12] | -0.10% | -0.05% | -0.13% | 0.22%*** | 0.22%*** | 0.18%*** |
| | (-0.72) | (-0.31) | (-0.79) | (28.74) | (25.03) | (29.67) |
| [13,18] | -0.22% | -0.07% | -0.41%** | 0.21%*** | 0.22%*** | 0.17%*** |
| | (-1.30) | (-0.44) | (-2.05) | (21.87) | (19.60) | (26.21) |
| [1,18] | -0.85%*** | -0.60%*** | -0.93%*** | 0.52%*** | 0.53%*** | 0.42%*** |
| | (-3.51) | (-2.80) | (-2.78) | (16.76) | (15.05) | (19.20) |
| [1,18] – [-18,-1] | 1.21%*** | 1.01%** | -0.34% | 0.01% | 0.02% | 0.00% |
| | (2.80) | (2.13) | (-0.78) | (0.24) | (0.53) | (0.08) |

**Table 12. Mutual Fund Performance and Expense Ratio around Sub-Advisor Change: Double Sorted Benchmarks**

This table presents the average return and the average expense ratio of funds with a sub-advisor change in excess of the double sorted benchmarks. It is calculated as follows. Step 1, for each mutual fund that ever has a sub-advisor change in our sample (target), we calculate its raw return (before fees) and expense ratio around “date zero”. Step 2, for each target, we calculate its benchmark raw return and expense ratio during the same period. The benchmarks are essentially all funds in the same Lipper category, in the same past return quintile and in the same past flow quintile as the target on “date zero”. Benchmark 1 used in Column (1) and (4) is based on past 12 month return and flow. Benchmark 2 used in Column (2) and (5) is based on past 6 month return and flow. Benchmark 3 used in Column (3) and (6) is based on past 1 month return and flow. To calculate the benchmarks, for each month, we first assign each fund a return quintile number (1 through 5) based on its past raw return within the same category and we assign a flow quintile number (1 through 5) based on its past flow within the same category. Then, for each potential “date zero”, a portfolio is formed with all funds in the same category as well as in the same return and flow quintile as the target. We are then able to track the monthly performance and expense ratio of the portfolio around “date zero”. Step3, we calculate the return and expense ratio of each target in excess of that of the benchmark around “date zero”. Step 4, for funds that have sub-advisor changes in the same calendar month, we aggregate them into a single observation to overcome cross correlation. Step 5, for each calendar month, we sum up excess returns over the windows for different “date zeros”. Step 6, we take the average cumulative excess return across different calendar months. The last two steps follow the methodology used in Jegadeesh and Titman (1993). t-statistics are presented in the parenthesis. *, ** and *** indicate statistical significant at less than the 10%, 5% and 1% level, respectively.

| | Cumulative Excess Return | | | Cumulative Excess Expense Ratio | | |
|---|---|---|---|---|---|---|
| | (1) RetExDD12 | (2) RetExDD6 | (3) RetExDD1 | (4) ExpExDD12 | (5) ExpExDD6 | (6) ExpExDD1 |
| [-18,-13] | -0.48%*** | -0.42%** | -0.46%*** | 0.13%*** | 0.12%*** | 0.12%*** |
| | (-2.92) | (-2.43) | (-3.23) | (27.19) | (27.08) | (31.24) |
| [-12,-7] | -0.11% | -0.97%*** | -0.71%*** | 0.13%*** | 0.13%*** | 0.13%*** |
| | (-0.76) | (-5.76) | (-4.98) | (27.80) | (28.70) | (29.65) |
| [-6,-1] | 0.02% | 0.07% | -0.44%*** | 0.14%*** | 0.14%*** | 0.15%*** |
| | (0.15) | (0.61) | (-4.03) | (30.88) | (26.53) | (28.72) |
| [-18,-1] | -0.49%*** | -1.14%*** | -1.38%*** | 0.35%*** | 0.34%*** | 0.34%*** |
| | (-2.87) | (-4.19) | (-5.43) | (24.46) | (25.29) | (23.91) |
| [1,6] | -0.38%** | -0.32%** | -0.30%** | 0.14%*** | 0.14%*** | 0.14%*** |
| | (-2.27) | (-2.06) | (-2.14) | (28.05) | (27.83) | (27.30) |
| [7,12] | -0.18% | -0.17% | -0.27%** | 0.14%*** | 0.14%*** | 0.14%*** |
| | (-1.01) | (-1.13) | (-2.43) | (26.49) | (26.91) | (25.94) |
| [13,18] | -0.45%** | -0.39%** | -0.36%** | 0.13%*** | 0.12%*** | 0.13%*** |
| | (-2.05) | (-2.54) | (-2.17) | (26.54) | (25.67) | (19.62) |
| [1,18] | -0.95%** | -0.81%*** | -0.86%*** | 0.32%*** | 0.31%*** | 0.33%*** |
| | (-2.56) | (-2.88) | (-3.25) | (21.19) | (19.73) | (18.41) |
| [1,18] – [-18,-1] | -0.47% | 0.33% | 0.53% | -0.02% | -0.03% | 0.01% |
| | (-1.06) | (0.83) | (1.42) | (-1.06) | (-1.32) | (0.43) |

## B. Essay 2

### Table 1: Variable Definitions

| **Variable** | **Definition** |
|---|---|
| Fund Level Data | |
| *Age* | The number of years since a fund's inception in 13F reporting. |
| *Flow* | The change in the value of a fund's equity portfolio due to changes in investment by the fund over the quarter (and not due to the changes in the stock prices), calculated as $Flow_{j,t} = (Size_{j,t} - Size_{j,t-1}(1 + Ret_{j,t}))/Size_{j,t-1}$. It is a proxy for the net fund flows. |
| *Herfindahl* | The sum of the squared fractions of investments in each stock. Herfindahl is an indicator of fund concentration. |
| *Perct* | The fractional rank of a fund's performance (*Ret*) ranging from 0 to 1. |
| $Perf^L$ | The bottom rank of a fund's return. It is calculated as the minimum of 0.5 and *Perct*. |
| $Perf^H$ | The top rank of a fund's return. It is calculated as the minimum of 0.5 and the difference between *Perct* and $Perf^L$. |
| *Retail* | A dummy variable for whether a hedge fund is a retail-oriented fund. It equals one if individuals and wealthy individuals represent over 50% of its clients, and zero otherwise. |
| *Size* | Total stock holdings of a fund in millions of dollars. |
| *NumStocks* | The number of stocks in the hedge fund portfolio. |
| *Ret* | The value weighted return on a fund's portfolio over the quarter. |
| *Turnover* | Trading unrelated to inflows or outflows. It is calculated as the minimum of the total values of buys and sells of a fund over the quarter scaled by the last quarter end total stock holdings, where buys (sells) are calculated as the sum of the products of positive (negative) changes in the number of shares in the holdings over the quarter and the previous stocks prices. |
| *Weight* | The market value of a fund's holding in REITs scaled by the market value of a fund's total holdings. |
| Aggregate Data | |
| *HFWeight*(%*Capital*) | The total market value of REITs held by hedge funds scaled by the total hedge fund holdings. |
| *HFWeight*(%*Shares*) | The total shares of REITs held by hedge funds scaled by the total shares of stocks held by all hedge funds. |
| *MktWeight*(%*Capital*) | The total market capital of REITs scaled by the total market capital of all stocks in NYSE/NASDAQ/AMEX markets. |
| *MktWeight*(%*Shares*) | The total shares outstanding of REITs scaled by the total shares outstanding of all stocks in NYSE/NASDAQ/AMEX markets. |
| *NumMgrs* | The number of hedge funds with a valid 13F filing. |
| *AggSize* | Total stock holdings of all hedge funds in billion dollars. |

**Table 2: Summary Statistics**

The total sample consists of 434 hedge fund managers that satisfy the inclusion criteria described in the text. All variables are defined in Table 1. S.i.q.r. represents the cross-sectional semiinterquartile ranges (one-half the difference between the 75th and 25th percentile).

| Year | Qtr | Num Mgrs | NumStocks Mean | NumStocks Median | NumStocks S.i.q.r | Size ($mm) Mean | Size ($mm) Median | Size ($mm) S.i.q.r | Turnover Mean | Turnover Median | Turnover S.i.q.r | Aggregate ($ bill) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) | (13) |
| 2003 | 1 | 231 | 183 | 95 | 66 | 914 | 294 | 352 | 0.93 | 0.73 | 0.56 | 211 |
| 2003 | 2 | 235 | 195 | 102 | 74 | 1106 | 375 | 407 | 1.06 | 0.92 | 0.65 | 260 |
| 2003 | 3 | 238 | 196 | 105 | 79 | 1135 | 386 | 399 | 0.99 | 0.77 | 0.62 | 270 |
| 2003 | 4 | 273 | 188 | 103 | 77 | 1186 | 400 | 396 | 0.98 | 0.74 | 0.62 | 324 |
| 2004 | 1 | 281 | 192 | 104 | 77 | 1272 | 422 | 453 | 1.10 | 0.93 | 0.63 | 357 |
| 2004 | 2 | 282 | 195 | 106 | 78 | 1343 | 478 | 430 | 1.02 | 0.85 | 0.62 | 379 |
| 2004 | 3 | 286 | 193 | 104 | 73 | 1332 | 471 | 454 | 0.99 | 0.83 | 0.56 | 381 |
| 2004 | 4 | 320 | 190 | 96 | 71 | 1433 | 458 | 527 | 1.03 | 0.89 | 0.57 | 458 |
| 2005 | 1 | 332 | 185 | 96 | 67 | 1432 | 479 | 515 | 1.02 | 0.85 | 0.61 | 475 |
| 2005 | 2 | 335 | 189 | 93 | 66 | 1499 | 488 | 570 | 0.95 | 0.79 | 0.54 | 502 |
| 2005 | 3 | 341 | 198 | 99 | 70 | 1677 | 517 | 611 | 1.04 | 0.94 | 0.63 | 572 |
| 2005 | 4 | 376 | 194 | 91 | 66 | 1600 | 450 | 555 | 1.00 | 0.87 | 0.55 | 602 |
| 2006 | 1 | 383 | 202 | 95 | 70 | 1714 | 511 | 698 | 1.12 | 0.93 | 0.61 | 656 |
| 2006 | 2 | 387 | 199 | 91 | 74 | 1676 | 476 | 643 | 1.09 | 0.91 | 0.57 | 649 |
| 2006 | 3 | 386 | 200 | 90 | 70 | 1775 | 477 | 631 | 1.01 | 0.87 | 0.57 | 685 |
| 2006 | 4 | 424 | 196 | 91 | 74 | 1770 | 439 | 606 | 1.01 | 0.78 | 0.58 | 751 |
| 2007 | 1 | 434 | 200 | 90 | 74 | 1860 | 476 | 650 | 1.07 | 0.90 | 0.59 | 807 |
| 2007 | 2 | 434 | 208 | 95 | 81 | 2129 | 570 | 763 | 1.06 | 0.90 | 0.59 | 924 |
| 2007 | 3 | 434 | 190 | 93 | 76 | 2023 | 520 | 734 | 1.03 | 0.85 | 0.54 | 878 |
| 2007 | 4 | 428 | 192 | 89 | 75 | 1936 | 481 | 696 | 0.95 | 0.80 | 0.48 | 829 |
| 2008 | 1 | 426 | 188 | 82 | 73 | 1736 | 430 | 659 | 0.96 | 0.78 | 0.55 | 739 |
| 2008 | 2 | 421 | 195 | 81 | 75 | 1818 | 450 | 723 | 0.98 | 0.84 | 0.55 | 765 |
| 2008 | 3 | 408 | 177 | 74 | 68 | 1517 | 331 | 557 | 0.88 | 0.72 | 0.47 | 619 |
| 2008 | 4 | 401 | 169 | 67 | 65 | 977 | 205 | 363 | 0.89 | 0.69 | 0.48 | 392 |
| 2009 | 1 | 397 | 164 | 63 | 61 | 941 | 192 | 330 | 0.98 | 0.68 | 0.61 | 374 |

**Table 3: Implied Weights from Return Regressions**

This table presents the results of time-series regressions of monthly hedge fund index returns on $R_{M,t}$, the CRSP value-weighted NYSE/AMEX/Nasdaq market index, and $R_{REITs,t} - R_{M,t}$, the REITs return in excess of the market return (the excess REITs factor), as in Equation:

$$R_t = \alpha + \beta R_{M,t} + \gamma\left(R_{REITs,t} - R_{M,t}\right) + \varepsilon_t$$

The sample period is January 2003 to June 2007. Standard errors are adjusted for heteroskedasticity and reported in parentheses. *** indicates statistical significant at less than the 1% level. I use β and γ estimates to compute $w_{REITs}$, the implied ratio of net investments in REITs to net investments in stocks overall as in Equation:

$$w_{REITs} = m_{REITs} + \frac{\gamma}{\beta}(1 - m_{REITs})$$

The dependent variables in Panel A are returns on HFR style indexes, classified by HFR as follows: *Equity Hedge* funds invest in core holding of long equities, hedged at all times with short sales of stocks and/or stock index options. *Market Neutral* funds seeks to profit by exploiting pricing inefficiencies between related equity securities, neutralizing exposure to market risk by combining long and short positions. *Event Driven* funds target on corporate transactions such as mergers, financial distressing, tender offers etc. Macro involves investing by making leveraged bets on anticipated price movements of stock markets, interest rates, foreign exchange, and physical commodities. *Arbitrage* focuses on exploiting pricing anomalies on equity, fixed income, derivative and other security types. *Short Bias* specializes in short-selling securities. *Real Estate* funds emphasize investment in securities of the real estate arena. In Panel B, the dependent variable is the monthly return on the aggregate long positions of hedge funds, as reported in their 13F filings.

| | Factor Loading | | Adj. $R^2$ | Implied Weight |
|---|---|---|---|---|
| | $\beta$ | $\gamma$ | | |
| | Panel A: HFR Hedge Fund Style Indexes (2003.01-2007.06) | | | |
| Equity Hedge | 0.446*** | -0.015 | 0.610 | 0.013 |
| | (0.06) | (0.03) | | |
| Market Neutral | -0.020 | 0.019 | 0.014 | 0.013 |
| | (0.04) | (0.04) | | |
| Event Driven | 0.401*** | -0.023 | 0.669 | 0.013 |
| | (0.04) | (0.02) | | |
| Macro | 0.384*** | 0.002 | 0.274 | 0.013 |
| | (0.10) | (0.07) | | |
| Arbitrage | 0.111*** | 0.014 | 0.169 | 0.013 |
| | (0.04) | (0.03) | | |
| Short Bias | -1.096*** | -0.062 | 0.874 | |
| | (0.09) | (0.05) | | |
| Real Estate | 0.644*** | 0.214*** | 0.615 | 0.341 |
| | (0.09) | (0.06) | | |
| | Panel B: Aggregate Long portfolio (2003.01-2007.06) | | | |
| 13F All | 1.135*** | 0.005 | 0.962 | 0.013 |
| | (0.04) | (0.02) | | |

## C. Essay 3

### Table 1: Effects of Investor Composition on Investment

This table presents the coefficient estimates of Equation (1) in the real estate sample (2003Q1 to 2009Q1):

$$Weight_{j,t} = \beta Overprice_t + \gamma Retail_j + \delta Retail_j Overprice_t + Controls_{j,t} + \varepsilon_{j,t}$$

*Overprice* is a dummy variable that equals one if the observation is between 2003Q1 and 2007Q2 (the period of real estate overpricing) and zero otherwise. Definitions of all other variables are listed in Table 1 of Essay 2. Observations are at the fund-quarter level. Standard errors adjust for heteroskedasticity and within-cluster correlation at the fund level. *, **, and *** indicate statistical significant at less than the 10%, 5% and 1% level, respectively.

| VARIABLES | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| *Overprice* | 0.046 | 0.020 | 0.563 | 0.624 |
| | (0.299) | (0.245) | (0.755) | (0.656) |
| *Retail*Overprice* | 0.489* | 0.454* | 0.480* | 0.433* |
| | (0.285) | (0.254) | (0.290) | (0.261) |
| *Retail* | 0.007 | | 0.024 | |
| | (0.305) | | (0.304) | |
| *Herfindahl* | -15.411*** | -11.592*** | -14.399*** | -10.064*** |
| | (2.318) | (3.023) | (2.338) | (3.059) |
| *Turnover* | -0.378** | 0.000 | -0.378** | -0.033 |
| | (0.169) | (0.137) | (0.169) | (0.139) |
| *Herfindahl*Overprice* | 3.048 | 5.807* | 2.270 | 5.047* |
| | (2.808) | (2.994) | (3.053) | (3.019) |
| *Turnover*Overprice* | 0.273 | 0.269 | 0.277 | 0.278* |
| | (0.186) | (0.165) | (0.185) | (0.163) |
| *Size* | | | 0.097 | 0.179* |
| | | | (0.082) | (0.099) |
| *Size*Overprice* | | | -0.077 | -0.086 |
| | | | (0.095) | (0.085) |
| *Constant* | 0.926*** | 1.019*** | 0.265 | -0.189 |
| | (0.295) | (0.187) | (0.612) | (0.701) |
| | | | | |
| Fund Dummy | NO | YES | NO | YES |
| Observations | 8,216 | 8,216 | 8,216 | 8,216 |
| Pseudo $R^2$ | 0.02 | 0.22 | 0.02 | 0.22 |

**Table 2: Effects of Investor Composition: Technology Sample**

This table presents the coefficient estimates of Equation (1) in the technology sample (1998Q1 to 2002Q4):

$$Weight_{j,t} = \beta Overprice_t + \gamma Retail_j + \delta Retail_j Overprice_t + Controls_{j,t} + \varepsilon_{j,t}$$

*Overprice* is a dummy variable that equals one if the observation is between 1998Q1 and 2000Q4 (the technology overpricing period) and zero otherwise. Definitions of all other variables are listed in Table 1 of Essay 2. Analyses from Table 1 (of this essay) are replicated on the technology sample. Observations are at the fund-quarter level. Standard errors adjust for heteroskedasticity and within-cluster correlation at the fund level. *, **, and *** indicate statistical significant at less than the 10%, 5% and 1% level, respectively.

| VARIABLES | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Overprice | 2.116** | 1.821** | -3.138 | -1.447 |
| | (0.857) | (0.799) | (3.126) | (2.495) |
| Retail*Overprice | 2.391** | 3.202*** | 2.105* | 2.952*** |
| | (1.150) | (0.973) | (1.184) | (0.991) |
| Retail | 1.073 | | 1.060 | |
| | (1.462) | | (1.479) | |
| Herfindahl | -38.561*** | -0.380 | -38.092*** | 2.579 |
| | (9.562) | (6.489) | (10.257) | (7.541) |
| Turnover | -0.632 | 0.136 | -0.634 | -0.059 |
| | (0.959) | (0.558) | (0.957) | (0.555) |
| Herfindahl*Overprice | -31.418** | -21.205 | -21.876 | -16.446 |
| | (14.687) | (14.126) | (14.463) | (14.134) |
| Turnover*Overprice | 0.515 | 0.500 | 0.459 | 0.475 |
| | (0.759) | (0.606) | (0.769) | (0.614) |
| Size | | | 0.044 | 1.198** |
| | | | (0.495) | (0.510) |
| Size*Overprice | | | 0.818* | 0.512 |
| | | | (0.490) | (0.398) |
| Constant | 11.309*** | 0.949 | 11.031*** | -4.608 |
| | (0.941) | (0.900) | (3.282) | (2.912) |
| | | | | |
| Fund Dummy | NO | YES | NO | YES |
| Observations | 3,598 | 3,598 | 3,598 | 3,598 |
| Pseudo $R^2$ | 0.01 | 0.17 | 0.01 | 0.18 |

**Table 3: Effects of Investor Composition on Flow-Performance Sensitivity**

This table presents the coefficient estimates of Equation (5) from 2003Q1 to 2009Q1:

$$Flow_{j,t} = \beta_L Perf^L_{j,t-1} + \beta_H Perf^H_{j,t-1} + \gamma_L Retail_j \cdot Perf^L_{j,t-1} + \gamma_H Retail_j \cdot Perf^H_{j,t-1} + Retail_j + Controls_{j,t-1} + \varepsilon_{j,t}$$

Definitions of all variables are listed in Table 1 of Essay 2. Observations are at the fund-quarter level. Standard errors adjust for heteroskedasticity and within-cluster correlation at the fund level. *, **, and *** indicate statistical significant at less than the 10%, 5% and 1% level, respectively.

| VARIABLES | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| $Perf^L$ | -0.032 | -0.032 | -0.029 | -0.028 |
| | (0.035) | (0.035) | (0.035) | (0.035) |
| $Perf^H$ | 0.040 | 0.040 | 0.037 | 0.036 |
| | (0.030) | (0.030) | (0.030) | (0.029) |
| $Retail*Perf^L$ | 0.072* | 0.073* | 0.072* | 0.070* |
| | (0.042) | (0.042) | (0.041) | (0.041) |
| $Retail*Perf^H$ | -0.051 | -0.052 | -0.051 | -0.049 |
| | (0.036) | (0.036) | (0.036) | (0.035) |
| Retail | -0.033** | -0.030* | -0.029* | -0.029* |
| | (0.015) | (0.016) | (0.016) | (0.015) |
| Size | -0.015*** | -0.014*** | -0.013*** | -0.013*** |
| | (0.003) | (0.003) | (0.003) | (0.003) |
| Turnover | 0.015*** | 0.014** | 0.014** | 0.013** |
| | (0.006) | (0.006) | (0.006) | (0.006) |
| Age | | -0.010** | -0.010** | -0.009* |
| | | (0.005) | (0.005) | (0.005) |
| Herfindahl | | | 0.031 | 0.030 |
| | | | (0.087) | (0.087) |
| Flow(-1) | | | | 0.012 |
| | | | | (0.019) |
| Constant | 0.112*** | 0.120*** | 0.114*** | 0.116*** |
| | (0.024) | (0.024) | (0.026) | (0.026) |
| | | | | |
| Observations | 8216 | 8216 | 8216 | 8216 |
| $R^2$ | 0.012 | 0.012 | 0.012 | 0.013 |

**Table 4: Effects of Investor Composition on Flow Volatility**

This table presents the coefficient estimates of Equation (6):

$$Vol_{Flow_j} = \gamma Retail_j + Controls_j + \varepsilon_j$$

In Column (1) to (3), the dependent variable is the volatility of fund flows for each hedge fund from 2003Q1 to 2009Q1. In Column (4) to (6), the dependent variable is the volatility of absolute fund flows for each hedge fund during this sample period. All control variables in this regression are sample averages of the fund characteristics as defined in Table 1 of Essay 2. Standard errors are adjusted for heteroskedasticity. *, ** and ***indicate statistical significant at less than the 10%, 5% and 1% level, respectively.

| | Volatility of Flows | | | Volatility of Absolute Flows | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Retail | 0.012** | 0.013** | 0.016*** | 0.006** | 0.007** | 0.008** |
| | (0.005) | (0.005) | (0.005) | (0.003) | (0.003) | (0.003) |
| Turnover | 0.055*** | 0.055*** | 0.054*** | 0.024*** | 0.024*** | 0.024*** |
| | (0.005) | (0.005) | (0.005) | (0.003) | (0.003) | (0.003) |
| Herfindahl | 0.432*** | 0.444*** | 0.434*** | 0.206*** | 0.212*** | 0.210*** |
| | (0.093) | (0.095) | (0.094) | (0.037) | (0.038) | (0.039) |
| Size | | 0.003 | 0.004** | | 0.002 | 0.002 |
| | | (0.002) | (0.002) | | (0.001) | (0.001) |
| Age | | | -0.012** | | | -0.002 |
| | | | (0.005) | | | (0.003) |
| Constant | 0.036*** | 0.017 | 0.037** | 0.035*** | 0.024** | 0.028** |
| | (0.006) | (0.015) | (0.017) | (0.004) | (0.009) | (0.011) |
| $R^2$ | 0.442 | 0.449 | 0.464 | 0.301 | 0.308 | 0.309 |

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# Appendix: List of REITs

| Company Name | Ticker | Company Name | Ticker |
|---|---|---|---|
| A G Mortgage Investment Tr Inc | MITT | Host Marriott Corp New | HMT |
| A M B Property Corp | AMB | Hudson Pacific Properties Inc | HPP |
| Aames Investment Corp Md | AIC | Humphrey Hospitality Trust Inc | HUMP |
| Aegis Realty Inc | AER | I R T Property Co | IRT |
| Affordable Residential Cmntys Inc | ARC | Impac Mortgage Holdings Inc | IMH |
| Agree Realty Corp | ADC | Inland Real Estate Corp | IRC |
| Alesco Financial Inc | AFN | Invesco Mortgage Capital Inc | IVR |
| Alexanders Inc | ALX | Istar Financial Inc | SFI |
| Alexandria Real Est Equities Inc | ARE | J D N Realty Corp | JDN |
| America First Apt Inv Inc | APRO | J E R Investors Trust Inc | JRT |
| American Assets Trust Inc | AAT | Jameson Inns Inc | JAMS |
| American Campus Communities Inc | ACC | K K R Financial Corp | KFN |
| American Capital Agency Corp | AGNC | Kilroy Realty Corp | KRC |
| American Capital Mtg Invt Corp | MTGE | Kimco Realty Corp | KIM |
| American Community Pptys Tr | APO | Kite Realty Group Trust | KRG |
| American Home Mortgage Invt Corp | AHH | Koger Equity Inc | KE |
| American Home Mortgage Invt Corp | AHM | L T C Properties Inc | LTC |
| American Land Lease Inc | ANL | La Quinta Corp | LQI |
| American Realty Capital Prop Inc | ARCP | Lexington Corporate Pptys Trust | LXP |
| Amerivest Properties Inc | AMV | Lexington Realty Trust | LXP |
| Amreit | AMY | Longview Fibre Co | LFB |
| Annaly Capital Management Inc | NLY | Luminent Mortgage Capital Inc | LUM |
| Annaly Mortgage Management Inc | NLY | M F A Financial Inc | MFA |
| Anthracite Capital Inc | AHR | M F A Mortgage Investments Inc | MFA |
| Anworth Mortgage Asset Corp | ANH | M H I Hospitality Corp | MDH |
| Apartment Investment & Mgmt Co | AIV | M P G Office Trust Inc | MPG |
| Apex Mortgage Capital Inc | AXM | Macerich Co | MAC |
| Apollo Commercial Rl Est Fin Inc | ARI | Mack Cali Realty Corp | CLI |
| Apollo Residential Mortgage Inc | AMTG | Maguire Properties Inc | MPG |
| Arbor Realty Trust Inc | ABR | Malan Realty Investors Inc | MAL |
| Arden Realty Inc | ARI | Manufactured Home Communities In | MHC |
| Arizona Land Income Corp | AZL | Maxus Realty Trust Inc | MRTI |
| Armour Residential Reit Inc | ARR | Medical Properties Trust Inc | MPW |
| Ashford Hospitality Trust Inc | AHT | Meredith Enterprises Inc | MPQ |
| Associated Estates Realty Corp | AEC | Meristar Hospitality Corp | MHX |
| Avalonbay Communities Inc | AVB | Mid America Apt Communities Inc | MAA |
| B N P Residential Properties Inc | BNP | Middleton Doll Company | DOLL |
| B R E Properties Inc | BRE | Mills Corp | MLS |
| Bedford Property Investors Inc | BED | Mission West Pptys Inc Md | MSW |
| Bimini Capital Management Inc | BMN | Monmouth Real Estate Invt Corp | MNR |
| Bimini Mortgage Management Inc | BMM | Monmouth Real Estate Invt Corp | MNRTA |
| Biomed Realty Trust Inc | BMR | Mortgageit Holdings Inc | MHL |
| Boston Properties Inc | BXP | National Golf Properties Inc | TEE |
| Boykin Lodging Co | BOY | National Health Investors Inc | NHI |
| C B L & Associates Pptys Inc | CBL | National Health Realty Inc | NHR |

| | | | |
|---|---|---|---|
| C B R E Realty Finance Inc | CBF | National Retail Properties Inc | NNN |
| C R T Properties Inc | CRO | Nationwide Health Properties Inc | NHP |
| C Y S Investments Inc | CYS | New Century Financial Corp Md | NEW |
| Campus Crest Communities Inc | CCG | New Plan Excel Realty Trust Inc | NXL |
| Capital Alliance Income Trust Lt | CAA | New York Mortgage Trust Inc | NTR |
| Capital Lease Funding Inc | LSE | New York Mortgage Trust Inc | NYMT |
| Capitalsource Inc | CSE | Newcastle Investment Corp | NCT |
| Caplease Inc | LSE | Newkirk Realty Trust Inc | NKT |
| Capstead Mortgage Corp | CMO | Northstar Realty Finance Corp | NRF |
| Care Investment Trust Inc | CRE | Novastar Financial Inc | NFI |
| Carramerica Realty Corp | CRE | Omega Healthcare Investors Inc | OHI |
| Catellus Development Corp New | CDX | One Liberty Properties Inc | OLP |
| Cedar Income Fund Ltd New | CEDR | Opteum Inc | OPX |
| Cedar Realty Trust Inc | CDR | Origen Financial Inc | ORGN |
| Cedar Shopping Centers Inc | CDR | P S Business Parks Inc Ca | PSB |
| Cedar Shopping Centers Inc | CEDR | Pacific Office Pptys Trust Inc | PCE |
| Center Trust Inc | CTA | Pan Pacific Retail Properties In | PNP |
| Chateau Communities Inc | CPJ | Parkway Properties Inc | PKY |
| Chelsea Property Group Inc | CPG | Piedmont Office Realty Trust Inc | PDM |
| Chimera Investment Corp | CIM | Plum Creek Timber Co Inc | PCL |
| Cogdell Spencer Inc | CSA | Post Properties Inc | PPS |
| Colony Financial Inc | CLNY | Potlatch Corp | PCH |
| Columbia Equity Trust Inc | COE | Potlatch Corp New | PCH |
| Commercial Net Lease Realty Inc | NNN | Preferred Apartment Cmntys Inc | APTS |
| Coresite Realty Corp | COR | Presidential Realty Corp New | PDL |
| Cornerstone Realty Income Tr Inc | TCR | Price Legacy Corp | PLRE |
| Corporate Office Properties Tr | OFC | Price Legacy Corp | XLG |
| Cousins Properties Inc | CUZ | Prologis Inc | PLD |
| Crescent Real Estate Equities Co | CEI | Public Storage | PSA |
| Crexus Investment Corp | CXS | Public Storage Inc | PSA |
| Criimi Mae Inc | CMM | Quadra Realty Trust Inc | QRR |
| Crystal River Capital Inc | CRZ | R F S Hotel Investors Inc | RFS |
| Cypress Sharpridge Invts Inc | CYS | Rayonier Inc | RYN |
| D C T Industrial Trust Inc | DCT | Realty Income Corp | O |
| D D R Corp | DDR | Reckson Associates Realty Corp | RA |
| Deerfield Capital Corp | DFR | Redwood Trust Inc | RWT |
| Deerfield Triarc Capital Corp | DFR | Regency Centers Corp | REG |
| Developers Diversified Rlty Corp | DDR | Republic Property Trust | RPB |
| Diamondrock Hospitality Co | DRH | Resource Capital Corp | RSO |
| Digital Realty Trust Inc | DLR | Retail Opportunity Invst Corp | NAQ |
| Douglas Emmett Inc | DEI | Retail Opportunity Invst Corp | ROIC |
| Duke Realty Corp | DRE | Roberts Realty Investors Inc | RPI |
| Dupont Fabros Technology Inc | DFT | Rouse Company | RSE |
| Dynex Capital Inc | DX | S L Green Realty Corp | SLG |
| E C C Capital Corp | ECR | Sabra Healthcare Reit Inc | SBRA |
| Eagle Hospitality Pptys Tr Inc | EHP | Saul Centers Inc | BFS |
| Eastern Light Capital Inc | ELC | Saxon Capital Inc New | SAX |
| Eastgroup Properties Inc | EGP | Saxon Capital Inc New | SAXN |
| Education Realty Trust Inc | EDR | Shelbourne Properties I Inc | HXD |
| Equity Inns Inc | ENN | Shelbourne Properties Ii Inc | HXE |
| Equity Lifestyle Properties Inc | ELS | Shelbourne Properties Iii Inc | HXF |

| | | | |
|---|---|---|---|
| Equity One Inc | EQY | Shurgard Storage Centers Inc | SHU |
| Essex Property Trust Inc | ESS | Simon Property Group Inc New | SPG |
| Excel Trust Inc | EXL | Sizeler Property Investors Inc | SIZ |
| Extra Space Storage Inc | EXR | Sovran Self Storage Inc | SSS |
| F B R Asset Investment Corp | FB | Spirit Finance Corp | SFC |
| Felcor Lodging Trust Inc | FCH | Stag Industrial Inc | STAG |
| Feldman Mall Properties Inc | FMP | Stag Industrial Inc | STIR |
| Fieldstone Investment Corp | FICC | Starwood Property Trust Inc | STWD |
| First Industrial Realty Tr Inc | FR | Strategic Hotel Capital Inc | SLH |
| Fog Cutter Capital Group Inc | FCCG | Strategic Hotels & Resorts Inc | BEE |
| Franklin Street Properties Corp | FSP | Summit Hotel Properties Inc | INN |
| Friedman Billings Ramsey Grp New | FBR | Summit Properties Inc | SMT |
| General Growth Pptys Inc New | GGP | Sun Communities Inc | SUI |
| General Growth Properties Inc | GGP | Sunset Financial Resources Inc | SFO |
| Getty Realty Corp New | GTY | Sunstone Hotel Investors Inc New | SHO |
| Gladstone Commercial Corp | GOOD | Supertel Hospitality Inc | SPPR |
| Glenborough Realty Tr Inc | GLB | Tanger Factory Outlet Centers In | SKT |
| Global Signal Inc | GSL | Taubman Centers Inc | TCO |
| Government Properties Income Tr | GOV | Terreno Realty Corp | TRNO |
| Government Properties Trust Inc | GPP | Thornburg Mortgage Inc | TMA |
| Government Properties Trust Inc | GPT | Trizec Properties Inc | TRZ |
| Gramercy Capital Corp | GKK | Trustreet Properties Inc | TSY |
| Gyrodyne Company America Inc | GYRO | Two Harbors Investment Corp | TWO |
| H C P Inc | HCP | U D R Inc | UDR |
| H M G Courtland Properties Ltd | HMG | U M H Properties Inc | UMH |
| Hanover Capital Mtg Hldgs Inc | HCM | U S Restaurants Properties Inc | USV |
| Hatteras Financial Corp | HTS | United Dominion Realty Tr Inc | UDR |
| Health Care Ppty Invs Inc | HCP | United Mobile Homes Inc | UMH |
| Health Care Reit Inc | HCN | Urstadt Biddle Properties Inc | UBA |
| Healthcare Realty Trust Inc | HR | Urstadt Biddle Properties Inc | UBP |
| Heritage Property Invest Tr Inc | HTG | Ventas Inc | VTR |
| Highland Hospitality Corp | HIH | Vestin Realty Mortgage I Inc | VRTA |
| Highwoods Properties Inc | HIW | Vestin Realty Mortgage Ii Inc | VRTB |
| Home Properties Inc | HME | Walter Investment Mgmt Corp | WAC |
| Home Properties N Y Inc | HME | West Coast Realty Investors Inc | MPQ |
| Homebanc Corp Ga | HMB | Weyerhaeuser Co | WY |
| Horizon Group Properties Inc | HGPI | Windrose Medical Pptys Tr | WRS |
| Host Hotels & Resorts Inc | HST | Winston Hotels Inc | WXH |