# The Role of Hedge Funds in the Security Price Formation Process

Charles Cao[†]
Penn State University

Yong Chen[‡]
Texas A&M University

William Goetzmann[§]
Yale School of Management

Bing Liang[**]
University of Massachusetts

November 20, 2012

* We are grateful to Vikas Agarwal, Nick Bollen, Stephen Brown, William Fung, Wayne Ferson, Bill Kracaw, Andrew Metrick, Chester Spatt, and participants at Vanderbilt University Hedge Fund Conference, Paris Europlace Institute, and the 2011 Financial Research Association meetings (early ideas session) for helpful comments. We also thank Jiahan Li for diligent research assistance.

† Smeal College of Business, Penn State University, qxc2@psu.edu.
‡ Mays Business School, Texas A&M University, ychen@mays.tamu.edu.
§ School of Management, Yale University; william.goetzmann@yale.edu.
** Isenberg School of Management, University of Massachusetts, bliang@isenberg.umass.edu.

# The Role of Hedge Funds in the Security Price Formation Process


## Abstract

We present evidence on the role of hedge funds in the price formation process by using data on hedge fund equity ownership. Compared to other institutional investors, hedge funds tend to hold stocks that plot above the security market plane and stocks with larger deviations from model values in the cross-section. Focusing on the set of stocks plotting above the security market plane, we find that an increase of hedge fund ownership is significantly related to subsequent reduction in the stock's deviation from model values. Overall, these findings suggest that hedge funds play a role in reducing asset mispricing.



*Keywords*: Hedge fund holdings, undervalued stocks, alphas, investment value.

*JEL Classification*: G11, G23

## 1. Introduction

The industrial organization of investment has gradually shifted over the past 30 years to a predominantly institutional one. A distinctive feature of this shift has been the emergence of hedge funds as intermediaries in the publicly traded securities markets. While speculation is as old as stock markets and neo-classical asset pricing models presume the existence of active traders in equilibrium, the change in the way speculation is organized represents a potentially important shift in the enforcement of market efficiency. For example, the emergence of hedge funds as large-scale enterprises has enabled innovation in information processing and trading technologies. Large funds can afford high fixed costs of investment in research, data, trading platforms and regulatory compliance. Similarly, organizational changes due to the agency relationship have engendered the need for performance using standard statistical measures, making the use of alphas, Sharpe ratios and other metrics ubiquitous. Finally, the broad acceptance of quantitative asset pricing models based on factor exposures and security characteristics has led to a common, conceptual framework of relative valuation.

In this paper, we focus on this last point. Given the prevalence of risk-based asset pricing models in academic research and practice, we should expect to find at least some speculative entities engaged in relative-value arbitrage. That is, trading securities based on their price deviation from assets of similar risk characteristics. Relative value arbitrage – or the potential for it – is at the foundation of neo-classical asset pricing models such as the Arbitrage Pricing Theory (c.f. Ross, 1976). Modifications of the theory point out that agency and funding frictions limit the capacity of hedge funds to enforce the law of one price and make predictions about the conditions that limit arbitrageurs (c.f. Shleifer and Vishny, 1992). An extensive theoretical literature has developed to analyze the institutional conditions that affect the limits of arbitrage, and to study welfare and policy implications of these limits. Considerable financial theory has focused on the role of arbitrageurs as liquidity providers and modeled how financial constraints impede this function.[1]

Neo-classical asset pricing theory has been regularly applied in practice. Grinold and Kahn (1999) for example, develop an approach to active portfolio management based on the information ratio: the expected ratio of alpha to its tracking error.[2] Their framework makes several general predictions about active manager behavior. Managers seeking to add alpha will increase their probability of doing so by (1) taking positions in proportion to the information ratio, (2) increasing the breadth of their positive alpha holdings to diversify risk, (3) holding long-short portfolios that eliminate benchmark risk, and offset the market positive exposure of their long positions by the negative market exposure of their short position, and (4) incorporate costs and frictions (such as the cost of information acquisition).

While many institutional investors may use this framework for active investing most have goals other than simply maximizing alpha. Long-only equity managers, for example, supply positive exposure to market factors in addition to seeking superior risk-adjusted returns. Other types of managers face institutional constraints aimed at maintaining a consistent exposure to a given market factor. Hedge funds, at least in theory, are less constrained to deliver factor exposures, are able to take short positions, and are evaluated on their alpha. As such, we would expect them to conform more closely to the predictions of Grinold and Kahn.

The empirical literature has thus far tested relatively few theoretical predictions about the behavior of arbitrageurs. Up to this point, empirical researchers have not been able to comprehensively study the activities of hedge funds in the markets except in specialized circumstances and on limited datasets. In recent years, however, these barriers to research have declined. While hedge funds are often described as lightly-regulated, opaque investment

[1] C.f. Gromb and Vayanos (2002), Morris and Shin (2004), Brunnermeier and Pedersen (2009), Pontiff (1996 and 2006), and Gromb and Vayanos (2010) provide a comprehensive overview.
[2] This is equivalent to the t-statistic of alpha scaled by sqrt(T). See Grinold and Kahn (1999), p. 327.

vehicles it turns out that, with some serious effort, it is possible to gather considerable information about their securities holding and trading activities, albeit with a temporal lag.[3] The institutionalization of speculation has brought hedge funds increasingly into the regulatory fold and mandated the quarterly disclosure of holdings for funds above a certain size threshold. While it remains difficult to comprehensively observe their short-sales positions, a large fraction of quarterly long positions for major funds can be studied.[4] In this paper we assemble an extensive database of hedge fund equity holdings from 13F filings and use it to examine the evolving role of hedge funds in asset pricing. Our analysis includes information on virtually all of the major hedge funds that hold and trade U.S. equities.[5] This is important, given that we are interested not only in the funds' behavior but in their potential market impact.

We use this data to pose the question of whether hedge funds - and the assets they trade - behave as neo-classical theory predicts. Do hedge funds take positions in stocks that deviate from the pricing model; i.e. in a multi-factor world, the security market plane? Once they take a position in a stock does its price converge to model value? In short, do hedge funds function as enforcers of relative-value market efficiency? The limits of arbitrage literature likewise provides testable hypotheses to take to this data. Do deviations from the security market plane persist despite the action of hedge funds? Is mispricing associated with reduced hedge fund activity and shocks to funding liquidity?

## 2. Background

Some recent evidence on the trading behavior of hedge funds suggests a potentially significant role in price formation. Brunnermeier and Nagel (2004) collect 13F filings for 56

[3] This lag and its strategic implications is explored in Brown and Schwarz (2011)

[4] Derivatives position data are also available. Aragon and Martin (2010) and Zuckerman (2011) make use of hedge fund put and call positions.

[5] Fung and Hsieh (2011) highlight the challenges of identifying some very large funds which do not report to standard databases. This requires augmenting automated search processes with significant amount of hand-collecting of information.

hedge fund management companies and find hedge funds made money by chasing returns during the tech bubble period. Their evidence is consistent with hedge funds exacerbating the mispricing of securities. Griffin and Xu (2009) study hedge-fund managers' stock selection ability using a larger sample of 306 hedge fund companies and find modest evidence of stock selection ability. In a recent work, Griffin, Harris, Shu and Topaloglu (2011) find evidence more consistent with destabilization the market during the tech bubble period. Several empirical studies have documented that hedge fund play an important microstructure role.[6] These studies show that hedge funds seem to affect the price formation process.

Our paper differs from prior hedge fund/asset pricing studies in that we focus on mispricing relative to a factor model and examine the question of whether hedge funds play a role in convergence to that model. In particular, we study the institutional behavior with respect to the set of stocks that are "undervalued" (i.e. stocks with positive historic alphas with respect to the Fama-French-Carhart four factor model). We find that hedge fund holdings and purchases of these undervalued securities are positively related to the degree of mispricing as well as to the residual variance. This not true for non-hedge fund institutions.

Next we follow the subsequent price behavior of undervalued stocks purchased and held by hedge funds vs. non-hedge fund institutions. We find that mispricing and residual variance both decline for stocks held or purchased by hedge funds, but this is not the case for non-hedge fund institutions. Finally, using the full sample of stocks with 13F holding data, we show that an *increase* in hedge fund ownership is informative and predicts future stock returns positively in the horizon of up to one quarter, consistent with the hypothesis that hedge fund managers possess skill. This finding is also consistent with the limits to arbitrage hypothesis which predicts

[6] Choi, Getmansky, Henderson and Tookes (2010) study convertible bond arbitrageurs as capital suppliers, Aragon and Strahan (2012), use the Lehman failure as an event to study shocks to hedge fund liquidity and consequent security price dynamics. Jylhä, Rinne and Suominen (2012) study short-term price reversals as a measure of market liquidity and conclude that hedge funds in the equity markets function as "immediacy" providers. Hong and Jiang (2011) find that stock return dynamics around institutional purchases and sales by clienteles including hedge funds are consistent with binding short-sale constraints and mispricing.

delayed convergence despite activities by hedge funds. On the other hand, the changes in holdings of other types of institutional investors do not forecast future stock returns.

Taken together, our findings suggest that hedge-fund trading may play a role in enforcing efficiency, but that the convergence to the security market plane is not instantaneous, and may extend over a quarter or more. The remaining paper is organized as follows. Section 3 describes the data collection process of hedge fund ownership data and provides summary statistics of our hedge fund management company sample. Section 4 reports the empirical results and Section 5 concludes.

## 3. Data

This paper represents a major data collection effort. Following the approach of Brunnermeier and Nagel (2004) and Griffin and Xu (2009), we compile a comprehensive dataset of hedge fund equity ownership. Our goal is to collect a comprehensive sample, despite the challenge that all extant databases of hedge funds rely on self-reporting. Matching management companies in hedge fund databases and 13F filings is non-trivial. Our final sample of hedge fund ownership data includes a universe of 1,356 hedge fund management companies which together manage more than 5,071 funds and spans the period from 1981 through 2009 (Note: 5,071 funds is a lower bound because fund level info is only available when a HF company is in one of the five hedge fund databases we used). It covers substantially all the major hedge funds trading in the U.S. market.

### 3.1. Hedge Fund Identification

The starting point for identifying all hedge fund firms is to match management company names in various hedge fund databases with those in the CDA/Spectrum 13F institutional ownership database. We compile a master list of names of hedge funds and their respective management companies using information from TASS, HFR, CISDM, Barclay Hedge and Morningstar databases. While hedge funds are private investment companies that have historically been exempt from registration with the SEC as an investment company, they are subject to various trading reporting requirements. Similar to other institutional investors, hedge fund management companies with more than $100 million in assets under management are required to file quarterly reports disclosing their holdings of registered equity securities. All common stock positions greater than 10,000 shares or $200,000 in market value are subject to reporting. 13F filings contain long positions in stocks while short equity positions are not required to be reported. Option positions by funds are selectively reported but their interpretation is not clear and thus we have excluded them from our analysis.

The institutional ownership data from CDA/Spectrum classifies five groups of institutional investors: Banks, Insurance Companies, Investment Companies, Independent Investment Advisers and Others. Hedge funds do not have a separate classification – at least in the databases available to academic researchers. This may be due, in part, to the lack of a clear definition of what constitutes a hedge fund. In our approach, we define a hedge fund as an investment company included in a hedge fund database, a firm that identifies itself as a hedge fund, or a firm that has a specific threshold of high-net-worth investors and a substantial fraction of performance compensation.

After compiling a master list of hedge fund management companies from various hedge fund databases, we match them with institutional investors in the 13F holding data. One difficulty is that a hedge fund manager may not appear in any of hedge fund databases because reporting to a hedge fund database is voluntary.[7] Another difficulty is that the name of a hedge fund (or a hedge fund company) may not be the same in different databases. This required manually checking unmatched investment advisers and money managers from the 13F data to

[7] This point is made by Fung and Hsieh (2011).

determine whether they are hedge fund management companies (or sponsors), using a variety of online resources. This procedure yields a sample of 1,582 institutions of potential hedge fund companies. The sample also contains investment advisers who manage hedge funds, but whose main business is mutual fund management or investment banking.

To ensure the primary business of an institutional investor is operating a hedge fund, we adopt the approach of Brunnermeier and Nagel (2004) and Griffin and Xu (2009) to cross-check the 1,582 companies. Specifically, we manually check companies that are registered as investment advisers. Mutual fund, pension fund, and hedge fund managers are common examples of investment advisers. Although a hedge fund adviser may register with the SEC voluntarily as an investment adviser prior to 2004, the SEC issued a rule change in December, 2004 that required most hedge fund advisers to register with the SEC by February 2006 as investment advisers under the Investment Advisers Act. This requirement applied to all hedge fund advisers if they manage more than $25 million with over 14 investors. Most hedge fund advisers filed the ADV registration form although the SEC ruling was challenged and overturned in June 2006.

Among the 1,582 potential hedge fund companies, we find that more than 50% of them registered with SEC as investment advisers and filed ADV forms. We next follow Brunnermeier and Nagel (2004) and Griffin and Xu (2009) and require an investment adviser to meet two criteria: (1) More than 50% of its clients are high-net-worth individuals or more than 50% of its clients are invested in "other pooled investment vehicle (e.g., hedge funds)"; and (2) the adviser is compensated for its advisory service by charging a performance-based fees. For each of the 1,582 companies, if it filed an ADV form but did not pass the two criteria, we reclassify it as an investment adviser whose primary business is not managing hedge funds. Numerous money managers in our hedge fund databases (e.g., Boston Asset Management LLC and Neuberger Berman LLC) do not meet these criteria and are thus reclassified. Some U.S. and foreign investment banks and their asset management subsidiaries manage hedge funds (e.g., Goldman

Sachs and UBS Global Asset Management), but their hedge fund assets constitute only a small portion of their reported holdings. We apply the above two criteria and classify them as investment advisers rather than hedge funds.

Our final sample of hedge fund companies includes 1,356 hedge fund management firms whose holdings represent hedge fund ownership. Among the 1,356 hedge fund companies, 1,053 of them report fund-level information (including AUM) to one of the hedge fund databases we employed (e.g., TASS, HFR, CISDM, Barclay Hedge and Morningstar). A management company often offers multiple funds, and the 1,053 hedge fund companies in aggregate manage 5,071 individual hedge funds.[8]

To understand what percentage of assets are managed by hedge fund companies who are qualified institutional investors and who make to the 13F equity holding data, we obtain the ratio of AUM managed by the 1,053 hedge fund companies divided by the AUM of all hedge fund companies in the union of the five hedge fund databases at the end of each year. During 1981-2009, the average ratio is 29.5% and the ratio reached a peak of 36% in 1998.[9]

### 3.2 Other Institutional Investors

After identifying all hedge fund companies, we classify all 13F institutions into six types of institutional investors: (1) Banks, (2) Insurance Companies, (3) Investment Companies (or mutual funds),[10] (4) Independent Investment Advisors, (5) Hedge Funds, and (6) All Others. Since mutual fund companies dominate the universe of investment companies, we label type (3) institutions as mutual funds for convenience. The classifications of banks and insurance

[8] For the 303 hedge fund companies identified through sources other than the five hedge fund databases we employed, their AUMs are not available in the public domain.

[9] If a hedge fund company is not in the 13F holding data, it could be due to one or a combination of the following reasons: (1) the size of the AUM managed by a hedge fund company is not large enough to qualify to file 13F; (2) the equity position of the company is not large enough; or, (3) the fund pursues non-equity strategies

[10] According to the 2010 Investment Company Factbook, U.S.-registered investment companies managed $12.2 trillion at year-end 2009. Among various types of investment companies, mutual funds managed $11.1 trillion; closed-end funds, ETFS, and Unit Investment Trusts managed $1.1 trillion.

companies are based on the type codes available on CDA/Spectrum before 1998, extended to cover later years. The "typecode" variable from CDA/Spectrum has classification errors in recent years, and most institutions are improperly classified in the "Others" group in 1998 and beyond. For example, 71% of institutional investors are in the group of "Others" in 2009 when using CDA/Spectrum typecode. Thus, we do not use classification codes from CDA/Spectrum beyond 1998. We follow Bushee (2004) to identify Banks and Insurance Companies during the period 1998-2009 and we use mutual fund holdings information from CDA/Spectrum S12 data to identify mutual fund management companies. The group of Investment Advisers in our sample thus does not include hedge fund companies, but does include small independent advisers, broker-dealers, and major investment banks that were not registered as bank holding companies before 2008. Finally, the category "All Others" includes university and private endowments, philanthropic foundations, and corporate pension funds. For our analysis, we combine all non-hedge fund categories into one group.

### 3.3 Equity Data

We merge the 13F institutional holdings data with CRSP and COMPUSTAT and include only common shares listed on the NYSE, AMEX and NASDAQ. We obtain daily stock returns from CRSP and accounting data from the merged CRSP/COMPUSTAT quarterly industrial file. In each quarter all the stocks included must have more than 30 non-missing daily return for the previous three month, non-missing market capitalization at the end of the previous quarter, and non-negative book value of common equity. We also delete the last quarter of data for any firm delisted before our sample period ends. As is commonly done with COMPUSTAT data, we winsorize the firm-quarter panel data at both the upper and lower 2.5% levels to mitigate the impacts of outliers. Our merged panel data contains 389,982 firm-quarter observations over the period of 1981 through 2009.

### 3.4 Summary Statistics

Table 1 presents the summary statistics of our sample of hedge fund management companies identified by source. Among the 1,356 hedge fund companies that file 13F reports, 39% of them are the results of matching TASS with 13F institutional holdings data, 23% from matching HFR with 13F, and 8% from matching CISDM with 13F. About 22% (303) of hedge fund companies are not in any of the five commercial hedge fund databases we acquired – we classify these 13F institutions as hedge fund companies using variety of online resources and checking their ADV registration forms (if available). Our manual collection process reduces potential self-reporting bias.

Figure 1 plots the average fraction of shares held by type of institutions in each year and reveals the increasing importance of institutional investors, especially hedge funds over time. Previous studies, including Gompers and Metrick (2001), Bennett, Sias, and Starks (2002), and Sias, Starks, and Titman (2006), have documented this dramatic increase in the fraction of shares held by institutions. Our data reveal that the proportional increase in hedge fund ownership exceeds the increase in other types of ownership over the period, especially during a recent period of 2000-2009. The total institutional ownership of common stocks increased steadily from 15.32% in 1981 to 62.59% in 2009. Although all types of institutions experienced an increase in equity ownership over the subsequent 30 years, the increase in hedge fund ownership is the largest. Hedge fund ownership grew from 0.05% of outstanding shares in 1981 to almost 10% at the peak of 2007. In 2007 hedge funds exercised control of 16% of shares held by institutions, while mutual funds and banks controlled 40% and 17%, respectively.

### 3.5 The Evolution of Hedge Fund Demand for Stock Characteristics

Based on merged CRSP, COMPUSTAT and 13F institutional holding data (the full sample), Table 2 reports the stock characteristics at the firm-quarter panel level for the full sample of all stocks reported in 13F filings over the period (Panel A), and for a sub-sample of stocks within the top decile of hedge-fund ownership in each quarter (Panel B). The characteristics include book to market, size, dividend yield, age, price, S&P membership, average four factor alpha, t-value of the stock (similar to an information ratio used in practice) and average R-square.

The average book-to-market ratio is 0.68 with a median of 0.58 for the full sample, which is similar to the average book-to-market ratio of 0.64 for stocks with high hedge fund ownership. Stocks with high hedge fund ownership appear to be smaller firms. The average sizes are $2.1 billion and $800 million for the full sample and for stocks with high hedge fund ownership although the difference in median size is small. Finally, stocks with high hedge fund ownership have lower dividend yield (0.22% versus 0.36% per quarter), younger age (156 months versus 190 months) and lower percentage of S&P 500 index membership (8% versus 13%) in comparison to the sample of stocks in the merged CRSP/COMPUSTAT/13F file.

## 4. Empirical Results

In or analysis, we test whether hedge funds hold undervalued stocks, and whether their behavior in this regard differs from that of other institutional investors. We also examine whether hedge funds purchase stocks that deviate significantly from the security market plane in general, and whether this behavior differs from that of other institutions. Next we examine whether hedge fund holdings and change in holdings is associated with convergence of stock returns to the security market plane and the temporal characteristics of this convergence.

### 4.1 Estimation of a Factor Model

We first estimate a linear factor model to determine whether a stock is undervalued with respect to the security market plane in each quarter in the sample period. We calculate alpha from the Fama-French-Carhart (see Carhart (1997)) four-factor model, and we estimate alpha for each stock in each quarter using daily returns:

$$r_{i,\tau} = Alpha + \beta_1 MKT_\tau + \beta_2 SMB_\tau + \beta_3 HML_\tau + \beta_4 UMD_\tau + \varepsilon_\tau, \qquad (1)$$

where $r_{i,\tau}$ is the excess return on stock $i$ on day $\tau$, $MKT\tau$ is the value-weighted market excess return, and $SMB\tau$, $HML\tau$, and $UMD\tau$ are the returns of the value-weighted, zero-net-investment, factor-mimicking portfolios for size, book-to-market equity, and one-year momentum in stock returns. For simplicity, the subscript of quarter $t$ is omitted from the above equation.

In theory, alpha is the abnormal return on a stock in excess of what would be predicted by an equilibrium model. When using the Fama-French-Carhart model as a benchmark model, alpha is the difference between a stock's return and a "fair" compensation for the stock's systematic exposures to market, a size-, a value-, and a momentum-related factor.[11] In the context of security analysis and fund management, alpha is the key variable that tells managers whether a stock is a good investment. A stock with a positive alpha provides a premium over the premium it derives from its tendency to track benchmark factors, suggesting that the stock is undervalued and offers an attractive expected return. For a fund manager who invests in multiple stocks, the alpha of the fund is the weighted average of alphas of underlying individual stocks.

## 4.2 Positive Alpha Shares

The first question we address is whether hedge funds as a group tend to hold (or purchase) stocks that plot above the security market plane to a greater extent than other institutional investors. As we note above, an active manager seeking to generate a positive alpha portfolio

[11] We are grateful to Kenneth French for making the data on the four factors available for download from his website at http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

will take a broad set of offsetting long and short positions for which he or she has been able to form a reliable expectation (i.e. high information ratio) of future positive alpha. In our analysis, we assume that this expectation process relies in part on past positive alphas (i.e. plotting about the security market plane). Although many variables will go into the hedge fund manager's models – including fundamental ratios, news, industry analysis and so forth, our tests focus on the simple metric of past mispricing.

As pointed out above without comprehensive information about short sales, a test of whether hedge funds take short positions in stocks with negative alphas and positive positions in positive alpha stocks is severely attenuated by the censored data problem under the alternative. All of the short positions relying on negative expected alphas are missing from the sample. A Tobit specification to address this censoring problem requires a model of censoring.

Because of the censoring issue, we focus in the remaining analysis on the part of the distribution which is less subject to the attenuation: the stocks with the highest historical alphas. In particular, we compare holdings of undervalued stocks of hedge funds with that of non-hedge fund institutions. If hedge funds pursue arbitrage strategies and explore mispricing in security markets, their holdings (long positions) of undervalued stocks should be disproportionally large in comparison to holdings of other types of institutions (e.g., banks or mutual funds) whose investment objective is not absolute returns.

A stock is defined as an undervalued stock, or a positive alpha stock in quarter t, if its alpha in quarter t is positive and significant at the 5% level. For hedge funds, a positive alpha share in quarter t is the dollar holdings of hedge fund companies in all stocks with positive alpha divided by total dollar holdings of hedge funds in all stocks in quarter t:

$$\text{Positive alpha share}_t = \sum_{i=1}^{It} w_{i,t} = \sum_{i=1}^{It} \frac{\sum_{j=1}^{Jt} \text{dollar value of shares held}_{i,j,t}}{\text{total value of hedge fund}_t} \qquad (2)$$

where $I_t$ is the number of positive alpha stocks and $J_t$ is the number of hedge fund companies in quarter $t$. For non-hedge fund institutions, a positive alpha share is defined similarly.

We perform a t-test of the difference in average positive alpha shares between hedge funds and non-hedge fund institutions over the time period of our study. We find that the difference in average positive alpha shares between hedge funds and non-hedge fund institutions is 0.9% and is highly significant (*t*-statistic=5.01). This is consistent with the proposition that hedge funds seek arbitrage opportunities by buying under-valued stocks – where undervalued is defined as plotting above the security market plane.

One potential concern is that hedge funds simply invest in stocks that plot both above and below the security market line. In fact, as we show below, hedge funds tend to invest in stocks with high idiosyncratic volatility. To examine this issue, we perform the following test. For each quarter, we calculate the total investment in under-valued stock and in overvalued stocks, defined analogously as a stock with a *t*-value for a negative alpha of equal to and greater than 1.65. We calculate the ratio of capital in under-valued to over-valued stocks. For hedge funds, the average ratio over the sample period is 3.56. For non-hedge funds, the average ratio is 2.96. For all institutions together, the average ratio is 2.94. As before we use this time-series to perform a paired t-test of whether hedge funds have a higher proportional investment in positive vs. negative alpha stocks compared to non-hedge funds. The test rejects the null at the 10% level (*p*-value = .063).

### 4.3 Institutional Share of Undervalued Stocks

Table 3 tests whether the fraction of hedge fund ownership of undervalued stocks is explained in the cross-section by deviations above the security market plane. It reports the results of an estimation of a quarter-by-quarter Fama-MacBeth cross-sectional regression of each undervalued stock's hedge fund ownership fraction (IO_HF) and non-hedge-fund ownership fraction (IO_Non_HF) on previous-quarter's alpha. The Fama-MacBeth regression has the following specification:

$$IO_{i,t} = a_t + b_t\, Alpha_{i,t-1} + c_t' X_{i,t-1} + \varepsilon_{i,t}, \qquad (3)$$

where $IO_{i,t}$ is hedge fund holdings (or, non-hedge fund holdings) measured by percentage of share held in stock *i* in quarter *t*, $Alpha_{i,t-1}$ is the measure of under-valuation from the Fama-French-Carhart model for stock *i* in quarter *t-1*, and $X_{i,t-1}$ is a vector of stock characteristics, for stock *i* in quarter *t-1*.

We include control variables of lagged stock characteristics including book-to-market ratio, market capitalization, dividend yield, firm age, share price, and a dummy variable indicating S&P 500 index membership. They have been shown to explain total institutional ownership well (see Gompers and Metrick (2001)). Following the literature, the dependent and independent variables are standardized each quarter, using their respective means and standard deviations.[12] Because the ownership variable is measured in percent, we take the nature log for all stock characteristics variables (except for the dummy variable of S&P 500 membership) so that all variables have similar interpretations. For dividend yield (D/P), the logarithmic transformation is Ln (Dividend Yield) = Ln (1+D/P). *t*-statistics from the Fama-MacBeth regression are in parentheses.

In Table 3, model (1) shows that the average coefficient on the lagged alpha is positive and significant (with *t*-statistic=6.09). The interpretation of this finding is that stocks with significant and larger under-valuation with respect to the four-factor model in the previous quarter are associated with a significantly higher level of hedge fund holdings in the present quarter, after controlling for stock characteristics. In contrast, we do not find a significant relationship between non-hedge fund holdings and the measure of stock under-valuation in model (2).

[12] C.f. Gompers and Metrick (2001) and Griffin and Xu (2009).

We test for the differences in the average coefficients on lagged *Alpha* between hedge funds and non-hedge funds. The *p*-value from this test strongly rejects the null that the average regression coefficients are the same for hedge funds and non-hedge funds. These findings support the hypothesis that hedge funds seek inefficiencies in the equity market and hold under-valued stocks. We show that other types of institutional investors including banks, insurance companies and mutual funds, in aggregate, do not pursue a similar strategy and do not play the same role as hedge funds in equity markets.

Table 3 also examines the relationship between stock characteristics observed in the previous quarter and equity holdings by hedge funds in the current quarter. The coefficients on book-to-market ratio and market capitalization are positive and significant, suggesting that hedge funds tend to hold under-valued stocks with larger capitalization and higher book-to-market ratios. In addition, the coefficients on dividend yield and S&P 500 membership dummy are negative and significant. Thus, hedge funds prefer holding under-valued stocks with lower dividend yields and stocks that do not belonging to the S&P 500 index. Given the high correlation between size and S&P 500 inclusion, we may interpret the opposite signs on these variables as a contrast. In comparison, Griffin and Xu (2009) find that hedge funds tend to hold small, value, and past loser stock relatively to mutual funds.

Comparing the results in models (1) and (2) in Table 3, we find that, relative to non-hedge fund institutions, hedge funds tend to hold small, under-valued stocks; the coefficient on market capitalization is 0.19 for hedge fund ownership and 0.53 for non-hedge fund ownership, and the difference is significant. Relative to non-hedge fund institutions, hedge funds also prefer to hold younger, under-valued stocks with lower dividend yield, lower share price, and those that do not belong to the S&P 500 index.

### 4.4 Idiosyncratic Volatility

Much current research on idiosyncratic risk has focused on its relationship to market efficiency. Low R-square (i.e. high proportional idiosyncratic risk) has been used as a measure of pricing efficiency (Mork, Yueng and Yu, 2000) and also as an indicator of firm-specific uncertainty (Teoh, Yang and Zhang, 2007, Hou, Xiong and Peng, 2006). Teo et al. find that low R-square is associated with standard accounting anomalies, suggesting that the financial statements of low R-square firms are less revealing. Hou et al. find that low R-square stocks exhibit more over-reaction and price momentum consistent with price inefficiency.

Shleifer and Vishny (1997) argue that idiosyncratic volatility may be an inherent characteristic that impedes price discovery because it exposes arbitrageurs to funding risk. Stocks with high alphas but high idiosyncratic volatility are less attractive not only because of concern over estimation error in alpha, but also because the implied arbitrage exposes the arbitrageur to residual risk that must be diversified. When positive alpha opportunities are limited, or they are all correlated within a given industry or security style, such diversification may not be achievable. Thus opportunities for arbitrage in expectation are likely to be correlated to high idiosyncratic risk. In the framework of Grinold and Kahn, the high idiosyncratic risk reduces the information ratio and thus makes the position less attractive.

The pricing efficiency interpretation, together with the Shleifer and Vishny argument, predicts that hedge funds will avoid high idiosyncratic risk stocks because they already efficiently incorporate firm-specific information, and they are also riskier to hedge. On the other hand the price inefficiency interpretation would suggest that such stocks represent potential opportunities for hedge fund investors seeking to exploit their relative analytical advantage, and that the degree to which they exploit these opportunities depends upon market frictions.[13] In

[13] Hong and Jiang (2011) find evidence that short-sales constraints are one such friction.

other words, the high idiosyncratic risk may be indicative of the potential for mispricing and thus positive expected alpha.

In this section, we examine the cross-sectional relationship between hedge fund ownership share and idiosyncratic volatility of undervalued stocks. In each quarter, we estimate idiosyncratic risk using Fama-French-Carhart four-factor model, where idiosyncratic risk is defined as the standard deviation of the time-series of daily residual terms. The regression model is estimated as follows:

$$IO_{i,t} = a_t + b_t \, Idio.Risk_{i,t-1} + c_t' X_{i,t-1} + \varepsilon_{i,t}, \tag{4}$$

where $IO_{i,t}$ is hedge fund holdings (or, non-hedge fund holdings) in stock *i* in quarter *t*, $Idio.Risk_{i,t-1}$ is idiosyncratic risk for stock *i* in quarter *t-1* which is obtained by using the Fama-French-Carhart four factor model, and $X_{i,t-1}$ is a vector of stock characteristics defined in the previous section.

Table 4 presents the results. For the set of undervalued stocks, we find a strong relationship between hedge fund holdings and stock's idiosyncratic volatility. The coefficient on lagged idiosyncratic volatility is significant at the 1% level (with a *t*-statistic of 6.28). The estimated coefficients of book-to-market ratio and market capitalization are positive and significant. For the other two control variables, dividend yield and S&P 500 membership, the coefficients are negative and significant. Regressing non-hedge fund ownership on lagged idiosyncratic volatility and control variables, we find that the coefficient on lagged idiosyncratic volatility is not significant (*t*-statistic = -0.01).

The *p*-value from a *t*-test shows that the average coefficient on idiosyncratic volatility for hedge funds is significantly different from that for non-hedge funds; a one standard deviation shock to idiosyncratic volatility leads to a 0.13 standard deviation increase in next-quarter hedge fund ownership in the set of undervalued stocks and no increase in non-hedge fund ownership in that set. In sum, for the set of stocks that plot above the security market plane as define above, there is a significant relationship between idiosyncratic volatility and hedge fund ownership, but such a relationship is insignificant for non-hedge funds. Our results can be interpreted as evidence in favor the price inefficiency interpretation of idiosyncratic volatility.

**4.5 Regressions of Change in Hedge Fund Ownership on Alphas and Idiosyncratic Risk**

Our analysis so far has focused on the level of hedge fund ownership. In this section, we investigate the relationship between changes in hedge fund ownership and mispricing. We estimate the Fama-MacBeth regression model and regress the quarter-on-quarter change in hedge fund ownership on alpha (the measure of under-valuation) from the previous quarter and control variables. Table 5 presents the estimation results from the following model:

$$\Delta IO_{i,t} = a_t + b_t \, Alpha_{i,t-1} + c_t' X_{i,t-1} + \varepsilon_{i,t}, \qquad (5)$$

where $\Delta IO_{i,t}$ is the change in hedge fund ownership (or, the change in non-hedge fund ownership) from quarter *t-1* to *t*, $Alpha_{i,t-1}$ is the measure of stock under-valuation in quarter *t-1*, and $X_{i,t-1}$ is a vector of one-quarter lagged stock characteristics. As before, in each quarter *t*, the cross-sectional regression utilizes firm-quarter observations for which the stock is under-valued in the previous quarter and the *t*-statistic of $Alpha_{i,,t-1}$ is equal to and greater than 1.65.

Table 5 shows that, after controlling for stock characteristics, the lagged alpha is significantly associated with the change in hedge fund ownership (*t*-statistic = 2.44), but not with the change in non-hedge fund ownership. For hedge funds, a one standard deviation increase in under-valuation measure leads to a 0.04 standard deviation increase in the change of hedge fund ownership. This finding suggests that when stocks are underpriced, hedge funds increase their holdings of such stocks but non-hedge fund institutions do not do so. In model (1), all control variables of stock characteristics, such as book-to-market ratio and market capitalization, are not significant in this test. Thus the change in hedge fund ownership is primarily related to our measure of potential arbitrage profits, not driven by changes in stock characteristics.

Next we examine the relation between the changes in hedge fund ownership and lagged idiosyncratic volatility. Using firm-quarter observations when the *t*-statistic of alpha is positive and significant at the 5% level in quarter *t-1*, we estimate the following Fama-MacBeth regression model:

$$\Delta IO_{i,t} = a_t + b_t \, Idio.Risk_{i,t-1} + c_t' X_{i,t-1} + \varepsilon_{i,t}, \qquad (6)$$

In Table 6 we examine the specifications with the change in hedge fund ownership and the change in non-hedge fund ownership as dependent variables, respectively, and test whether there is a difference in the coefficients on lagged idiosyncratic volatility between hedge funds and non-hedge funds. For under-valued stocks, idiosyncratic volatility is positively and significantly associated with the change in hedge fund ownership with a *t*-statistic of 2.17, and a one standard deviation shock in idiosyncratic volatility is associated with a 0.052 standard deviation increase in the change of hedge fund ownership. By contrast, there is no significant relation between idiosyncratic risk and the change in non-hedge fund ownership.

### 4.6 Do Hedge Funds Reduce Mispricing?

Now we turn to examining the convergence to the security market plane as measured by the change in alpha. Specifically, we perform Fama-MacBeth regressions of the change in alpha from the previous quarter to the current quarter on the previous quarter's stock ownership by both hedge funds and non-hedge funds:

$$\begin{aligned} \Delta Alpha_{i,t} = a_t &+ b_{1t} \, IO\_HF_{i,t-1} + b_{2t} \, IO\_Non\_HF_{i,t-1} \\ &+ b_{3t} \, \Delta IO\_HF_{i,t-1} + b_{4t} \, \Delta IO\_Non\_HF_{i,t-1} + c_t' X_{i,t-1} + \varepsilon_{i,t}, \end{aligned} \qquad (7)$$

where $\Delta Alpha_{i,t}$ is the change in *Alpha* from quarter *t-1* to *t* for stock *i*, $IO\_HF_{i,t-1}$ is the one-quarter lagged hedge fund ownership, $IO\_Non\_HF_{i,t-1}$ is the lagged non-hedge fund ownership, $\Delta IO\_HF_{i,t-1}$ is the change in hedge fund ownership from quarter *t-1* to *t*, and $X_{i,t-1}$ is a vector of one-quarter lagged stock characteristics.

As in the previous tests, we standardize the dependent and independent variables in each quarter using their respective means and standard deviation, and focus only on positive alpha stocks as define before. If hedge funds explore arbitrage opportunities and their holding or trading (e.g., change in holdings) helps to reduce mispricing and restore equilibrium, we would expect that the coefficient on lagged hedge fund holdings (or lagged change in hedge fund ownership) to be negative and significant. On the other hand, if the primary investment objectives of non-hedge fund institutions (e.g., banks, insurance companies and mutual funds, etc.) is not to arbitrage mispricing, we would expect to see that the coefficient on lagged non-hedge fund holdings (and lagged change in non-hedge fund holdings) insignificant.

The cross-sectional regression results displayed in Table 7 show that one-quarter lagged hedge fund ownership is significantly associated with the reduction in mispricing measure alpha (*t*-statistic = -4.44). In particular, a one standard deviation increase in hedge fund ownership in the previous quarter leads to a 0.047 standard deviation reduction in alpha from the previous quarter to the current quarter, after stock characteristics are controlled.

A natural question is whether this convergence is due simply to a reversion to the mean. This would be the case, for example, if a high positive alpha were due to a non-recurring, idiosyncratic positive news announcement that attracted institutional purchases. While the intercept of the regression should control for the average reversion effect, there is still a conditional effect due to purchases and deviation from the pricing plane being caused by the same thing. If this conditional reversion to the mean explained the results, we would again expect a negative coefficient on non-hedge fund holding as well. In contrast, we do not observe a significant relationship between lagged ownership by non-hedge funds and changes in the stock mispricing measure. However, we do find that the coefficient on the lagged change in non-hedge fund ownership is negative and significant, although its magnitude is smaller than that of lagged change in hedge fund ownership. This suggests either that non-hedge funds have a similar price impact, or that there is some evidence that the event that caused the deviation (and rebound) to the plane also caused an institutional purchase.

A related test of convergence conditional on hedge fund purchases is whether there is a subsequent reduction in idiosyncratic risk conditional on hedge fund ownership share. To test this we run a Fama-MacBeth regression similar to (7) with change in idiosyncratic risk as the dependent variable. We estimate the following Fama-MacBeth regression model on the positive-*Alpha* stock sample:

$$\begin{aligned}\Delta IdioRisk_{i,t} = {} & a_t + b_{1t}\, IO\_HF_{i,t-1} + b_{2t}\, IO\_Non\_HF_{i,t-1} \\ & + b_{3t}\, \Delta IO\_HF_{i,t-1} + b_{4t}\, \Delta IO\_Non\_HF_{i,t-1} + c_t' X_{i,t-1} + \varepsilon_{i,t},\end{aligned} \tag{8}$$

where $\Delta IdioRisk_{i,t}$ is the change in daily idiosyncratic volatility for stock *i* from quarter *t-1* to *t*, $IO\_HF_{i,\ t-1}$ is the one-quarter lagged hedge fund ownership, $IO\_Non\_HF_{i,\ t-1}$ is the one-quarter lagged non-hedge fund ownership, $\Delta IO\_HF_{i,t-1}$ is the change in hedge fund ownership from quarter *t-1* to *t*, and $X_{i,t-1}$ is a vector of one-quarter lagged stock characteristics.

Table 8 presents the regression results. The coefficient on lagged hedge fund ownership is negative and significant (*t*-statistic = -3.02), which suggests that hedge fund holding is associated with a reduction in the idiosyncratic volatility of under-valued stocks. The coefficient on non-hedge fund ownership is positive and significant (*t*-statistic = 3.53) after controlling for stock characteristics, again consistent with an explanation of a jointly determined deviation from the pricing plane and purchase decision by institutions.

In another specification, we replace hedge fund holdings by the change in hedge fund holdings, and find that the coefficient on the change in hedge fund holding is negative and significant. Thus, the larger the increase in hedge fund holding, the greater the reduction in idiosyncratic volatility. The sign of the coefficient on the change in non-hedge fund holdings is also negative.

In sum, the results in both Tables 7 and 8 suggest that ownership and changes in ownership by hedge funds, rather than by other types of institutional investors, is associated with a reduction in mispricing and idiosyncratic volatility. At the very least, this suggests that hedge funds, and to some extent other institutions, are exploiting a pattern of reversion to the pricing plane following a deviation. This finding is also consistent with hedge funds playing a positive role in reducing mispricing and improving market efficiency. We find no evidence that hedge fund purchases of these stocks – or purchases by other institutional investors – amplify mispricing.

### 4.7 Price Changes and Hedge Fund Holdings

So far we have examined the sample of undervalued stocks with positive and significant alphas. We now use the full sample of stocks with 13F holding data to answer a more fundamental question of whether hedge fund holdings and purchases are prospectively informative about stock returns.

To answer this question, we perform the following Fama-MacBeth regressions of quarterly future stock returns on hedge fund ownership and the changes in hedge fund ownership, and we consider two holding periods: one and two quarters. For comparison purposes, we perform the same tests using the fraction of non-hedge fund ownership and the changes in fraction of non-hedge funds ownership as explanatory variables. Specifically, we estimate the following model:

$$\begin{aligned} r_{i,t+m} = {} & a_t + b_{1t}\, IO\_HF_{i,t-1} + b_{2t}\, IO\_Non\_HF_{i,t-1} + c_{1t}\, \Delta IO\_HF_{i,t} + + c_{2t}\, \Delta IO\_Non\_HF_{i,t} \\ & + d_t' X_{i,t-1} + \varepsilon_{i,t}, \end{aligned} \tag{9}$$

where $r_{i,t+m}$ is the quarterly return on stock *i* over the horizon of the next m quarters, $IO\_HF_{i,t-1}$ is the hedge fund ownership in quarter *t-1*, and $\Delta IO\_HF_{i,t-1}$ is the change in hedge fund ownership from quarter *t-1* to *t*. The other two variables for non-hedge fund ownership are defined similarly.

Panel A of Table 9 reports the results. The level of hedge fund ownership is not significantly related to future stock returns, nor is the level of non-hedge fund ownership. There is some evidence that changes in hedge fund holdings predict future stock returns over a horizon of one quarter. For example, at the one quarter horizon the coefficient on the change in hedge fund ownership is significant, with a *t*-statistic of 3.31 (see model (2)). In unreported tests, we do not standardize returns and we re-estimate equation (9). The coefficients from this specification can be interpreted directly. We find that a one standard deviation shock to the change in hedge fund ownership leads to a 25 bp increase in the next quarter return (or, one percent per year). When the holding period is two quarters, the coefficient on the change in hedge fund ownership is not significant (see models (3) and (4) in Panel A).

These results are consistent with limits to arbitrage theories which predict less-than-immediate convergence, and profitability of arbitrage in expectations – as predicted by costly arbitrage models such as Grossman & Stiglitz (1976). The lack of return predictability at horizons longer than one quarter is consistent with the funding risk necessitating timely convergence. We do not find a similar result for non-hedge fund holdings or the change in non-hedge fund holdings; the changes in their stock holdings bear no relationship to subsequent stock returns. When the investment horizon is beyond two quarters, the unreported results show that the change in hedge fund holdings is not significant and no longer informative about future returns.

One question is whether we are simply picking up the tendency of hedge funds to buy momentum stocks. To address this concern, we add lagged one-, two-, three- and four-quarter returns in equation (9) and report results in Panel B of Table 9. Indeed, lagged returns up to three quarters are positive and significant, suggesting evidence of momentum up to nine months. After controlling for the momentum effect, the coefficient on the changes in hedge fund holdings is still positive and significant (*t*-statistic=2.68). Thus, the cross-sectional predictability of the changes in hedge fund holdings remains significant up to one quarter.

A recent study by Agarwal, Jiang, Tang and Yang (2010) documents that confidential holdings of hedge funds exhibit superior performance up to the typical confidential period of twelve months. Our results suggest that the information content of hedge fund holdings in 13F is short-lived, in that the return predictability only lasts for about one quarter and becomes insignificant for longer horizons.

Chen, Jegadeesh, and Wermers (2000) show that mutual fund trading (but not their holdings) has predictive power for the stock returns, whereas Bennett, Sias, and Starks (2003) find that the trading of all institutions does not predict future returns. Recently, Griffin and Xu (2009) compare return predictability between mutual fund ownership and hedge fund ownership. They find that, without controlling for previous stock returns, changes in hedge fund ownership are associated with higher future stock returns in the cross-section, whereas return predictability is weaker for mutual fund holdings. However, after past stock returns are controlled for in the cross-sectional regression, they find such predictability disappeared. In our sample, the predictability is robust to past returns.

In sum, we find evidence that changes in hedge fund ownership significantly predict stock returns in the cross-section up to one quarter, a pattern that is not true for non-hedge fund institutional share of ownership. This is consistent with profitability in hedge fund trades before accounting for transactions and information costs.

### 4.8 Stock Illiquidity and Under-Valuation Measures

Some stocks listed on organized exchanges are traded infrequently and may have zero returns and zero volume on some days. This introduces into the Fama-French-Carhart model the econometric problem of errors in variables. According to Scholes and Williams (1977), stocks trading very infrequently have ordinary least squares estimators asymmetrically biased upward for alphas and downward for betas.

One important question is, if an estimated alpha from the Fama-French-Carhart model is biased because the stock is illiquid and zero returns are included in the estimation of alpha, does it affect our results reported in previous sections? In addition, extant literature has shown that liquidity is important for asset pricing and illiquid stocks trade at low prices relative to their expected cash flows. In the absence of a liquidity risk factor in an equilibrium model, the liquidity risk premium can also be translated into a positive alpha.

One way to address this concern is to include a daily liquidity risk factor in the Fama-French-Carhart model and to control for a liquidity risk premium explicitly when estimating alpha. Unfortunately, this approach is hindered by several difficulties. The construction of a daily liquidity risk factor requires daily measures of liquidity at the firm level. Chordia, Roll and Subrahmanyam (2001, 2004) calculate daily measures of liquidity as quoted and effective bid–ask spreads using intraday trade and quote data. However, the detailed microstructure data does not go back to the beginning of our sample period of 1981. Next, the Pástor-Stambaugh (2003) liquidity measure captures liquidity associated with temporary price fluctuations induced by order flow, which can be interpreted as volume-related price reversals attributable to liquidity effects. The measure can be estimated by regressing daily stock return on daily signed trading volume. Unfortunately, the Pástor-Stambaugh liquidity measure can only be computed at the monthly frequency. Amihud (2002) measures stock illiquidity as the ratio of the daily absolute return to the dollar trading volume. This measure can be interpreted as the daily price impact of an order flow. However, this measure requires positive volume on each day for each firm, a problem particularly acute for illiquid stocks.

We address the above-mentioned concern in two ways. In the first test, we use the method described below to assess the impact of zero-return days on alpha. For each stock and in each quarter, we identify days with zero return and zero volume. Assume that the return on stock ABC is zero on day $\iota$, $\iota+1$,……$\iota+k-1$, and is non-zero on day $\iota+k$ ($k > 1$). We drop daily stock returns and observations of the Fama-French risk factors on day $\iota$, $\iota+1$, …… $\iota+k-1$, replace stock return on day $\iota+k$ by the average stock return over the interval $[\iota, \iota+k]$ and replace values of the Fama-French factors on day $\iota+k$ by their respective averages during $[\iota, \iota+k]$. We then use newly constructed daily stock returns and risk factors to re-estimate alpha and its standard error. We use generalized least squares (GLS) instead of OLS because the error structure is no longer homogeneous.

Comparing two sets of estimated alphas, we find a large overlap between the sample of undervalued stocks used in the previous sections and the sample of undervalued stocks after we control for zero-return days without trading volume. Among all firm-quarter observations with positive and significant alphas that are used in previous sections, 98% still have positive and significant alphas and are still undervalued when we use GLS to address the concern that including zero-return days in the estimation may bias a stock's alpha.

Table 10 presents test results corresponding to results in Tables 3-6. Models (1) and (2) show that, after controlling for zero-returns in the estimation of alphas, there is still a positive and significant association between hedge fund ownership and lagged alpha (*t*-statistic = 6.04) in the cross-section of undervalued stocks, but the relationship between ownership of non-hedge fund institutions and lagged alphas is insignificant. Turning to models (3) and (4), we find that hedge fund ownership is positively and significantly related to the lagged idiosyncratic volatility, but such a relationship is not significant for non-hedge fund institutions.

In models (5) – (8) of Table 10, we use changes in hedge fund ownership and changes in non-hedge fund ownership as dependent variables. For undervalued stocks, the Fama-MacBeath regression coefficient on lagged alpha is positive and significant (*t*-statistic = 2.48) when regressing changes in hedge fund ownership on lagged alpha. The coefficient on the lagged idiosyncratic volatility is also significant with a *t*-statistic of 2.01 when regressing changes in hedge fund ownership on the lagged idiosyncratic volatility. In contrast, the coefficients on lagged alpha and lagged idiosyncratic volatility are insignificant when the dependent variable is changes in non-hedge fund ownerships.

We repeat tests in Tables 8-9, controlling for zero-return observations in the estimation of alpha. For IO_HF and ΔIO_HF, we find qualitatively identical results in Table 11 as in Tables 8 and 9. The coefficients on IO-HF and ΔIO_HF are negative and significant at the 5% level. The results for IO_Non_HF and ΔIO_Non_HF are also similar to those in Tables 8-9.

In the second test, we address the concern of non-synchronous trading by including lagged factors in the Fama-French-Carhart model. We perform this test in the spirit of Scholes and Williams (1977), estimate the following regression model and obtain alpha for each stock in each quarter using the following model:

$$
\begin{aligned}
r_{i,\tau} = {} & Alpha + \beta_1 MKT_{\tau} + \beta_2 SMB_{\tau} + \beta_3 HML_{\tau} + \beta_4 UMD_{\tau} \\
& + \beta_5 MKT_{\tau-1} + \beta_6 SMB_{\tau-1} + \beta_7 HML_{\tau-1} + \beta_8 UMD_{\tau-1} + \varepsilon_{\tau}, \qquad (9)
\end{aligned}
$$

In unreported tables, we repeat the experiment in Tables 3-8, using alphas from equation (9) and corresponding undervalued stocks. The results overwhelmingly indicate that our findings reported in Tables 3-8 are robust, even after we take non-synchronous trading into account when estimating alphas.

Overall, we see that controlling for zero-return and zero-volume days in estimating *Alphas* or controlling for non-synchronous trading in the spirit of Scholes and Williams (1997) does not alter our conclusion. Our findings in Sections 4.1-4.6 are not driven by undervalued stocks with zero-return and zero-volume days.

## 5. Conclusion

In this paper we use hand-collected data on hedge fund ownership that covers virtually all hedge fund management companies from 1981 to 2009 in order to understand the role of hedge funds in the price formation process of equity markets.

Our empirical results show that under-valuation, as defined by positive deviations from the security market plane using a standard factor model is positively related to hedge fund holdings, but not non-hedge fund ownership, in the cross-section. Hedge funds hold a proportionately greater amount of under-priced stocks vs. overpriced stocks compared to non-hedge funds. This basic finding is consistent with the hypothesis that hedge funds use factor models to identify investment opportunities. This may not be completely surprising given the prevalence of factor models in the investment industry however it has not previously been documented. Khandani and Lo (2011) have shown that the "Quant Meltdown" of August 2007 was consistent with hedge funds taking long-short positions above and below the security market plane defined using standard factor models, including a book-to-market factor. Our analysis suggests that this hedge fund strategy was not confined to that event, but has been common over many years. In fact, neo-classical asset pricing models predict exactly such behavior. In an economy in which there are a few widespread factors, but sufficient frictions to cause deviations from the pricing plane, some set of agents with a comparative informational or operational advantage will exploit the deviation by buying "under-valued" securities. Our empirical results suggest that hedge funds may play that role in the U.S. equity market.

Or research also addresses the current debate about the interpretation of idiosyncratic risk with respect to market efficiency. If high idiosyncratic risk is a measure of the degree to which value-relevant information is impounded in prices, then such stocks would be unattractive to investors seeking to exploit mispricing. On the other hand, if high idiosyncratic risk is indicative of behavioral bias if the marginal investor or of opaque or misleading financial statements, this would potentially attract arbitrageurs. We find that the idiosyncratic volatility of under-valued stocks is positively related to hedge fund holdings, consistent with the hypothesis that hedge funds perceive these stocks as inefficiently priced. We also document that the measure of stock under-valuation is positively related to an increase in the hedge fund ownership,

We next turn to the consequences of hedge fund ownership and purchases of underpriced stocks. We examine the change in mispricing and idiosyncratic risk in the quarters following an observation of high hedge fund holdings or a positive change in hedge fund holdings. We find a negative relationship – i.e. the larger the hedge fund holdings, the larger the reduction in mispricing in the following quarter. This is true for idiosyncratic volatility as well. We also examine a more general question of whether hedge fund holdings or the changes in hedge fund holdings predict performance of stocks and find that a positive change in hedge fund ownership is informative about future stock returns. That is, an *increase* in hedge fund ownership in stocks predicts positive future stock returns up to one quarter.

In sum, the holdings data from government filings allow us examine the role of a major class of institutional investor whose broad intent is to generate positive risk adjusted returns. For hedge funds trading U.S. equities, this implies a positive alpha with respect to standard asset pricing models. Hedge funds appear to pursue a strategy of buying undervalued stocks as measured by standard models, and their holdings and purchases in these stocks predict future price adjustments towards the security market plane.

## References


Ackermann, Carl, Richard McEnally, and David Ravenscraft, 1999, The performance of hedge funds: Risk, return, and incentives, *Journal of Finance* 54, 833-874.

Agarwal, Vikas, Wei Jiang, Yuehua Tang, and Baozhong Yang, 2012, Uncovering hedge fund skill from the portfolio holdings they hide, *Journal of Finance, Forthcoming*.

Ali, Ashiq, Lee-Seok Hwang, and Mark Trombley, 2003, Arbitrage risk and the book-to-market anomaly, *Journal of Financial Economics* 69, 355-373.

Aragon, George, and Spencer Martin, 2010, A unique view of hedge fund derivatives usage: Safeguard or speculation?, Working paper, Arizona State University.

Aragon, George, and Philip Strahan, 2012, Hedge funds as liquidity providers: Evidence from the lehman bankruptcy, *Journal of Financial Economics* 103, 570-587.

Bennett, James, Richard Sias, and Laura Starks, 2003, Greener pastures and the impact of dynamic institutional preferences, *Review of Financial Studies* 16, 1203-1238.

Brennan, Michael, and Ashley Wang, 2010, The mispricing return premium, *Review of Financial Studies* 23, 3437-3468.

Brown, Stephen, William Goetzmann, and Roger Ibbotson, 1999, Offshore hedge funds: Survival and performance, 1989-95, *Journal of Business* 72, 91-117.

Brown, Stephen, William Goetzmann, Bing Liang, and Christopher Schwarz, 2012, Trust and delegation, *Journal of Financial Economics* 103, 221-234.

Brown, Stephen, William Goetzmann, and James Park, 2000, Hedge funds and the asian currency crisis - global hedge funds did not move exchange rates, *Journal of Portfolio Management* 26, 95-101.

Brunnermeier, Markus, and Stefan Nagel, 2004, Hedge funds and the technology bubble, *Journal of Finance* 59, 2013-2040.

Brunnermeier, Markus, and Lasse Pedersen, 2009, Market liquidity and funding liquidity, *Review of Financial Studies* 22, 2201-2238.

Bushee, Brian, 2004, Identifying and attracting the “right” investors: Evidence on the behavior of institutional investors, *Journal of Applied Corporate Finance* 16, 28-35.

Chen, Hsiu-Lang, Narasimhan Jegadeesh, and Russ Wermers, 2000, The value of active mutual fund management: An examination of the stockholdings and trades of fund managers, *Journal of Financial and Quantitative Analysis* 35, 343-368.

Choi, Darwin, Mila Getmansky, Brian Henderson, and Heather Tookes, 2010, Convertible bond arbitrageurs as suppliers of capital, *Review of Financial Studies* 23, 2492-2522.

Fama, Eugene, 1970, Efficient capital markets - review of theory and empirical work, *Journal of Finance* 25, 383-423.

Fama, Eugene, and James Macbeth, 1973, Risk, return, and equilibrium - empirical tests, *Journal of Political Economy* 81, 607-636.

Fung, William, and David Hsieh, 2011, The risk in hedge fund strategies: Theory and evidence from long/short equity hedge funds, *Journal of Empirical Finance* 18, 547-569.

Gompers, Paul, and Andrew Metrick, 2001, Institutional investors and equity prices, *Quarterly Journal of Economics* 116, 229-259.

Griffin, John, Jeffrey Harris, Tao Shu, and Selim Topaloglu, 2011, Who drove and burst the tech bubble?, *Journal of Finance* 66, 1251-1290.

Griffin, John, and Jin Xu, 2009, How smart are the smart guys? A unique view from hedge fund stock holdings, *Review of Financial Studies* 22, 2531-2570.

Grinold, Richard, and Ronald Kahn, 1999, Active Portfolio Management, second edition, McGraw Hill, New York.

Grinold, Richard, and Ronald Kahn, 2000, The efficiency gains of long-short investing, *Financial Analysts Journal* 56, 40-53.

Gromb, Denis, and Dimitri Vayanos, 2002, Equilibrium and welfare in markets with financially constrained arbitrageurs, *Journal of Financial Economics* 66, 361-407.

Grossman, Sanford, and Joseph Stiglitz, 1976, Information and competitive price systems, *American Economic Review* 66, 246-253.

Grossman, Sanford, and Joseph Stiglitz, 1980, On the impossibility of informationally efficient markets, *American Economic Review* 70, 393-408.

Hong, Harrison G. and Wenxi Jiang, 2011, When Some Investors Head for the Exit, SSRN Working Paper.

Hou, Kewei, Wei Xiong and Lin Peng, 2006, $R^2$ and Price Inefficiency , Fisher College of Business Working Paper No. 2006-03-007; Charles A. Dice Center Working Paper No. 2006-23.

Jylha, Petri, Kalle Rinne, and Matti Suominen, 2012, Do hedge funds supply or demand immediacy?, Working paper, Aalto University.

Liang, Bing, 1999, On the performance of hedge funds, *Financial Analysts Journal* 55, 72-85.

Amir E. Khandani, Andrew W. Lo,, 2011, What happened to the quants in August 2007? Evidence from factors and transactions data, Journal of Financial Markets, Volume 14, Issue 1, Pages 1-46.

Mashruwala, Christina, Shivaram Rajgopal, and Terry Shevlin, 2006, Why is the accrual anomaly not arbitraged away? The role of idiosyncratic risk and transaction costs, *Journal of Accounting and Economics* 42, 3-33.

Mendenhall, Richard, 2004, Arbitrage risk and post-earnings-announcement drift, *Journal of Business* 77, 875-894.

Morris, Stephen, and Hyun Song Shin, 2004, Coordination risk and the price of debt, *European Economic Review* 48, 133-153.

Morck, R., Yeung, B., Yu, W., 2000, The information content of stock markets: why do emerging markets have synchronous stock price movements? *Journal of Financial Economics* 58, 215-260.

Pontiff, Jeffrey, 1996, Costly arbitrage: Evidence from closed-end funds, *Quarterly Journal of Economics* 111, 1135-1151.

Pontiff, Jeffrey, 2006, Costly arbitrage and the myth of idiosyncratic risk, *Journal of Accounting & Economics* 42, 35-52.

Ross, Stephen, 1976, The arbitrage theory of capital asset pricing, *Journal of Economic Theory* 13, 341-360.

Shleifer, Andrei, and Robert Vishny, 1992, Liquidation values and debt capacity - a market equilibrium approach, *Journal of Finance* 47, 1343-1366.

Shleifer, Andrei, and Robert Vishny, 1997, The limits of arbitrage, *Journal of Finance* 52, 35-55.

Sias, Richard, Laura Starks, and Sheridan Titman, 2001, The price impact of institutional trading, Working paper, University of Arizona.

Sias, Richard, Laura Starks, and Sheridan Titman, 2006, Changes in institutional ownership and stock returns: Assessment and methodology, *Journal of Business* 79, 2869-2910.

Stulz, Rene, 2007, Hedge funds: Past, present, and future, *Journal of Economic Perspectives* 21, 175-194.

Teo, Siew Hong, Yong Yang and Yinglei Zhang, 2007, R-Square: Noise or Firm-Specific Information?, working paper NUS.

Wei, John K. C., and Jie Zhang, 2007, Arbitrage risk and arbitrage returns: Evidence from the fundamental value-to-price anomaly, Working paper, Hong Kong University of Science and Technology.

Zuckerman, Roy, 2011, Synchronized arbitrage and the value of public announcements, Working paper, Rutgers Business School.

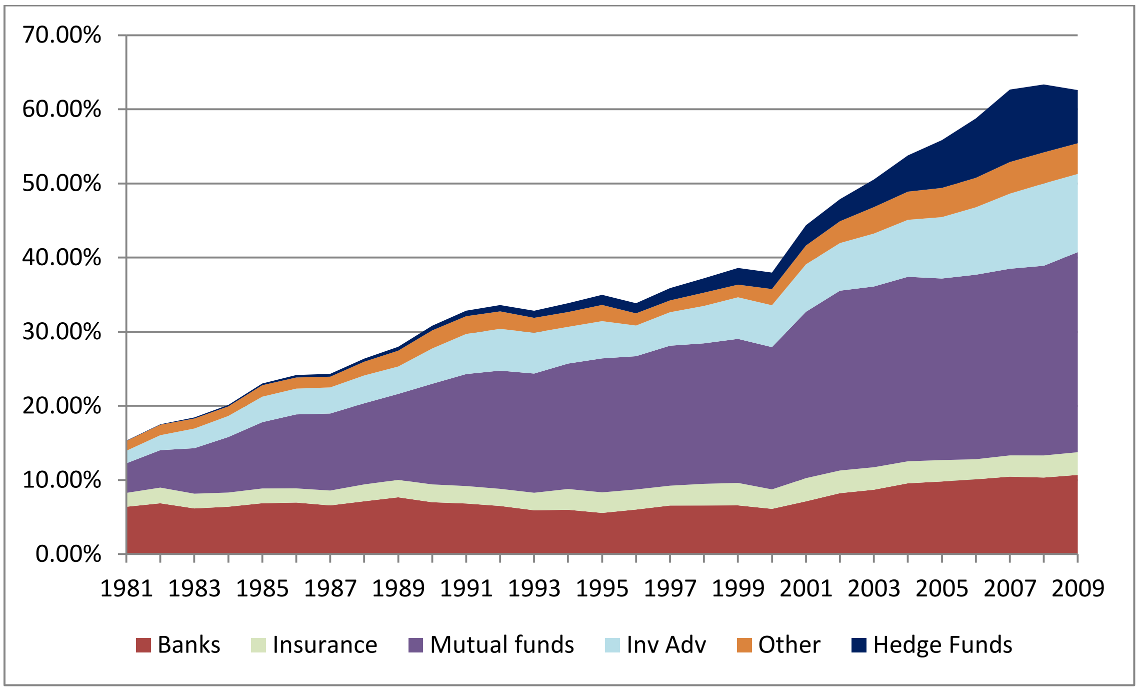


**Figure 1 Evolution of stock ownership by institutional investors**

This figure plots the evolution of average stock ownership by different types of institutional investors, including banks, insurance companies, mutual funds, investment advisors, hedge funds, and all others. The sample period extends from 1981 through 2009.

**Table 1: Summary Statistics of Hedge Fund Companies and Hedge Fund Data Sources**

This table presents summary statistics by data source for the number of hedge fund companies, and the number of hedge fund companies that can be matched with 13F institutional holding data from CDA/Spectrum. The source of hedge fund management companies are TASS, HFR, CISDM, Barclay Hedge, Morningstar databases and online resources such as Business Week list of private companies and SEC ADV registration forms. To classify an institutional investor a hedge fund company, we require that the company's primary business is managing hedge funds. If an institutional investor is a registered investment advisor, we check its ADV registration form and classify it a hedge fund company if it meets two criteria: (1) More than 50% of its clients are high-net-worth individuals or more than 50% of its clients are invested in "other pooled investment vehicle (e.g., hedge funds)"; and (2) the advisor is compensated for its advisory service by charging a performance-based fees.

| Source | No. of hedge fund companies | No. of unique hedge fund companies matched with 13F | % | Sample period |
|---|---|---|---|---|
| TASS | 4,394 | 533 | 39% | 1977-2009 |
| HFR | 4,369 | 304 | 23% | 1970-2009 |
| CISDM | 3,894 | 112 | 8% | 1972-2009 |
| Barclay Hedge | 5,345 | 81 | 6% | 1975-2009 |
| Morningstar | 2,183 | 23 | 2% | 1974-2009 |
| Other sources | | 303 | 22% | |
| Total | | 1,356 | | |

**Table 2: Panel Data Summary Statistics of Stock Characteristics**

This table provides summary statistics of characteristics for all equity securities reported in 13F filings from 1981 through 2009. These include book-to-market ratio, market capitalization (in $ billion), dividend yield per quarter (in %), firm age (in months), share price (in $), and a dummy variable indicating S&P 500 index membership. The full sample is based on merged CRSP, COMPUSTAT and 13F institutional holdings data and contains 389,982 firm-quarter observations over the period from 1981 to 2009.

Panel A Summary statistics of full Sample

| Variable | Mean | Std. Dev. | Median | 25% | 75% |
|---|---|---|---|---|---|
| Book/Market | 0.67 | 0.42 | 0.58 | 0.35 | 0.89 |
| Market cap ($bil) | 2.10 | 11.09 | 0.24 | 0.07 | 0.92 |
| Dividend yield (%) | 0.36 | 0.52 | 0.00 | 0.00 | 0.61 |
| Age (month) | 190.05 | 183.21 | 136.00 | 57.00 | 257.00 |
| Price ($) | 22.42 | 22.81 | 18.13 | 10.68 | 29.69 |
| SP500 dummy | 0.13 | 0.33 | 0.00 | 0.00 | 0.00 |

Panel B Summary statistics of stocks with top 10% HF ownership in each quarter

| Variable | Mean | Std. Dev. | Median | 25% | 75% |
|---|---|---|---|---|---|
| Book/Market | 0.64 | 0.43 | 0.55 | 0.32 | 0.87 |
| Market cap ($bil) | 0.80 | 1.69 | 0.30 | 0.12 | 0.81 |
| Dividend yield (%) | 0.22 | 0.45 | 0.00 | 0.00 | 0.25 |
| Age (month) | 156.18 | 166.97 | 100.00 | 42.00 | 205.00 |
| Price ($) | 22.35 | 20.38 | 17.56 | 10.69 | 28.37 |
| SP500 dummy | 0.08 | 0.28 | 0.00 | 0.00 | 0.00 |

**Table 3: Lagged Alpha and Institutional Ownership for Positive Alpha Stocks**

This table reports the estimation results from the Fama-MacBeth cross-sectional regressions of stock's hedge fund ownership (IO_HF) and non-hedge-fund ownership (IO_Non_HF) on one-quarter lagged *Alpha*. The control variables are lagged stock characteristics including book-to-market ratio, market capitalization, dividend yield, firm age, share price, and a dummy variable indicating S&P 500 index membership. In quarter *t*, $Alpha_{t-1}$ is the intercept from the Fama-French-Carhart four-factor model and is estimated by using each stock's daily returns in quarter *t-1*. For a stock to be included in the analysis in quarter *t*, we require its *t*-statistic associated with the lagged *Alpha* equal to and greater than 1.65 in quarter *t-1* (e.g., the stock is under-valued in quarter *t*-1 as judged by the Fama-French-Carhart four-factor model). The dependent and independent variables are standardized each quarter, using their respective means and standard deviations. *t*-statistics from the Fama-MacBeth regression are in parentheses. The sample period is from 1981 to 2009. ***, **, * denote statistically significance at 1%, 5%, and 10% levels, respectively.

| | (1) | (2) | (1) – (2) |
|---|---|---|---|
| VARIABLES | $IO\_HF_t$ | $IO\_Non\_HF_t$ | *p-value of difference* |
| $Alpha_{t-1}$ | 0.096*** | -0.011 | |
| | (6.09) | (-0.91) | 0.00 |
| $Ln(Book/Market)_{t-1}$ | 0.046*** | 0.106*** | |
| | (4.33) | (9.94) | 0.00 |
| $Ln(Market\ Cap)_{t-1}$ | 0.187*** | 0.532*** | |
| | (11.15) | (28.00) | 0.00 |
| $Ln(Dividend\ yield)_{t-1}$ | -0.128*** | -0.191*** | |
| | (-12.50) | (-15.10) | 0.00 |
| $Ln(Age)_{t-1}$ | -0.060*** | 0.041*** | |
| | (-4.40) | (4.27) | 0.00 |
| $Ln(Price)_{t-1}$ | -0.050*** | 0.110*** | |
| | (-3.56) | (7.02) | 0.00 |
| $SP500\ dummy_{t-1}$ | -0.084*** | -0.055*** | |
| | (-5.87) | (-4.04) | 0.14 |
| Constant | -0.117*** | 0.109*** | |
| | (-4.03) | (4.46) | |
| R-squared | 0.13 | 0.39 | |

**Table 4: Lagged Idiosyncratic Risk and Institutional Ownership for Positive Alpha Stocks**

This table presents the estimation results from the Fama-MacBeth cross-sectional regressions of stock's hedge fund ownership (IO_HF) and non-hedge-fund ownership (IO_Non_HF) on one-quarter lagged idiosyncratic risk (Idio. risk). The control variables are lagged stock characteristics including book-to-market ratio, market capitalization, dividend yield, firm age, share price, and a dummy variable indicating S&P 500 index membership. In quarter *t*, idio. $risk_{t-1}$ is the Fama-French-Carhart based idiosyncratic return standard deviation and is estimated by using each stock's daily returns in quarter *t-1*. For a stock to be included in the analysis in quarter *t*, we require its *t*-statistic associated with the lagged *Alpha* equal to and greater than 1.65 in quarter *t-1* (e.g., the stock is under-valued in quarter t-1 as judged by the Fama-French-Carhart four-factor model). The dependent and independent variables are standardized each quarter, using their respective means and standard deviations. *t*-statistics from the Fama-MacBeth regression are in parentheses. The sample period is from 1981 to 2009. ***, **, * denote statistically significance at 1%, 5%, and 10% levels, respectively.

| | (1) | (2) | (1) – (2) |
|---|---|---|---|
| VARIABLES | $IO\_HF_t$ | $IO\_Non\_HF_t$ | *p-value of difference* |
| Idio. $risk_{t-1}$ | 0.127*** | -0.001 | |
| | (6.28) | (-0.01) | 0.00 |
| $Ln(Book/Market)_{t-1}$ | 0.050*** | 0.108*** | |
| | (4.53) | (10.35) | 0.00 |
| $Ln(Market\ Cap)_{t-1}$ | 0.187*** | 0.534*** | |
| | (11.26) | (28.50) | 0.00 |
| $Ln(Dividend\ yield)_{t-1}$ | -0.125*** | -0.191*** | |
| | (-11.47) | (-15.03) | 0.00 |
| $Ln(Age)_{t-1}$ | -0.058*** | 0.042*** | |
| | (-4.32) | (4.45) | 0.00 |
| $Ln(Price)_{t-1}$ | -0.040*** | 0.112*** | |
| | (-2.62) | (6.85) | 0.00 |
| SP500 $dummy_{t-1}$ | -0.084*** | -0.055*** | |
| | (-5.87) | (-4.03) | 0.14 |
| Constant | 0.086*** | 0.092*** | |
| | (5.90) | (5.76) | |
| R-squared | 0.14 | 0.40 | |

**Table 5: Lagged Alpha and the Changes in Institutional Ownership**

This table reports the estimation results from the Fama-MacBeth cross-sectional regressions of the change in stock's hedge fund ownership (ΔIO_HF) and non-hedge-fund ownership (ΔIO_Non_HF) on one-quarter lagged *Alpha*. The control variables are lagged stock characteristics including book-to-market ratio, market capitalization, dividend yield, firm age, share price, and a dummy variable indicating S&P 500 index membership. In quarter $t$, $Alpha_{t-1}$ is the intercept from the Fama-French-Carhart four-factor model and is estimated by using each stock's daily returns in quarter $t-1$. For a stock to be included in the analysis in quarter $t$, we require its $t$-statistic associated with the lagged *Alpha* equal to and greater than 1.65 in quarter $t-1$ (e.g., the stock is under-valued in quarter $t$-1 as judged by the Fama-French-Carhart four-factor model). The dependent and independent variables are standardized each quarter, using their respective means and standard deviations. $t$-statistics from the Fama-MacBeth regression are in parentheses. The sample period is from 1981 to 2009. ***, **, * denote statistically significance at 1%, 5%, and 10% levels, respectively.

| | (1) | (2) | (1) – (2) |
|---|---|---|---|
| VARIABLES | $\Delta IO\_HF_t$ | $\Delta IO\_Non\_HF_t$ | *p-value of difference* |
| $Alpha_{t-1}$ | 0.043** | 0.007 | |
| | (2.44) | (0.31) | 0.08 |
| $Ln(Book/Market)_{t-1}$ | 0.003 | -0.027 | |
| | (0.26) | (-1.61) | 0.12 |
| $Ln(Market\ Cap)_{t-1}$ | 0.009 | 0.006 | |
| | (0.47) | (0.27) | 0.91 |
| $Ln(Dividend\ yield)_{t-1}$ | 0.006 | -0.016 | |
| | (0.58) | (-1.27) | 0.17 |
| $Ln(Age)_{t-1}$ | 0.007 | -0.106*** | |
| | (0.62) | (-7.13) | 0.00 |
| $Ln(Price)_{t-1}$ | -0.013 | -0.098*** | |
| | (-0.86) | (-4.48) | 0.00 |
| $SP500\ dummy_{t-1}$ | -0.010 | -0.001 | |
| | (-0.78) | (-0.08) | 0.64 |
| Constant | -0.068** | 0.111*** | |
| | (-2.04) | (2.97) | |
| R-squared | 0.07 | 0.11 | |

**Table 6: Lagged Idiosyncratic Risk and the Changes in Institutional Ownership**

This table provides the estimation results from the Fama-MacBeth cross-sectional regressions of the change in stock's hedge fund ownership (ΔIO_HF) and non-hedge-fund ownership (ΔIO_Non_HF) on one-quarter lagged idiosyncratic risk (Idio. risk). The control variables are lagged stock characteristics including book-to-market ratio, market capitalization, dividend yield, firm age, share price, and a dummy variable indicating S&P 500 index membership. In quarter *t*, idio. $risk_{t-1}$ is the Fama-French-Carhart based idiosyncratic return standard deviation and is estimated by using each stock's daily returns in quarter *t-1*. For a stock to be included in the analysis in quarter *t*, we require its *t*-statistic associated with the lagged *Alpha* equal to and greater than 1.65 in quarter *t-1* (e.g., the stock is under-valued in quarter t-1 as judged by the Fama-French-Carhart four-factor model). The dependent and independent variables are standardized each quarter, using their respective means and standard deviations. *t*-statistics from the Fama-MacBeth regression are in parentheses. The sample period is from 1981 to 2009. ***, **, * denote statistically significance at 1%, 5%, and 10% levels, respectively.

| | (1) | (2) | (1) – (2) |
|---|---|---|---|
| VARIABLES | $\Delta IO\_HF_t$ | $\Delta IO\_Non\_HF_t$ | *p-value of difference* |
| Idio. $risk_{t-1}$ | 0.052** | -0.005 | |
| | (2.17) | (-0.23) | 0.03 |
| $Ln(Book/Market)_{t-1}$ | 0.004 | -0.032* | |
| | (0.28) | (-1.91) | 0.06 |
| $Ln(Market\ Cap)_{t-1}$ | 0.006 | 0.005 | |
| | (0.36) | (0.21) | 0.74 |
| $Ln(Dividend\ yield)_{t-1}$ | 0.007 | -0.021 | |
| | (0.61) | (-1.59) | 0.06 |
| $Ln(Age)_{t-1}$ | 0.008 | -0.105*** | |
| | (0.70) | (-7.03) | 0.00 |
| $Ln(Price)_{t-1}$ | -0.010 | -0.106*** | |
| | (-0.55) | (-4.67) | 0.00 |
| SP500 $dummy_{t-1}$ | -0.011 | -0.001 | |
| | (-0.86) | (-0.08) | 0.64 |
| Constant | 0.020 | 0.124*** | |
| | (1.40) | (7.94) | |
| R-squared | 0.07 | 0.11 | |

## Table 7: Institutional Ownership and Changes in *Alpha*

This table reports the estimation results from the Fama-MacBeth cross-sectional regressions of the change in stock's *Alpha* on lagged hedge fund ownership ($IO\_HF_{t-1}$) and non-hedge-fund ownership ($IO\_Non\_HF_{t-1}$), as well as lagged changes in hedge fund ownership ($\Delta IO\_HF_{t-1}$) and non-hedge-fund ownership ($\Delta IO\_Non\_HF_{t-1}$). The control variables are lagged stock characteristics including book-to-market ratio, market capitalization, dividend yield, firm age, share price, and a dummy variable indicating S&P 500 index membership. In quarter *t*, $Alpha_t$ is the intercept from the Fama-French-Carhart four-factor model and is estimated by using each stock's daily returns in quarter *t*. For a stock to be included in the analysis in quarter *t*, we require its *t*-statistic associated with the lagged *Alpha* equal to and greater than 1.65 in quarter *t-1* (e.g., the stock is under-valued in quarter *t*-1 as judged by the Fama-French-Carhart four-factor model). The dependent and independent variables are standardized each quarter, using their respective means and standard deviations. *t*-statistics are in parentheses. The sample period is from 1981 to 2009. ***, **, * denote statistically significance at 1%, 5%, and 10% levels, respectively.

| VARIABLES | $\Delta Alpha_t$ | $\Delta Alpha_t$ |
|---|---|---|
| $IO\_HF_{t-1}$ | -0.047*** | |
| | (-4.44) | |
| $IO\_Non\_HF_{t-1}$ | 0.019 | |
| | (1.36) | |
| $\Delta IO\_HF_{t-1}$ | | -0.053*** |
| | | (-4.80) |
| $\Delta IO\_Non\_HF_{t-1}$ | | -0.019* |
| | | (-1.81) |
| $Ln(Book/Market)_{t-1}$ | 0.199*** | 0.194*** |
| | (13.88) | (14.23) |
| $Ln(Market\ Cap)_{t-1}$ | -0.007 | 0.004 |
| | (-0.39) | (0.19) |
| $Ln(Dividend\ yield)_{t-1}$ | 0.115*** | 0.117*** |
| | (10.87) | (12.12) |
| $Ln(Age)_{t-1}$ | -0.003 | -0.002 |
| | (-0.25) | (-0.12) |
| $Ln(Price)_{t-1}$ | 0.300*** | 0.292*** |
| | (20.34) | (20.28) |
| $SP500\ dummy_{t-1}$ | 0.006 | -0.001 |
| | (0.56) | (-0.06) |
| Constant | -1.237*** | -1.226*** |
| | (-71.24) | (-70.25) |
| R-squared | 0.26 | 0.26 |

## Table 8: Institutional Ownership and Changes in Idiosyncratic Risk

This table presents the estimation results from the Fama-MacBeth cross-sectional regressions of the change in stock's idiosyncratic risk (ΔIdioRisk) on lagged hedge fund ownership ($IO\_HF_{t-1}$) and non-hedge-fund ownership ($IO\_Non\_HF_{t-1}$), as well as lagged changes in hedge fund ownership ($\Delta IO\_HF_{t-1}$) and non-hedge-fund ownership ($\Delta IO\_Non\_HF_{t-1}$). The control variables are lagged stock characteristics including book-to-market ratio, market capitalization, dividend yield, firm age, share price, and a dummy variable indicating S&P 500 index membership. In quarter *t*, the idiosyncratic risk is the Fama-French-Carhart based idiosyncratic return standard deviation and is estimated by using each stock's daily returns in quarter *t*. For a stock to be included in the analysis in quarter *t*, we require its *t*-statistic associated with the lagged *Alpha* equal to and greater than 1.65 in quarter *t-1* (e.g., the stock is under-valued in quarter *t*-1 as judged by the Fama-French-Carhart four-factor model). The dependent and independent variables are standardized each quarter, using their respective means and standard deviations. *t*-statistics are in parentheses. The sample period is from 1981 to 2009. ***, **, * denote statistically significance at 1%, 5%, and 10% levels, respectively.

| VARIABLES | $\Delta IdioRisk_t$ | $\Delta IdioRisk_t$ |
|---|---|---|
| $IO\_HF_{t-1}$ | -0.035*** | |
| | (-3.02) | |
| $IO\_Non\_HF_{t-1}$ | 0.039*** | |
| | (3.53) | |
| $\Delta IO\_HF_{t-1}$ | | -0.045*** |
| | | (-3.32) |
| $\Delta IO\_Non\_HF_{t-1}$ | | 0.021** |
| | | (2.19) |
| $Ln(Book/Market)_{t-1}$ | -0.005 | -0.004 |
| | (-0.39) | (-0.40) |
| $Ln(Market Cap)_{t-1}$ | -0.105*** | -0.093*** |
| | (-6.83) | (-6.19) |
| $Ln(Dividend yield)_{t-1}$ | -0.004 | 0.000 |
| | (-0.33) | (0.03) |
| $Ln(Age)_{t-1}$ | -0.038*** | -0.031** |
| | (-3.27) | (-2.57) |
| $Ln(Price)_{t-1}$ | 0.131*** | 0.134*** |
| | (9.97) | (9.84) |
| SP500 $dummy_{t-1}$ | 0.005 | 0.006 |
| | (0.51) | (0.59) |
| Constant | 0.032* | 0.031* |
| | (1.95) | (1.92) |
| R-squared | 0.10 | 0.11 |

**Table 9: Predicting Stock Returns based on Institutional Ownership**

This table presents the estimation results from the Fama-MacBeth cross-sectional regressions of future stock returns (with holding periods of one, two, three and four quarters) on stock's hedge fund ownership (IO_HF), non-hedge-fund ownership (IO_Non_HF), the change in hedge fund ownership (ΔIO_HF) and the change in non-hedge-fund ownership (ΔIO_Non_HF). The control variables are lagged stock characteristics including book-to-market ratio, market capitalization, dividend yield, firm age, share price, a dummy variable indicating S&P 500 index membership, and lagged quarterly stock returns. The future stock returns are quarterly returns for the next first (t+1) and second (t+2) quarters. The dependent and independent variables are standardized each quarter, using their respective means and standard deviations. *t*-statistics from the Fama-MacBeth regression are in parentheses. The sample period is from 1981 to 2009. ***, **, * denote statistically significance at 1%, 5%, and 10% levels, respectively.

Panel A: Without controls for lagged quarterly stock returns

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| VARIABLES | $Ret_{t+1}$ | $Ret_{t+1}$ | $Ret_{t+2}$ | $Ret_{t+2}$ |
| $IO\_HF_{t-1}$ | 0.002 | | 0.001 | |
| | (0.56) | | (0.28) | |
| $IO\_Non\_HF_{t-1}$ | 0.004 | | 0.008 | |
| | (0.61) | | (1.15) | |
| $\Delta IO\_HF_{t}$ | | 0.009*** | | 0.002 |
| | | (3.31) | | (0.98) |
| $\Delta IO\_Non\_HF_{t}$ | | 0.001 | | 0.004 |
| | | (0.18) | | (1.32) |
| $Ln(Book/Market)_{t-1}$ | 0.017* | 0.019** | 0.024*** | 0.026*** |
| | (1.80) | (2.02) | (2.68) | (2.92) |
| $Ln(Market\ Cap)_{t-1}$ | -0.014* | -0.014 | -0.014* | -0.010 |
| | (-1.70) | (-1.42) | (-1.78) | (-1.12) |
| $Ln(Dividend\ yield)_{t-1}$ | 0.019** | 0.019** | 0.013 | 0.014 |
| | (2.27) | (2.04) | (1.59) | (1.51) |
| $Ln(Age)_{t-1}$ | 0.016*** | 0.016*** | 0.018*** | 0.019*** |
| | (3.09) | (3.02) | (3.51) | (3.69) |
| $Ln(Price)_{t-1}$ | 0.014 | 0.014 | 0.012 | 0.014 |
| | (1.42) | (1.45) | (1.24) | (1.53) |
| $SP500\ dummy_{t-1}$ | 0.001 | 0.001 | 0.002 | 0.001 |
| | (0.15) | (0.17) | (0.40) | (0.34) |
| Constant | 0.001 | 0.001 | 0.002 | 0.002 |
| | (0.37) | (0.48) | (1.20) | (1.43) |
| R-squared | 0.05 | 0.05 | 0.05 | 0.05 |

Table 9 (continued)

Panel B: With controls for lagged quarterly stock returns

| VARIABLES | (1) $Ret_{t+1}$ | (2) $Ret_{t+1}$ | (3) $Ret_{t+2}$ | (4) $Ret_{t+2}$ |
|---|---|---|---|---|
| $IO\_HF_{t-1}$ | -0.001 | | -0.001 | |
| | (-0.41) | | (-0.29) | |
| $IO\_Non\_HF_{t-1}$ | 0.002 | | 0.004 | |
| | (0.33) | | (0.72) | |
| $\Delta IO\_HF_{t}$ | | 0.007*** | | 0.000 |
| | | (2.68) | | (0.02) |
| $\Delta IO\_Non\_HF_{t}$ | | -0.008*** | | -0.002 |
| | | (-3.44) | | (-0.77) |
| $Ret_{t-1}$ | 0.035*** | 0.036*** | 0.034*** | 0.035*** |
| | (4.31) | (4.52) | (4.11) | (4.12) |
| $Ret_{t-2}$ | 0.037*** | 0.036*** | 0.028*** | 0.029*** |
| | (4.33) | (4.31) | (3.64) | (3.61) |
| $Ret_{t-3}$ | 0.026*** | 0.027*** | -0.007 | -0.008 |
| | (4.04) | (4.09) | (-1.20) | (-1.34) |
| $Ret_{t-4}$ | -0.007 | -0.006 | -0.015*** | -0.014*** |
| | (-1.17) | (-1.03) | (-2.88) | (-2.69) |
| $Ln(Book/Market)_{t-1}$ | 0.027*** | 0.028*** | 0.024*** | 0.025*** |
| | (3.33) | (3.55) | (3.10) | (3.31) |
| $Ln(Market\ Cap)_{t-1}$ | -0.015** | -0.016* | -0.018** | -0.016* |
| | (-2.03) | (-1.88) | (-2.44) | (-1.85) |
| $Ln(Dividend\ yield)_{t-1}$ | 0.014* | 0.015* | 0.007 | 0.009 |
| | (1.88) | (1.80) | (1.08) | (1.17) |
| $Ln(Age)_{t-1}$ | 0.013*** | 0.013*** | 0.015*** | 0.015*** |
| | (2.73) | (2.69) | (3.16) | (3.22) |
| $Ln(Price)_{t-1}$ | 0.014 | 0.014 | 0.017* | 0.019** |
| | (1.51) | (1.54) | (1.87) | (2.14) |
| $SP500\ dummy_{t-1}$ | 0.001 | 0.001 | 0.001 | 0.001 |
| | (0.15) | (0.30) | (0.28) | (0.28) |
| Constant | 0.003* | 0.003* | 0.004*** | 0.005*** |
| | (1.76) | (1.84) | (2.68) | (2.97) |
| R-squared | 0.08 | 0.07 | 0.07 | 0.07 |

**Table 10: Robustness based on the GLS method: The relation between institutional ownership and lagged *Alpha* and idiosyncratic volatility**

This table repeats the tests presented in Tables 5, 6, 7 and 8 with stock *Alphas* and idiosyncratic volatility estimated based on the generalized-least-square (GLS) method. We control for zero-return, zero-volume days when estimating Alphas and idiosyncratic volatility.

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| VARIABLES | $IO\_HF_t$ | $IO\_Non\_HF_t$ | $IO\_HF_t$ | $IO\_Non\_HF_t$ | $\Delta IO\_HF_t$ | $\Delta IO\_Non\_HF_t$ | $\Delta IO\_HF_t$ | $\Delta IO\_Non\_HF_t$ |
| $Alpha_{t-1}$ | 0.097*** | -0.018 | | | 0.043** | 0.005 | | |
| | (6.04) | (-1.43) | | | (2.48) | (0.23) | | |
| Idio. $risk_{t-1}$ | | | 0.130*** | -0.005 | | | 0.050** | -0.009 |
| | | | (6.59) | (-0.31) | | | (2.01) | (-0.38) |
| $Ln(Book/Market)_{t-1}$ | 0.041*** | 0.113*** | 0.045*** | 0.116*** | 0.001 | -0.023 | 0.000 | -0.027 |
| | (3.47) | (10.10) | (3.75) | (10.62) | (0.10) | (-1.35) | (0.03) | (-1.62) |
| $Ln(Market\ Cap)_{t-1}$ | 0.187*** | 0.513*** | 0.185*** | 0.515*** | 0.011 | -0.003 | 0.006 | -0.005 |
| | (10.14) | (26.08) | (10.10) | (26.61) | (0.52) | (-0.15) | (0.27) | (-0.25) |
| $Ln(Dividend\ yield)_{t-1}$ | -0.126*** | -0.193*** | -0.123*** | -0.191*** | 0.009 | -0.021* | 0.011 | -0.025* |
| | (-10.43) | (-15.25) | (-9.81) | (-14.98) | (0.73) | (-1.68) | (0.85) | (-1.92) |
| $Ln(Age)_{t-1}$ | -0.063*** | 0.037*** | -0.061*** | 0.037*** | 0.003 | -0.114*** | 0.004 | -0.114*** |
| | (-4.15) | (3.53) | (-4.05) | (3.56) | (0.25) | (-7.48) | (0.27) | (-7.42) |
| $Ln(Price)_{t-1}$ | -0.054*** | 0.111*** | -0.041** | 0.114*** | -0.022 | -0.094*** | -0.020 | -0.101*** |
| | (-3.59) | (6.89) | (-2.55) | (6.80) | (-1.21) | (-4.72) | (-0.94) | (-4.81) |
| SP500 $dummy_{t-1}$ | -0.081*** | -0.047*** | -0.080*** | -0.047*** | -0.004 | 0.006 | -0.004 | 0.006 |
| | (-5.28) | (-3.31) | (-5.27) | (-3.31) | (-0.29) | (0.40) | (-0.27) | (0.41) |
| Constant | -0.119*** | 0.137*** | 0.087*** | 0.105*** | -0.070** | 0.126*** | 0.019 | 0.134*** |
| | (-3.99) | (4.98) | (5.76) | (6.19) | (-2.05) | (3.29) | (1.20) | (8.66) |
| R-squared | 0.15 | 0.39 | 0.15 | 0.39 | 0.08 | 0.11 | 0.08 | 0.11 |

**Table 11: Robustness based on the GLS method: The relation between institutional ownership and changes in *Alpha* and idiosyncratic volatility**

This table repeats the tests presented in Tables 10 and 11 with stock *Alphas* and idiosyncratic volatility estimated based on the generalized-least-square (GLS) method. We control for zero-return, zero-volume days when estimating Alphas and idiosyncratic volatility.

| VARIABLES | (1)<br>$\Delta Alpha_t$ | (2)<br>$\Delta Alpha_t$ | (3)<br>$\Delta IdioRisk_t$ | (4)<br>$\Delta IdioRisk_t$ |
|---|---|---|---|---|
| $IO\_HF_{t-1}$ | -0.045*** | | -0.034*** | |
| | (-4.02) | | (-2.91) | |
| $IO\_Non\_HF_{t-1}$ | 0.025 | | 0.041*** | |
| | (1.64) | | (3.48) | |
| $\Delta IO\_HF_{t-1}$ | | -0.056*** | | -0.050*** |
| | | (-5.30) | | (-4.07) |
| $\Delta IO\_Non\_HF_{t-1}$ | | -0.024** | | 0.023** |
| | | (-2.14) | | (2.13) |
| Ln(Book/Market)$_{t-1}$ | 0.182*** | 0.185*** | -0.001 | -0.003 |
| | (11.17) | (13.06) | (-0.06) | (-0.31) |
| Ln(Market Cap)$_{t-1}$ | 0.009 | 0.028 | -0.111*** | -0.103*** |
| | (0.45) | (1.22) | (-6.54) | (-6.04) |
| Ln(Dividend yield)$_{t-1}$ | 0.115*** | 0.119*** | -0.017 | -0.010 |
| | (11.03) | (11.23) | (-1.44) | (-0.92) |
| Ln(Age)$_{t-1}$ | 0.009 | 0.009 | -0.025* | -0.022 |
| | (0.71) | (0.68) | (-1.80) | (-1.62) |
| Ln(Price)$_{t-1}$ | 0.297*** | 0.286*** | 0.142*** | 0.128*** |
| | (18.52) | (17.84) | (9.86) | (9.41) |
| SP500 dummy$_{t-1}$ | -0.008 | -0.009 | 0.000 | 0.014 |
| | (-0.64) | (-0.67) | (0.01) | (1.24) |
| Constant | -1.254*** | -1.228*** | 0.027 | 0.041** |
| | (-66.97) | (-65.21) | (1.49) | (2.39) |
| R-squared | 0.27 | 0.27 | 0.12 | 0.12 |