The Role of Hedge Funds in the Security Price Formation Process

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Abstract

Using a comprehensive dataset of stock holdings by hedge funds, we empirically examine the role of hedge funds in the price formation process. We find that hedge funds tend to hold stocks plot above the security market plane, i.e., undervalued stocks. The sample of undervalued stocks provides a unique setting in which theory makes straightforward predictions about how arbitrageurs should trade and hold mispriced assets, and how their activities should predict future stock returns. In the cross-section of undervalued stocks, hedge fund ownership and trades are positively related to the degree of mispricing and arbitrage cost. A portfolio of undervalued stocks with high hedge fund ownership generates an out-of-sample risk-adjusted return of 0.48% per month, or 5.76% per year. Hedge fund ownership and trades also precede the dissipation of positive alpha. In contrast, all these patterns are either nonexistent or much weaker for non-hedge fund ownership. The findings are robust to alternative benchmark models and alternative misvaluation measures. Overall, our results suggest that hedge funds exploit and reduce stock mispricing.

Keywords: Hedge funds, stock mispricing, arbitrage cost, 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 the shift is the emergence of hedge funds 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. Similarly, organizational changes due to the agency relationship have engendered the need for statistical performance measures, making the use of metrics such as alpha and the Sharpe ratio ubiquitous. Finally, the broad acceptance of asset pricing models based on factor exposures and security characteristics has led to a common, conceptual framework of relative valuation. In this paper, we examine the extent to which hedge funds, as sophisticated investors, exploit and correct price inefficiency.

There are theoretical justifications why hedge funds may play an active role in identifying and correcting asset mispricing. Friedman (1953) argues that in securities markets where irrational and sophisticated investors coexist, sophisticated investors will trade against irrational ones and quickly eliminate mispricing. Given the prevalence of risk-based asset pricing models in academic research and practice, we should expect speculative entities like hedge funds to engage in relative-value arbitrage by trading securities based on their price deviation from assets of similar risk characteristics. Relative-value arbitrage is at the foundation of neo-classical asset pricing models such as the arbitrage pricing theory (Ross, 1976). Modifications of the theory point out that agency and funding frictions limit the capacity of arbitrageurs to enforce the law of one price (e.g., Shleifer and Vishny, 1992).

Although theory makes clear predictions about how arbitrageurs should engage in holding and trading mispriced assets and the potential impact of their existence in security markets, the empirical literature has thus far tested relatively few theoretical predictions about the behavior of arbitrageurs. In part this is due to the difficulty in identifying speculators as a group. The emergence and growth of hedge funds as specialized institutional vehicles for speculative trading offers an opportunity to empirically revisit some of the fundamental questions raised by neo-classical finance. Hedge funds often self-identify as investors seeking to exploit misvaluation in securities markets, and their ownership of U.S. equities has increased from a tiny fraction in the early 1980s to a peak 10% in 2007. Prior to the recent era, there were few good proxies for identifying traders who might potentially be conducting arbitrage in expectations and who, as a group might represent a significant fraction of the market and hence arguably represent the marginal investor in a given trade.

Recent scholarship (e.g., Brunnermeier and Nagel, 2004; Griffin and Xu, 2009) has recognized the potential of hedge fund holdings data to examine hedge fund behavior. However, practical considerations, including identification of hedge funds and reconciliation to regulatory filings, have made it difficult to comprehensively examine their positions and trades, except in specialized circumstances or on limited datasets. In recent years, however, the barriers to this research have declined. While hedge funds are often described as lightly-regulated opaque investment vehicles, it turns out that, with serious effort, it is possible to gather considerable information about their securities holding and trading activities, albeit with a temporal lag (e.g., Agarwal, Jiang, Tang, and Yang, 2013; Brown and Schwarz, 2013). 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 observe their short-sales positions, a sufficiently large fraction of quarterly long positions for major hedge funds can be studied.

In our paper, we assemble a comprehensive dataset of hedge fund equity holdings from 13F filings over the period of 1981–2012. We examine the evolving role of hedge funds in asset pricing with the data. Our analysis includes information on all the major hedge funds that hold and trade U.S. equities.[1] 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 explore whether hedge fund investment is driven by measures of security mispricing and whether their investment has an effect on subsequent security returns. Our empirical analysis produces three sets of main findings.

First, we test the hypothesis that hedge funds hold and trade stocks that plot above the security market plane dictated by the Fama and French (1993) and Carhart (1997) multi-factor models. Such positive-alpha stocks are underpriced according to the models and thus may represent arbitrage opportunities to investors with beliefs consistent with the models. If hedge funds act as arbitrageurs, we would expect them to hold and trade positive-alpha stocks. We find significant and robust evidence that hedge funds hold and trade stocks with high prior alphas, suggesting that they exploit stock mispricing. We also find that hedge fund holdings and trades are positively related to idiosyncratic volatility. Since idiosyncratic volatility has been suggested as a major arbitrage cost (Pontiff, 1996; Shleifer and Vishny, 1997), our result supports the notion that hedge funds bear arbitrage risk while exploiting mispricing.

We also document remarkable differences between hedge funds and other institutional investors. Although many institutional investors may use the relative-value arbitrage framework for active investing, most have goals other than simply maximizing alpha. For example, long-only equity managers supply positive market exposure 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 are less constrained to deliver factor exposures and more often evaluated on their alpha. In addition, the special management fee plus incentive fee structure allows hedge fund managers to balance between an optimal fund size and the best performance. Finally, other institutions usually manage their clients' money and suffer from the

[1] Edelman, Fung, and Hsieh (2013) highlight the challenges of identifying very large funds which do not report to commercial databases on a voluntary basis. This requires augmenting automated search processes with significant amount of hand-collecting of information.

agency problem while hedge fund managers normally serve as a general partner of their own funds. In line with this, our empirical result reveals no significant relationship between stock mispricing and non-hedge-fund ownership among positive-alpha stocks.

Second, we investigate whether hedge fund holdings and trades of positive-alpha stocks contains information about *future* stock returns—in particular whether their holdings are followed by a correction of deviations from the asset pricing model. Specifically, we follow the subsequent price behavior of positive-alpha stocks with high versus low hedge fund ownership. This is an important difference from extant studies that examine the relationship between hedge fund holdings and future stock returns for the entire sample of CRSP stocks. In such a setting, it would be difficult to tell whether a result of no relationship between hedge fund holdings and future stock returns is because hedge fund holdings are uninformative about future stock returns, or because trades for different reasons (e.g., arbitrage and hedging) are combined in aggregate to conceal the true purpose of the trades. In contrast, trading in undervalued stocks is likely to be started by hedge fund managers who pursue arbitrage strategy and possess superior skill and information. Therefore, undervalued stocks are ideal for studying the information content of hedge fund trades and holdings because the prediction for such stocks is not ambiguous.

We find that both the level and the change in hedge fund ownership within a quarter significantly and positively predict stock returns in the next three months.[2] For example, a portfolio of positive-alpha stocks with high hedge fund holdings would realize a risk-adjusted abnormal return of 0.44% per month (about 5.28% per year, *t*-statistic = 3.09), which significantly outperform another portfolio of positive-alpha stocks with low hedge fund holdings (0.09% per month, *t*-statistic = 0.56). Over our sample period of 32 years, the first portfolio would yield a cumulative return of 220-fold – at least prior to the trading cost. The finding is consistent with the limits to arbitrage theories that predict less-than-immediate convergence and profitability of

[2] We use “undervalued stocks” and “positive-alpha stocks” interchangeably.

arbitrage in expectations (Grossman and Stiglitz, 1976). In contrast, the holdings of other types of institutions do not forecast future stock returns.

Finally, we show that positive-alpha stocks with larger hedge fund holdings and trades in a quarter are more likely to get their mispricing corrected in the next quarter, compared to those with heavy non-hedge-fund ownership. This provides further support for the limited arbitrage theory that, while arbitrage activities help reduce market inefficiency, the price correction process is not instantaneous. Taken together, our findings suggest that hedge funds play a unique and important role in exploiting and reduce stock mispricing, and thus, as predicted by neo-classical models, arbitrageurs enforce efficiency and receive compensation for doing so.

Several prior studies on the trading behavior of hedge funds identify a significant role for hedge funds in price formation. For example, for the first time Brunnermeier and Nagel (2004) use hedge fund holding information from the 13F filings of 53 hedge fund management companies and find that hedge funds made money by chasing returns during the tech bubble period. Their evidence is consistent with hedge funds exacerbating the mispricing of securities. Further, Griffin and Xu (2009) comprehensively examine hedge fund long-equity positions through a sample of 306 hedge fund companies and find that hedge funds are only slightly better than mutual funds at picking stocks. Griffin, Harris, Shu and Topaloglu (2011) provide evidence consistent with hedge funds destabilizing the market during the tech bubble period. Giannetti and Kahraman (2014) show that hedge funds with stronger redemption restrictions trade more aggressively against mispricing. A few papers have documented that hedge fund play an important microstructure role.[3]

Our paper differs from the prior studies and contributes to the literature in several aspects. First, we link hedge fund holdings to stock mispricing (i.e., alpha), and test hypotheses about the

[3] 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 (2014) study short-term price reversals as a measure of market liquidity and conclude that hedge funds in the equity markets function as "immediacy" providers.

role that hedge funds play in enforcing market efficiency. While previous research examines hedge fund stock holdings and infers managerial skill, it is hard to infer the role played by hedge funds without controlling for hedge fund strategies (stocks may be purchased for arbitrage or hedging purpose). In contrast, our sample of undervalued stocks provides a unique setting in which theory makes clear predictions about how hedge funds, as arbitrageurs, should trade and hold mispriced assets that represent arbitrage opportunities. Further, we manually assemble a dataset of hedge fund stock holdings that, to our knowledge, is one of the most comprehensive used in the literature. The dataset enables us to obtain an inclusive view about the activities engaged by hedge funds towards positive-alpha stocks. Finally, we explore the relationship between hedge fund holdings and mispricing correction. Our findings are consistent with the limit-to-arbitrage theories that predict less-than-immediate convergence.

The remaining paper is organized as follows. Section 2 describes data collection of hedge fund holdings and offers summary statistics of our sample stocks. Section 3 reports the empirical results on the relation between hedge fund holdings (as well as trades) and the degree of mispricing and arbitrage cost in the cross section of positive-alpha stocks. Section 4 provides evidence that hedge fund ownership in positive-alpha stocks is informative about future stock returns. Section 5 examines the relation between hedge fund ownership and the subsequent mispricing correction. Finally, Section 6 concludes.

2. Data

Following the pioneer work of Brunnermeier and Nagel (2004) and Griffin and Xu (2009), we compile a dataset of hedge fund equity holdings. Our goal is to collect a comprehensive sample, despite the challenge that all extant databases of hedge funds rely on self-reporting and matching management companies in hedge fund databases and 13F filings is labor extensive. Our final sample of hedge fund holdings includes a universe of 1,517 hedge fund management companies which together manage more than 5,000 funds and spans the period from 1981 through 2012.[4] It covers all the major hedge funds trading in the U.S. equity markets.

2.1. Identifying Hedge Funds

The starting point for identifying all hedge fund firms is to match management company names in various hedge fund databases with those in the Thomson Reuters 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, Morningstar, and Bloomberg 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 and thus we have excluded them from our analysis.

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 the hedge fund databases because reporting to a hedge fund database is

[4] Note that 5,000 funds is a lower bound because fund-level information is only available when a hedge fund company is in one of the six hedge fund databases we used.

voluntary (see Edelman, Fung, and Hsieh, 2013). 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 determine whether they are hedge fund management companies (or sponsors), using a variety of online resources. This procedure yields a sample of 1,933 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 1,933 companies. Specifically, we manually check companies registered as investment advisers. Mutual fund, pension fund, and hedge fund managers are common examples of investment advisers. Among the 1,933 potential hedge fund companies, we find that more than 50% of them registered with the SEC as investment advisers and filed ADV forms. To be qualified as a hedge fund firm, we 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 performance-based fees.

For each of the 1,933 companies, if it filed an ADV form and passed the two criteria, we classify it as a hedge fund management company. 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 includes 1,517 hedge fund management firms whose holdings represent hedge fund ownership. A management company often offers multiple funds, and the 1,517 hedge fund companies in aggregate manage over 5,000 individual hedge funds.

2.2 Other Institutional Investors

After identifying hedge fund companies, we classify all 13F institutions into six categories: (1) banks, (2) insurance companies, (3) investment companies (or mutual funds),[5] (4) independent investment advisors, (5) hedge funds, and (6) 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 companies are based on the type codes available on CDA/Spectrum before 1998.[6] We follow Bushee (2004) to identify banks and insurance companies during the period 1998-2012 and we use mutual fund holdings information from Thomson Reuters S12 data to identify mutual fund management companies. The group of investment advisers in our sample does not include hedge fund companies, but includes small independent advisers, broker-dealers, and major investment banks that were not registered as bank holding companies before 2008. Finally, the category "others" includes university and private endowments, philanthropic foundations, and corporate pension funds. To streamline analysis, we combine all non-hedge fund categories into one group.[7]

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 (2003), and Sias, Starks, and Titman (2006), have documented a dramatic increase in the fraction of shares held by institutions. Our data reveal that the proportional increase in hedge fund ownership exceeds

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[5] According to the 2010 Investment Company Factbook, US investment companies managed $12.2 trillion at year-end 2009. Among different types of investment companies, mutual funds dominate by managing $11.1 trillion, while closed-end funds, ETFS and Unit Investment Trusts together managed $1.1 trillion.
[6] 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 afterwards. For example, 71% of institutional investors are in the group of "Others" in 2009 when using the CDA/Spectrum typecode. Thus, we do not use classification codes from CDA/Spectrum beyond 1998.
[7] We conducted analyses for each non-hedge fund group but did not find significant differences among them.

the increase in other types of ownership over the period, especially during a recent period since 2000. The total institutional ownership of common stocks increased steadily from 11.47% in 1981 to 55.53% in 2012. 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 0.02% of outstanding shares in 1981 to 10.05% at the peak of 2007. In 2007 hedge funds exercised control of 18% of shares held by all institutions, while mutual funds and banks controlled 44% and 15%, respectively.

2.3 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, and 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 at least 30 daily returns during the previous quarter, non-missing market capitalization, and non-negative book value of common equity at the end of the previous quarter. We also delete the last quarter of data for any firm delisted before our sample period ends. As is commonly done with the 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 414,745 firm-quarter observations over the period of 1981 through 2012.

Based on the merged CRSP, COMPUSTAT and 13F institutional holding data (i.e., the full sample), Table 1 reports the stock characteristics at the firm-quarter level for the full sample of stocks reported in 13F filings over the sample 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 ratio, firm size, dividend yield, firm age, price, and the S&P 500 index membership.

The average book-to-market ratio is 0.67 with a median of 0.58 for the full sample, which is slightly higher than the average (median) book-to-market ratio of 0.65 (0.55) for stocks with high hedge fund ownership. Stocks with high hedge fund ownership are smaller firms. The average sizes are $2.3 billion and $870 million for the full sample and for stocks with high hedge fund ownership respectively, though the difference in median size is small. Stocks with high hedge fund ownership have lower dividend yield (0.21% vs. 0.36% per quarter), younger age (157 months vs. 195 months) and lower percentage of the S&P 500 index membership (8% vs. 13%) in comparison to the full sample of stocks in the merged CRSP/COMPUSTAT/13F file.

3. Empirical Results

In this section, we first investigate whether hedge funds hold positive-alpha stocks (i.e., underpriced stocks), and whether the pattern is stronger than that for other institutional investors. Next, we relate hedge fund holdings and trades to the level of stock mispricing and idiosyncratic volatility. Further, we decompose stock returns into alpha and benchmark-matched returns, and investigate the relation of hedge fund ownership to the two components separately. Finally, we conduct a wide array of robustness tests.

3.1 Measuring Stock Mispricing

Mispricing is not directly observable. To have an empirical measure, we use the alpha term from the Fama-French-Carhart four-factor model to determine whether a stock plots above or below the security market plane in each quarter.[8] Our use of alpha to measure mispricing is justified by previous studies (e.g., Brennan and Xia, 2001) that define mispricing as a statistically

[8] For robustness, we also use the alphas from the CAPM and the Fama-French three-factor model, and find that our inference is unchanged. To conserve space, the details of the test results are not reported in the paper but are available upon request.

significant difference between the realized average return on a security and the return predicted by an asset pricing model. The Fama-French-Carhart model has been used extensively in academic research as well as the financial industry for the purpose of stock selection.[9] Using daily stock returns for each quarter, we estimate alpha for each stock in our sample that includes only those stocks identified in 13F filings.

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

where $r_{i,\tau}$ is the excess return on stock i on day τ, $MKT\tau$ is the value-weighted market excess return, and $SMB\tau$, $HML\tau$, and $UMD\tau$ are the returns of the zero-net-investment factor-mimicking portfolios for size, book-to-market equity, and one-year momentum in stock returns.[10] For simplicity, the subscript of quarter t is omitted from the above equation. It is well recognized that some stocks are traded infrequently and may have zero returns and zero volume on some days within the quarter. Scholes and Williams (1977) show that stocks trading infrequently have ordinary-least-squares estimators asymmetrically biased upward for alphas and downward for betas. We address this potential problem in measuring stock alpha in Section 3.6.

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, alpha is the difference between a stock's return and a "fair" compensation for the stock's exposures to the market, size, value and momentum factors. In the context of security analysis and fund management, past deviation from the security market plane may be relevant in determining whether a stock is undervalued. For example, a positive-alpha stock suggests that the stock is an attractive investment no matter the mispricing corrects (in which case a high return will be realized) or continues (in which case the stock is purchased at a "bargain price").

[9] We also consider characteristics-based alpha defined as the difference between a stock's return and the return of a benchmark portfolio with comparable characteristics to the stock (Daniel, Grinblatt, Titman, and Wermers, 1997) and report the results later in the paper.
[10] We are grateful to Kenneth French for making the data on the four factors available for download from his website http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

3.2 Positive Alpha Shares

Here, we examine whether hedge funds, compared to other institutions, tend to hold positive-alpha stocks. An active manager seeking to generate abnormal return may take long positions in undervalued stocks. In our analysis, we test whether this expectation relies in part on positive alphas in the past. Although many variables will go into the hedge fund manager's models such as fundamental ratios, news, industry analysis and so forth, our tests focus on mispricing according to a widely known asset pricing factor model.

In our analysis, a stock is defined as a positive alpha stock in quarter *t* if its alpha in quarter *t* is positive and significant at the 5% level in the one-tail test. Alpha is estimated by using daily stock returns in each quarter. To further examine whether hedge funds hold positive-alpha (and negative-alpha) stocks to a greater extent than non-hedge funds, we run a quarter-by-quarter Fama-MacBeth cross-sectional regression of each stock's hedge fund ownership fraction on two dummy variables indicating significant positive and negative alphas, respectively. The omitted dummy is for stocks that have insignificant alphas. For comparison purposes, we also run this regression for stock ownership by non-hedge funds. The Fama-MacBeth regression has the following specification for the full sample of stocks:

$$IO_{i,t} = a_t + b_t^{POS} D(Positive\ Alpha_{i,t-1}) + b_t^{NEG} D(Negative\ Alpha_{i,t-1}) + c_t' X_{i,t-1} + \varepsilon_{i,t}, \quad (2)$$

where $IO_{i,t}$ is hedge fund holdings (or, non-hedge fund holdings) measured as the fraction of shares held by all hedge funds (or, other types of institutional investors) over total shares outstanding in stock *i* in quarter *t*, $D(Positive\ Alpha_{i,t-1})$ is a dummy variable indicating whether stock *i* has a significantly positive alpha at the 5% level in one-side test from the Fama-French-Carhart model in quarter *t*-1, $D(Negative\ Alpha_{i,t-1})$ is a dummy variable indicating whether stock *i* has a significantly negative alpha 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 the 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 (except for the dummy variables) are standardized each quarter using their respective means and standard deviations, so that the regression coefficients can be compared across different years (see, e.g., Gompers and Metrick (2001) and Griffin and Xu (2009)). Because the ownership variable is measured in percent, we take the natural log for all stock characteristics variables (except for the dummy variables) so that all variables have similar interpretations. For dividend yield (D/P), the logarithmic transformation is Ln (Dividend Yield) = Ln(1+D/P) since not all stocks pay dividends in each quarter. We calculate t-statistics for the Fama-MacBeth regression coefficients based on Newey-West heteroskedasticity and autocorrelation-consistent standard errors.

Table 2 reports the results from the Fama-MacBeth regressions. For hedge fund ownership, the average coefficient on the positive-alpha dummy is positive and significant at the 1% level (t-statistic = 5.07). This indicates that positive-alpha stocks, relative to stocks with insignificant alphas, are associated with higher hedge fund ownership in the next quarter. However, there is no significant relation between a positive alpha and non-hedge fund holdings. Next, we test for the differences in the average coefficients on the positive-alpha dummy variable 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.

Table 2 also shows no significant relationship between negative-alpha stocks and hedge fund ownership. For non-hedge funds, negative-alpha stocks in quarter t-1 are associated with lower institutional ownership (*t*-statistic = –3.04). Hence, compared with hedge funds, other types of institutional investors show a strong tendency to avoid holding negative-alpha stocks. However, we note that it is difficult to draw inference on negative-alpha stocks because the SEC does not require institutional investors to report short positions. Our result may be driven by the fact that hedge funds use short positions to exploit arbitrage opportunities in overpriced stocks. Other institutions (e.g., mutual funds) mainly rely on reducing holdings of overpriced stocks to avoid losses, as their primary objective is not arbitrage and they may be subject to short-sale constraints.

In Table 2 we also examine the relationship between stock characteristics observed in the previous quarter and equity holdings by hedge funds in the current quarter. Comparing the results in models (1) and (2), we find that, relative to non-hedge fund institutions, hedge funds tend to hold smaller stocks; the coefficient on market capitalization is 0.18 for hedge fund ownership and 0.59 for non-hedge fund ownership, and the difference is significant. Relative to non-hedge fund institutions, hedge funds also prefer to hold growth stocks, younger stocks, stocks with lower prices, and those that do not belong to the S&P 500 index. Finally, we note that the regression R-squares are 6.3% and 42.2%, respectively, for hedge fund and non-hedge fund ownership.[11] This suggests greater heterogeneity in hedge fund strategies than in those of other institutions.

As pointed out above, all of the short positions relying on negative expected alphas are missing from our sample. Without information about short sales, a test of whether hedge funds take short positions in stocks with negative alphas is severely attenuated. Therefore, we focus our remaining analysis on positive alpha stocks and long positions of hedge funds and other types of institutional investors. In particular, we compare holdings of positive alpha stocks by hedge funds with that by non-hedge fund institutions. If hedge funds pursue arbitrage-in-expectation strategies that exploit mispricing in security markets with respect to the security market plane, their holdings

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[11] Fung and Hsieh (1997) find that, compared with mutual funds, hedge funds generally exhibit smaller *R*-square in a regression of fund returns on traditional asset class returns, which suggests that hedge funds employ different trading strategies than mutual funds do.

(long positions) of positive alpha stocks should be especially sensitive to stock mispricing in comparison to holdings by other types of institutions (e.g., mutual funds) whose investment objective has a large component of beta.

3.3 Hedge Fund Ownership of Positive Alpha Stocks

We now test whether the fraction of hedge fund ownership of positive alpha stocks is explained in the cross-section by the magnitude of deviations above the security market plane. Table 3 reports the results from a quarter-by-quarter Fama-MacBeth regression of positive-alpha stocks' hedge fund ownership on previous-quarter's alpha. The Fama-MacBeth regression has the following specification:

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

where $IO_{i,t}$ is hedge fund holdings (or, non-hedge fund holdings) measured as the fraction of shares held by all hedge funds (or, other types of institutional investors) over total shares outstanding in stock *i* in quarter *t*, $Alpha_{i,t\text{-}1}$ is the measure of deviation from the security market plane defined by the Fama-French-Carhart model for stock *i* in quarter *t*-1, and $X_{i,t\text{-}1}$ is a vector of stock characteristics for stock *i* in quarter *t*-1. For a stock to be included in the analysis in quarter *t*, we require the *t*-statistic associated with its lagged alpha to be greater than 1.65 in quarter *t*-1.

In Table 3, the estimation result of model (1) shows that the average coefficient on the lagged alpha is positive and significant (with *t*-statistic = 5.55), suggesting that stocks with significant and larger positive deviation from the security market plane 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 stock alpha. Table 3 also examines the relationship between stock characteristics observed in the previous quarter and equity holdings by hedge funds and non-hedge funds in the current quarter. The evidence is very similar to that presented in Table 2 based on the full sample of all stocks. The adjusted *R*-squares are 14% and 40% for the samples of hedge fund and non-hedge fund ownership, respectively.

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

3.4 Idiosyncratic Volatility

The results in the previous section suggest that hedge funds seek inefficiencies, consistent with the activity of arbitrageurs. But, do hedge funds bear arbitrage cost? We now examine the relation between hedge fund ownership and idiosyncratic volatility, a measure of arbitrage cost that has been proposed in the literature.

Idiosyncratic volatility is an arbitrage cost for several reasons. Shleifer and Vishny (1997) argue that idiosyncratic volatility impedes price discovery because it exposes arbitrageurs to funding risk. Pontiff (1996) shows empirically that idiosyncratic volatility prevents mispricing from being eliminated by arbitrage trades. These studies suggest that arbitrageurs need to bear idiosyncratic volatility to exploit efficiencies, and that arbitrage opportunities are likely to be correlated to idiosyncratic risk in expectation. Ang, Hodrick, Xing, and Zhang (2006, 2009) find that stocks with high idiosyncratic volatility have low subsequent returns. Recently, Stambaugh, Yu, and Yuan (2014) find that the relation between idiosyncratic volatility and stock return is negative among overpriced stocks but positive among underpriced stocks, which the authors interpret as evidence that idiosyncratic volatility is arbitrage risk. McLean and Pontiff (2014) study stock return predictability patterns identified by academic research and find that the declines of post-publication return predictability are smaller for stocks with high idiosyncratic risk, which is consistent with the costly arbitrage explanation.

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

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

where $IO_{i,t}$ is hedge fund holdings (or, non-hedge fund holdings) measured as the fraction of shares held by all hedge funds (or, other types of institutional investors) over total shares outstanding in stock i in quarter t, $IdioVol_{i,t\text{-}1}$ is idiosyncratic volatility for stock i in quarter t-1 which is obtained by using residuals from the Fama-French-Carhart four factor model, and $X_{i,t\text{-}1}$ is a vector of stock characteristics defined as before.

Table 4 presents the results. For the set of positive alpha stocks, we find a strong relationship between hedge fund holdings and the lagged idiosyncratic volatility. The coefficient on idiosyncratic volatility is significant at the 1% level (with a t-statistic of 5.30) for hedge fund ownership. The estimated coefficients of book-to-market ratio and market capitalization are positive and significant. For the other control variables, dividend yield, firm age, stock price, and S&P 500 membership, the coefficients are negative and significant.

Regressing non-hedge fund institutional ownership on lagged idiosyncratic volatility and control variables, we find that the coefficient on idiosyncratic volatility is not significant (t-statistic = –0.02). 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 increase in idiosyncratic volatility leads to a 0.12 standard deviation increase in the next-quarter hedge fund ownership among positive alpha stocks, while there is no increase in non-hedge fund ownership.

In sum, for the set of stocks that plot above the security market plane as defined above, there is a significant relationship between the lagged idiosyncratic volatility and hedge fund ownership, but such a relationship is insignificant for non-hedge funds. Our results can be interpreted as an evidence to support the arbitrage cost interpretation of idiosyncratic volatility, that is, hedge funds bear arbitrage cost when exploiting arbitrage opportunities.

3.5 Regressing Hedge Fund Trades on Alpha and Idiosyncratic Volatility

Our analysis so far has focused on the level of hedge fund ownership. In this subsection, we investigate the relationship between hedge fund trades (i.e., changes in hedge fund ownership) and deviations from the security market plane. Following prior research (e.g., Chen, Jegadeesh, and Wermers, 2000; Griffin and Xu, 2009), we use the change in fund ownership of a stock as a measure of fund trades. Specifically, we estimate the Fama-MacBeth regression of quarterly hedge fund trades on alpha from the previous quarter. Table 5 presents the results from the following regression model:

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

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, $Alpha_{i,t\text{-}1}$ is the measure of alpha in quarter t-1, and $X_{i,t\text{-}1}$ is a vector of one-quarter lagged stock characteristics. As before, in each quarter t, the cross-sectional regression uses firm-quarter observations for which the stock has a positive alpha in the previous quarter with a t-statistic 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 = 2.52), but not with the change in non-hedge fund ownership. For hedge funds, a one standard deviation increase in alpha is associated with a 0.05 standard deviation increase in the change of hedge fund ownership. This finding suggests that when stocks plot above the security market plane, 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 (alpha).

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

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

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.

Table 6 reports the results. For positive alpha stocks, the lagged idiosyncratic volatility is positively and significantly associated with the change in hedge fund ownership with a *t*-statistic of 2.30, suggesting that a one standard deviation shock in idiosyncratic volatility is associated with a 0.06 standard deviation increase in the change of hedge fund ownership. By contrast, there is no significant relation between idiosyncratic volatility and the change in non-hedge fund ownership. The test result also suggests that, between hedge funds and non-hedge fund institutions, the difference in the average coefficients of lagged idiosyncratic volatility is significant (*p*-value = 0.03).

Taken together, the results in Tables 5 and 6 reinforce our earlier results that hedge funds exploit arbitrage opportunities by trading undervalued stocks. Hedge fund trades are significantly related to the measure of arbitrage profit as well as arbitrage cost. Overall, the findings suggest that hedge funds bear arbitrage cost when pursuing arbitrage profit.

3.6 Stock Illiquidity

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

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, the extant literature has shown that the aggregate market liquidity is an important state variable 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 the Fama-French-Carhart model, the liquidity risk premium might manifest itself as 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, Pástor-Stambaugh (2003) propose a liquidity measure that captures stock liquidity associated with temporary price fluctuations induced by order flows, which can be interpreted as volume-related price reversals attributable to liquidity effects. This 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 ι, ι+1,……ι+k-1, and is non-zero on day ι+k (k > 1). We drop daily stock returns and observations of the Fama-French risk factors on day ι, ι+1, …… ι+k-1, replace stock return on day ι+k by the average stock return over the interval [ι, ι+k] and replace values of the Fama-French factors on day ι+k by their respective averages during [ι, ι+k]. The intuition is that, in the absence of trading for an illiquid stock, a large return during [ι, ι+k] can be the accumulation of smaller returns that would otherwise be realized on each day. 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 positive alpha stocks used in the previous sections and the sample of positive alpha 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% of them still have positive and significant alphas when we use GLS to address the concern that including zero-return days in the estimation may bias a stock's alpha.

Table 7 presents test results based on the GLS method, and these results correspond to those 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 = 5.76) in the cross-section of positive alpha stocks, while 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 7, we use changes in hedge fund ownership and changes in non-hedge fund ownership as dependent variables. For positive alpha stocks, the Fama-MacBeth regression coefficient on lagged alpha is positive and significant (*t*-statistic = 2.62) 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 2.17 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.

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), by estimating the following regression model and obtain alpha for each stock in each quarter:

$$\begin{aligned} r_{i,\tau} = {} & Alpha + \beta_1 MKT_\tau + \beta_2 SMB_\tau + \beta_3 HML_\tau + \beta_4 UMD_\tau \\ & + \beta_5 MKT_{\tau-1} + \beta_6 SMB_{\tau-1} + \beta_7 HML_{\tau-1} + \beta_8 UMD_{\tau-1} + \varepsilon_\tau . \end{aligned} \tag{7}$$

In unreported tables, we repeat the experiment in Tables 3–6, using alphas from equation (7) and corresponding positive alpha stocks. The results overwhelmingly indicate that our findings reported in Tables 3–6 are robust, even after we take non-synchronous trading into account.

Overall, we find that controlling for zero-return and zero-volume days in estimating alphas or controlling for non-synchronous trading does not alter our conclusion. Therefore, our findings are not driven by zero-return and zero-volume days.

3.7 Contemporaneous Relationship

So far, we have focused on the relationship between one-quarter lagged stock alpha (and lagged idiosyncratic volatility) and hedge fund ownership. Given that hedge funds can trade rapidly and exploit inefficiencies within the same quarter, we now examine the contemporaneous relationship between stock alpha (and idiosyncratic volatility) and hedge fund ownership.

Table 8, Panel A presents consistent evidence that stocks with higher alpha and higher idiosyncratic volatility are associated with higher hedge fund ownership in the same quarter. In contrast, there is no significant relationship between stock alpha (or idiosyncratic volatility) and non-hedge fund ownership.

Panel B of Table 8 reports the results of the contemporaneous relationship between alpha (and idiosyncratic volatility) and the change in hedge fund ownership. The change in institutional ownership for a given stock can be interpreted as institutional trade into that security over the quarter. Among positive alpha stocks, we find a significantly positive relationship between the change in hedge fund ownership and alpha (and idiosyncratic volatility) in the cross-section, which is consistent with the one-quarter lagged result. Interestingly, there is a marginally significant relationship between alpha (but not idiosyncratic volatility) and the change in non-hedge fund ownership, but the magnitude is much smaller than that of hedge funds (0.045 versus 0.16) and the difference between the two coefficients is also statistically significant. This finding is consistent with a notion that, although non-hedge fund institutions trade positive alpha stocks within a quarter when arbitrage opportunity is present, they do not trade as aggressively as hedge fund companies do.

3.8 Are Hedge Fund Holdings Related to Alpha or Benchmark-Matched Return?

To further investigate the relationship between stock return and institutional ownership, we decompose stock return in each quarter into two parts, alpha and benchmark-matched return (i.e., alpha- and beta-component of stock return), for positive-alpha stocks. As before, a stock's alpha is the regression intercept from the Fama-French-Carhart four-factor model using each stock's daily returns. The corresponding benchmark-matched return is computed by subtracting alpha from the stock return in the quarter, reflecting a fair compensation for factor exposures. We perform Fama-MacBeth regressions to evaluate the sensitivity of institutional ownership to both stock alpha and benchmark-matched return, with controls of stock characteristics. We examine both a one-quarter lead-lag relationship and a contemporaneous relationship for hedge funds and non-hedge funds, separately. In expectation, the holdings and trades of more sophisticated investors like hedge funds should be more closely related to alpha rather than benchmark-matched return.

Panel A of Table 9 presents the result of the lead-lag relationship. We find that both hedge fund holdings and trades are significantly and positively associated with lagged stock alpha. For example, the coefficient on lagged stock alpha is 0.08 (*t*-statistic = 4.48) for hedge fund holdings and 0.03 (*t*-statistic = 1.74) for hedge fund trades, which is consistent with the result reported in earlier sections. Meanwhile, the coefficient on benchmark-matched return is insignificant for hedge fund holdings and trades. Interestingly, non-hedge-fund trades exhibit a positive association with lagged benchmark-matched stock return at the 1% level, which provides supporting evidence of momentum trading by non-hedge-fund institutions.

Panel B of the table examines the contemporaneous relationship. Similar to the evidence in Panel A, we find hedge fund holdings and trades significantly positively related to stock alpha but not to benchmark-match return. By contrast, non-hedge fund holdings and trades are unrelated to stock alpha, though the change in non-hedge fund ownership is significantly related to benchmark-matched return.

To summarize, these findings show that hedge funds hold and trade stocks with positive alpha, suggesting that one important source of hedge fund performance is investing in undervalued stocks. In sharp contrast, non-hedge funds trades are significantly related to the beta-component, but not the alpha-component, of stock returns. These results reveal a fundamental difference in managerial skill between hedge funds and non-hedge-fund institutions. The above findings are also consistent with Sharpe (1992) that the performance of conservative institutions like mutual funds can be largely explained by the style effects while managerial skills are scarce.

3.9 Alternative Measures of Stock Misvaluation

In section 3.3, we obtain our main results using alpha from the Fama-French-Carhart four-factor model as a measure of misvaluation. This subsection contains an assessment of the impact of alternative definitions of misvaluation on the results. We first employ an alternative measure of stock misvaluation proposed by Daniel, Grinblatt, Titman, and Wermers (DGTW, 1997). For each stock in each quarter, the DGTW alpha is computed as the return difference between the stock and a portfolio of stocks that have comparable characteristics in size, book-to-market ratio, and past stock returns. One advantage of using the DGTW alpha is that it does not rely on any factor model to estimate alpha. In our analysis, we identify "significant" alphas based on stocks with top 5% largest DGTW alphas.[12]

Table 10 reports the results corresponding to the previous tests based on the Fama-French-Carhart model alpha. Overall, we find that, regardless of examining one-quarter lagged or contemporaneous alpha, the DGTW alpha is significantly and positively associated with hedge fund ownership as well as the change in hedge fund ownership. The DGTW alpha appears to be negatively related to non-hedge fund ownership. At the same time, the tests for hedge funds exhibit a much larger average regression coefficient than those for non-hedge funds.

To further investigate the impact of alternative measures of misvaluation on our results, we consider two additional ways to estimate alpha by using the CAPM and the Fama-French three-

[12] For robustness, we also use stocks with top 10% largest DGTW alphas, and the empirical inference is unchanged.

factor model and find qualitatively similar results. The economic content of these results is that, regardless of the definition of stock undervaluation, lagged alphas and lagged idiosyncratic volatilities are significant in explaining hedge fund holdings and trades for the sample of undervalued stocks. To conserve space, these results are not tabulated but are available from the authors upon request.

In sum, using alternative factor models including the Fama-French-Carhart four-factor model, the CAPM, the Fama-French three-factor model, and an alternative measure of alpha based on the DGTW benchmark, we find strong and robust evidence that hedge fund holdings and trades of positive-alpha stocks are significantly related to the level of the lagged stocks' alpha and idiosyncratic volatilities. However, the pattern is either nonexistent or much weaker among non-hedge funds. In unreported tests, we obtain similar results by breaking the overall sample into three subperiods (the test details are available upon request).

4. Does Hedge Fund Ownership in Positive-Alpha Stocks Predict Stock Returns?

We now turn to another fundamental question: Are hedge fund holdings and trades prospectively informative about future stock returns? Again, we focus on positive-alpha stocks as they represent potentially profitable opportunities. As above, we first examine a one-quarter lead-lag relationship between hedge fund ownership (both level and change) and stock returns, and then look at a contemporaneous relationship.

Specifically, we evaluate the returns to two portfolios of positive-alpha stocks: in each quarter t, we first identify positive-alpha stocks as those with a t-value of alpha greater than 1.65. Then, we sort such stocks into two equal-weighted portfolios based on whether their hedge fund ownership in quarter $t+1$ exceeds the median level in the quarter. Both portfolios are held for the next three months before rebalancing. This way, we obtain a monthly time-series of portfolio returns over the sample period. For comparison purposes, we also constructed two similar portfolios based on non-hedge-fund ownership.

Table 11 reports the performance of these trading strategies. We find that the portfolio of positive-alpha stocks with large hedge fund holdings outperforms its counterpart with low hedge fund holdings. As shown in Panel A of Table 11, the high hedge-fund-holding portfolio has an average return of 1.64% per month, while the average return for the low hedge-fund-holding portfolio is 1.15% per month, resulting a return spread of 5.88% per year. Meanwhile, returns to stocks with high hedge fund holdings tend to be more volatile, consistent with the result in Section 3 that, by holding positive-alpha stocks, hedge funds bear arbitrage risk. Given that hedge fund holdings are associated with high idiosyncratic risk as shown in Section 3, we also examine the information ratio (or, appraisal ratio) that is the ratio of average excess return to idiosyncratic risk. The results about the information ratio as well as the Sharpe ratio suggest that stocks favored by hedge funds have a more attractive risk-return tradeoff. On the other hand, there is little difference in the subsequent performance for stocks with high and low non-hedge-fund holdings (1.42% vs. 1.35% per month).

Panel B of Table 11 reports risk-adjusted performance using the Fama-French-Carhart model. Based on the risk-adjusted performance, stocks with high hedge fund holdings generate significantly larger abnormal return than their counterparts. The portfolio of stocks with high hedge fund holdings shows an alpha of 0.48% per month (t-statistic = 3.82), whereas the portfolio of stocks with low hedge fund holdings only has an insignificant alpha of 0.04% per month. The difference in alphas between the two portfolios is 0.44% per month, or 5.28% per year. Thus, the performance difference between stocks with high hedge fund ownership and those with low hedge fund ownership is both statistically and economically significant.

We also construct and compare portfolios of positive-alpha stocks based on different levels of holdings by non-hedge funds. As shown in Panel B of Table 11, there is no significant difference in subsequent performance between the two groups of stocks. This is in sharp contrast to the result related to hedge fund holdings (reported in Panel A). Our result highlights the importance of separating holdings of hedge funds and other institutional investors when examining the relationship between institutional ownership and stock returns.

Figure 2 illustrates the economic value for the investment strategy of combining positive-alpha stocks and high hedge fund holdings. The figure plots the out-of-sample cumulative returns on the two portfolios of positive-alpha stocks with high and low hedge fund holdings, respectively, for a three-month holding period. For a 32-year period from July 1981 to March 2013, the portfolio of positive-alpha stocks with high hedge fund ownership yields a cumulative return of about 220-fold that translates to a geometric average return (GAR) of 18.4% per year, whereas holding positive-alpha stocks with low hedge fund ownership yields a GAR of 12.7% per year. Over the same period, the equal-weighted stock market index yields a GAR of 11.5% per year. The evidence that positive-alpha stocks generate higher returns than the market index suggests the incremental investment value of focusing on such stocks.

In addition, the portfolio of positive-alpha stocks with high hedge fund holdings has its three worst and best monthly returns realized in October 1987 (–27.38%), August 1998 (–22.94%), October 2008 (–20.76%), December 1999 (20.43%), February 2000 (23.86%), and June 2000 (24.19%), respectively.

Next, we examine the information content of hedge fund trades (i.e., change in their holdings) for positive-alpha stocks. In each quarter *t*, we first identify positive-alpha stocks as those with alpha *t*-value greater than 1.65, and then we sort such stocks into two equal-weighted portfolios based on whether their change in hedge fund ownership in quarter t+1 exceeds the median level in the quarter. The portfolios are held for the next three months before rebalancing.

Table 12 reports the portfolio performance based on the change in hedge fund ownership. In general, positive-alpha stocks with a large increase in hedge fund holdings exhibit better performance than their counterparts according to various measures. For example, the portfolio of positive-alpha stocks with hedge fund trades above the median level shows an alpha of 0.39% per month (*t*-statistic = 3.34), which is significantly higher than the monthly alpha of 0.11% (*t*-statistic = 0.76) for the portfolio of stocks with hedge fund trades below the median. The return spread between the two portfolios is about 3.36% per year, which is both economically and statistically significant. Meanwhile, there is little performance difference between positive-alpha stocks with large and small change in non-hedge-fund ownership. Figure 3 plots the cumulative returns on the two portfolios constructed based on hedge fund trades. As with the case of hedge fund holdings, positive-alpha stocks favored by hedge funds through their trading activities subsequently yield significantly higher returns. Again, both portfolios outperform the market index.

Chen, Jegadeesh, and Wermers (2000) show that mutual fund trades (but not their holdings) have predictive power for the stock returns, whereas Bennett, Sias, and Starks (2003) find that the trades of all institutions do not predict future returns. 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 controlling for past stock returns in the cross-sectional regression, they find that such predictability disappears. Agarwal, Jiang, Tang, and Yang (2013) document that hedge funds' confidential holdings exhibit superior performance up to a confidential period of 12 months. Our study investigates the relationship between stock mispricing and hedge fund ownership, *conditioning* on stocks being mispriced. Our findings shed light on these prior results by showing that the co-incidence of positive deviations from the security market plane and high hedge fund ownership is associated with future positive performance.

Our paper differs from the prior studies in that we focus on positive-alpha stocks that provide an ideal place to identify hedge fund skill. To further demonstrate this, we compare the strategy of investing in positive-alpha stocks with high hedge fund ownership with an alternative strategy of investing in *all* stocks with positive hedge fund ownership. We find that the former strategy has a monthly alpha of 0.48% (*t*-statistic = 3.82) which significantly outperforms the latter strategy with an alpha of 0.08% per month (*t*-statistic = 1.56), and the alpha spread is 0.40% per month (*t*-statistic = 3.02). We also compare the strategy of investing in positive-alpha stocks with high hedge fund trades with an alternative strategy of investing in *all* stocks with positive change in hedge fund ownership. Again, the strategy based on positive-alpha stocks fares much better than the alternative strategy based on all stocks. The former strategy shows an alpha of 0.39% per month (*t*-statistic = 3.34) while the latter one has an alpha of 0.11% per month (*t*-statistic = 2.06), and the spread is 0.28% per month (*t*-statistic = 2.06).[13] In sum, by focusing on positive-alpha stocks that are potentially more profitable but also subject to greater arbitrage risk than other stocks, we find a significant return predictability for stocks with high hedge fund holdings and stocks with larger increase in hedge fund holdings. Our results are consistent with the limit-to-arbitrage theory that predicts profitability of arbitrage and less-than-immediate convergence in expectations (e.g., Grossman and Stiglitz, 1976).

5. Hedge Fund Ownership and the Dissipation of Positive Alpha

In this section, we examine the potential relationship between hedge fund holdings (and trades) and the subsequent dissipation of positive alpha. As explained above, we focus on positive-alpha stocks as institutional investors are not required to disclose short positions. Although in this section we employ the full sample of all stocks to avoid a sample selection problem, we are mainly interested in the case where a stock had a significantly positive alpha in the previous quarter but the alpha is no longer significant in the present quarter. We test if hedge fund holdings and trades are associated with the correction of stock mispricing.

[13] To conserve space, the test details are not tabulated but are available upon request.

Table 13 reports the result from logit regressions in which the dependent variable is a dummy variable that equals 1 if the stock was a positive-alpha share in quarter t-1 but not anymore in quarter t, and 0 otherwise. The independent variables include hedge fund holdings and trades, non-hedge-fund holdings and trades, stock characteristics and time fixed effect. Standard errors are clustered at the stock level (Peterson, 2009).

According to the odds ratio, both hedge fund holdings and trades of the stock in a quarter are significantly positively related to the chances that the stock's positive alpha dissipates in the next quarter. From the model specification including both the level and change in hedge fund ownership, the odds ratio associated with hedge fund holdings is 1.068 (z-score = 3.29), and the odds ratio for hedge fund trades is 1.063 (z-score = 2.24). In contrast, the stock holdings by non-hedge funds exhibit an odds ratio of 0.872 (z-score = –3.38), suggesting that their ownership actually impedes mispricing from being corrected. This finding is consistent with Akbas, Armstrong, Sorescu, and Subrahmanyam (2015) and Kokkonen and Suominen (2015) who find that aggregate flows to hedge funds attenuate stock return anomalies. Further, Akbas, Armstrong, Sorescu, and Subrahmanyam (2015) show the aggregate flows to mutual funds exacerbate mispricing.[14]

Therefore, positive-alpha stocks with large hedge fund holdings and large increase in hedge fund holdings are more likely to revert to the security market plane in the next quarter, compared to those with large non-hedge-fund ownership. Taken together with the results shown in the previous sections, we find evidence supporting the hypothesis that hedge funds have played a salient role in security markets by exploiting and reducing asset mispricing. While hedge funds may not be the only economic agents that seek to exploit mispricing by arbitrage in expectations,

[14] Edelen, Ince, and Kadlec (2014) also find that institutional trades tend to be on the wrong side of mispricing implied by stock return anomalies, that is, institutional investors increase their ownership for overvalued stocks and decrease their ownership for undervalued stocks. However, they do not study hedge funds separately relative to other types of institutional investors.

the existence of holdings data allows us to test hypotheses from neo-classical finance with respect to forces that drive prices towards equilibrium values.

6. Conclusion

In this paper, we use hand-collected data on hedge fund holdings that covers all major hedge fund management companies from 1981 to 2012 to understand the role of hedge funds in the stock price formation process. Our empirical results show that, in the cross-section of stocks, positive deviations from the security market plane based on the Fama-French-Carhart four-factor model are positively related to hedge fund ownership (both level and change), but unrelated to non-hedge fund ownership in the future. This result suggests that hedge funds pursue arbitrage opportunities in the U.S. equity markets by investing in undervalued stocks, and their holdings and trades help eliminate stock misvaluation. Thus, as a group of institutional investors, hedge funds enforce market efficiency, and they play a more active role than other types of institutional investors in restoring the equilibrium prices of securities.

Khandani and Lo (2011) show that the “quant meltdown” of August 2007 was consistent with hedge funds taking long-short positions above and below the security market plane. Our analysis suggests that this hedge fund strategy was not confined to that event, but has been common over an extended period. 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 underpriced securities. Our results suggest that hedge funds play that role in the U.S. equity markets.

We also examine a more general question of whether hedge fund ownership predicts stock returns and find that a significantly positive relation between hedge fund ownership and future stock returns among underpriced stocks. In particular, a portfolio of positive-alpha stocks with high hedge fund ownership generates an out-of-sample return of 5.8% per year on a risk-adjusted basis, significantly higher than the low hedge fund ownership counterpart. While extant studies (e.g., Griffin and Xu, 2009) find limited evidence about the information content of hedge fund ownership for the entire universe of stocks, we show that it is important to identify a setting in which the action taken by hedge funds is not ambiguous. Using the sample of underpriced stocks as a laboratory, we find strong evidence to support the hypothesis that hedge fund holdings and trades are informative about future stock returns.

In summary, the stock holdings data from government filings allow us examine the role of a major class of institutional investors 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 positive-alpha stocks as measured by the standard multi-factor models, and their holdings and trades in these stocks predict future price adjustments towards the security market plane.

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Table 1 Summary Statistics of Stock Characteristics

This table provides summary statistics of characteristics for all stocks reported in 13F filings (Panel A) and for stocks belonging to the top decile of hedge fund ownership (Panel B) in each quarter. The reported statistics 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 over the period from 1981 to 2012.

	Mean	Std. Dev.	25%	Median	75%
Panel A: All Stocks in the Full Sample					
Book/Market	0.67	0.43	0.35	0.58	0.89
Market cap ($bil)	2.34	12.04	0.08	0.26	1.03
Dividend yield (%)	0.36	0.51	0.00	0.00	0.60
Age (month)	194.54	185.86	60.00	141.00	262.00
Price ($)	23.79	24.07	10.69	18.25	30.00
S&P500 dummy	0.13	0.33	0.00	0.00	0.00
Panel B: Stocks Belonging to the Top Decile of Hedge Fund Ownership					
Book/Market	0.65	0.43	0.32	0.55	0.87
Market cap ($bil)	0.87	1.88	0.13	0.32	0.87
Dividend yield (%)	0.21	0.43	0.00	0.00	0.22
Age (month)	156.81	165.85	43.00	102.00	208.00
Price ($)	22.37	21.82	10.50	17.38	28.25
SP500 dummy	0.08	0.27	0.00	0.00	0.00

Table 2 Hedge Fund (Non-Hedge-Fund) Ownership and Stock Mispricing: Full Sample Result

This table reports the results from the Fama-MacBeth cross-sectional regressions of hedge fund ownership and non-hedge-fund ownership in quarter *t* on two dummy variables: *D(Positive alpha)*$_{t-1}$ is a dummy variable indicating whether a stock has a significantly positive alpha at the one-sided 5% level from the Fama-French-Carhart model in quarter *t*-1, and *D(Negative alpha)*$_{t-1}$ is a dummy variable indicating whether a stock has a significantly negative alpha in quarter *t*-1. 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. 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. All the variables (except dummy variables) are standardized each quarter. *t*-statistics calculated using Newey-West standard errors are in parentheses. The full sample is based on merged CRSP, COMPUSTAT and 13F institutional holdings data over the period from 1981 to 2012. ***, **, * denote statistically significance at 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(1) – (2)
	HF_ownership$_t$	Non_HF_ownership$_t$	*p*-value of difference
D(positive alpha)$_{t-1}$	0.062***	-0.003	
	(5.07)	(-0.19)	0.00
D(negative alpha)$_{t-1}$	0.009	-0.038***	
	(0.62)	(-3.04)	0.00
Ln(Book/Market)$_{t-1}$	0.037***	0.092***	
	(10.43)	(11.98)	0.00
Ln(Market Cap)$_{t-1}$	0.176***	0.586***	
	(14.58)	(33.88)	0.00
Ln(Dividend yield)$_{t-1}$	-0.164***	-0.215***	
	(-17.33)	(-19.75)	0.00
Ln(Age)$_{t-1}$	-0.068***	0.084***	
	(-10.17)	(12.93)	0.00
Ln(Price)$_{t-1}$	-0.054***	0.121***	
	(-4.76)	(10.80)	0.00
S&P500 dummy$_{t-1}$	-0.264***	-0.223***	
	(-11.26)	(-4.14)	0.08
Constant	0.035***	0.034***	
	(10.92)	(4.00)	
Adj. *R*-squared	0.063	0.422	

Table 3 Regressions of Hedge Fund (Non-Hedge-Fund) Ownership on Lagged Alpha for Positive-Alpha Stocks

This table reports the results from the Fama-MacBeth cross-sectional regressions of hedge fund ownership and non-hedge-fund ownership on one-quarter lagged stock 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 greater than 1.65 in quarter t-1 (i.e., the stock has a positive alpha in quarter t-1 as judged by the Fama-French-Carhart four-factor model). All the variables (except dummy variables) are standardized each quarter based on the full sample. t-statistics calculated using Newey-West standard errors are in parentheses. The sample period is from 1981 to 2012. ***, **, * denote statistically significance at 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(1) – (2)
	$HF\_ownership_t$	$Non\_HF\_ownership_t$	*p*-value of difference
$Alpha_{t-1}$	0.089***	-0.015	
	(5.55)	(-1.15)	0.00
Ln(Book/Market)$_{t-1}$	0.048***	0.091***	
	(4.55)	(7.52)	0.01
Ln(Market Cap)$_{t-1}$	0.195***	0.544***	
	(11.16)	(26.04)	0.00
Ln(Dividend yield)$_{t-1}$	-0.140***	-0.192***	
	(-10.55)	(-14.11)	0.00
Ln(Age)$_{t-1}$	-0.067***	0.052***	
	(-4.64)	(4.83)	0.00
Ln(Price)$_{t-1}$	-0.055***	0.103***	
	(-3.71)	(6.22)	0.00
S&P500 dummy$_{t-1}$	-0.254***	-0.187***	
	(-5.38)	(-3.92)	0.08
Constant	-0.064**	0.084***	
	(-2.27)	(3.13)	
Adj. R-squared	0.140	0.395	

Table 4 Regressions of Hedge Fund (Non-Hedge-Fund) Ownership on Lagged Idiosyncratic Volatility for Positive-Alpha Stocks

This table presents the results from the Fama-MacBeth cross-sectional regressions of hedge fund ownership and non-hedge-fund ownership on one-quarter lagged idiosyncratic 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. vol_{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 greater than 1.65 in quarter *t*-1 (i.e., the stock has a positive alpha in quarter *t*-1 as judged by the Fama-French-Carhart four-factor model). All the variables (except dummy variables) are standardized each quarter based on the full sample. *t*-statistics calculated using Newey-West standard errors 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)
	$HF\_ownership_t$	$Non\_HF\_ownership_t$	*p*-value of difference
Idio. vol_{t-1}	0.117***	-0.001	
	(5.30)	(-0.02)	0.00
Ln(Book/Market)$_{t-1}$	0.050***	0.094***	
	(4.69)	(7.84)	0.00
Ln(Market Cap)$_{t-1}$	0.196***	0.545***	
	(11.29)	(26.37)	0.00
Ln(Dividend yield)$_{t-1}$	-0.137***	-0.191***	
	(-9.82)	(-13.92)	0.00
Ln(Age)$_{t-1}$	-0.065***	0.052***	
	(-4.56)	(5.05)	0.00
Ln(Price)$_{t-1}$	-0.047***	0.108***	
	(-2.77)	(6.23)	0.00
S&P500 $dummy_{t-1}$	-0.253***	-0.187***	
	(-5.38)	(-3.98)	0.18
Constant	0.126***	0.061***	
	(7.21)	(3.31)	
Adj. *R*-squared	0.142	0.396	

Table 5 Regressions of Changes in Hedge Fund (Non-Hedge-Fund) Ownership on Lagged Alpha for Positive-Alpha Stocks

This table reports the results from the Fama-MacBeth cross-sectional regressions of the change in stock's hedge fund ownership (ΔHF_ownership) and non-hedge-fund ownership (ΔNon_HF_ownership) 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 greater than 1.65 in quarter *t*-1 (i.e., the stock has a positive alpha in quarter *t*-1 as judged by the Fama-French-Carhart four-factor model. All the variables (except dummy variables) are standardized each quarter based on the full sample. *t*-statistics calculated using Newey-West standard errors are in parentheses. The sample period is from 1981 to 2012. ***, **, * denote statistically significance at 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(1) – (2)
	ΔHF_ownership$_t$	ΔNon_HF_ownership$_t$	*p*-value of difference
Alpha$_{t-1}$	0.047**	0.014	
	(2.52)	(0.79)	0.08
Ln(Book/Market)$_{t-1}$	0.002	-0.031*	
	(0.18)	(-1.79)	0.08
Ln(Market Cap)$_{t-1}$	0.009	-0.015	
	(0.50)	(-0.70)	0.32
Ln(Dividend yield)$_{t-1}$	0.004	-0.008	
	(0.36)	(-0.75)	0.46
Ln(Age)$_{t-1}$	0.009	-0.104***	
	(0.84)	(-6.70)	0.00
Ln(Price)$_{t-1}$	-0.011	-0.093***	
	(-0.66)	(-4.71)	0.00
S&P500 dummy$_{t-1}$	-0.010	0.019	
	(-0.25)	(0.40)	0.60
Constant	-0.068*	0.090***	
	(-1.91)	(2.70)	
Adj. *R*-squared	0.069	0.106	

Table 6 Regressions of Changes in Hedge Fund (Non-Hedge-Fund) Ownership on Lagged Idiosyncratic Volatility for Positive-Alpha Stocks

This table provides the results from the Fama-MacBeth cross-sectional regressions of the change in stock's hedge fund ownership (ΔHF_ownership) and non-hedge-fund ownership (ΔNon_HF_ownership) on one-quarter lagged idiosyncratic volatility. 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. vol_{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 greater than 1.65 in quarter *t*-1 (i.e., the stock is has a positive alpha in quarter *t*-1 as judged by the Fama-French-Carhart four-factor model). All the variables (except dummy variables) are standardized each quarter based on the full sample. *t*-statistics calculated using Newey-West standard errors are in parentheses. The sample period is from 1981 to 2012. ***, **, * denote statistically significance at 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(1) – (2)
	ΔHF_ownership$_t$	ΔNon_HF_ownership$_t$	*p*-value of difference
Idio. vol_{t-1}	0.058**	0.002	
	(2.30)	(0.10)	0.03
Ln(Book/Market)$_{t-1}$	0.002	-0.034**	
	(0.17)	(-2.04)	0.06
Ln(Market Cap)$_{t-1}$	0.008	-0.016	
	(0.43)	(-0.74)	0.33
Ln(Dividend yield)$_{t-1}$	0.006	-0.014	
	(0.44)	(-1.23)	0.27
Ln(Age)$_{t-1}$	0.010	-0.103***	
	(0.93)	(-6.56)	0.00
Ln(Price)$_{t-1}$	-0.007	-0.100***	
	(-0.40)	(-4.78)	0.00
S&P500 dummy$_{t-1}$	-0.015	0.018	
	(-0.36)	(0.37)	0.56
Constant	0.029*	0.118***	
	(1.87)	(6.40)	
Adj. *R*-squared	0.071	0.105	

Table 7 Regression Results from Using Alpha and Idiosyncratic Volatility Estimated by the GLS Method

This table reports the results from the Fama-MacBeth cross-sectional regressions of (the change in) hedge fund ownership and non-hedge-fund ownership on one-quarter lagged alpha as well as idiosyncratic risk estimated by the generalized-least-square (GLS) method. The control variables are one-quarter 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, and idio. vol_{t-1} is the idiosyncratic return standard deviation estimated by using each stock's daily returns. For a stock to be included in the analysis in quarter *t*, we require its *t*-statistic associated with the lagged alpha greater than 1.65 in quarter *t* (i.e., the stock has a positive alpha in quarter *t* as judged by the Fama-French-Carhart four-factor model). All the variables except dummy variables are standardized each quarter based on the full sample. *t*-statistics calculated using Newey-West standard errors are in parentheses. The sample period is from 1981 to 2012. ***, **, * denote statistically significance at 1%, 5%, and 10% levels, respectively.

Table 7, continued.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	HF_t	Non_HF_t	HF_t	Non_HF_t	ΔHF_t	ΔNon_HF_t	ΔHF_t	ΔNon_HF_t
$Alpha_{t-1}$	0.089***	-0.022			0.048***	0.011		
	(5.76)	(-1.63)			(2.62)	(0.61)		
Idio. vol_{t-1}			0.119***	-0.006			0.056**	-0.005
			(5.76)	(-0.42)			(2.17)	(-0.26)
$Ln(Book/Market)_{t-1}$	0.042***	0.096***	0.045***	0.100***	-0.001	-0.026	-0.002	-0.030*
	(3.50)	(8.06)	(3.65)	(8.37)	(-0.11)	(-1.51)	(-0.20)	(-1.75)
$Ln(Market\ Cap)_{t-1}$	0.196***	0.532***	0.195***	0.533***	0.012	-0.015	0.007	-0.017
	(10.89)	(25.32)	(10.68)	(25.59)	(0.61)	(-0.63)	(0.36)	(-0.72)
$Ln(Dividend\ yield)_{t-1}$	-0.137***	-0.190***	-0.134***	-0.188***	0.008	-0.015	0.010	-0.020*
	(-9.12)	(-14.03)	(-8.66)	(-13.60)	(0.56)	(-1.36)	(0.71)	(-1.72)
$Ln(Age)_{t-1}$	-0.070***	0.045***	-0.069***	0.045***	0.004	-0.111***	0.004	-0.111***
	(-4.54)	(3.57)	(-4.51)	(3.62)	(0.32)	(-7.44)	(0.29)	(-7.40)
$Ln(Price)_{t-1}$	-0.057***	0.102***	-0.048***	0.106***	-0.020	-0.089***	-0.017	-0.096***
	(-3.72)	(6.15)	(-2.63)	(6.24)	(-1.09)	(-4.90)	(-0.81)	(-5.08)
S&P500 $dummy_{t-1}$	-0.247***	-0.165***	-0.245***	-0.165***	0.000	0.035	0.000	0.035
	(-4.86)	(-3.30)	(-4.85)	(-3.34)	(0.00)	(0.74)	(0.00)	(0.74)
Constant	-0.068**	0.107***	0.121***	0.069***	-0.074**	0.102***	0.024	0.123***
	(-2.46)	(3.83)	(6.87)	(3.86)	(-2.08)	(2.88)	(1.42)	(6.82)
Adj. R-squared	0.152	0.394	0.154	0.395	0.078	0.114	0.080	0.114

Table 8 Regression Results on the Contemporaneous Relations

This table reports the results from the Fama-MacBeth cross-sectional regressions of hedge fund ownership and non-hedge-fund ownership on *contemporaneous* stock alpha as well as idiosyncratic risk. In Panel A, the dependent variable is the level of hedge fund ownership, while in Panel B, the dependent variable is change in hedge fund ownership. The control variables are one-quarter 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. $Alpha_t$ is the intercept from the Fama-French-Carhart four-factor model and is estimated by using each stock's daily returns in quarter *t*. In quarter *t*, idiosyncratic volatility is the idiosyncratic return standard deviation, 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 alpha greater than 1.65 in quarter *t* (i.e., the stock has a positive alpha in quarter *t* as judged by the Fama-French-Carhart four-factor model). All the variables except dummy variables are standardized each quarter based on the full sample. *t*-statistics calculated using Newey-West standard errors are in parentheses. The sample period is from 1981 to 2012. ***, **, * denote statistically significance at 1%, 5%, and 10% levels, respectively.

Panel A: Dependent variable = Level of HF (Non-HF) ownership

	(1)	(2)	(1) – (2)	(3)	(4)	(3) – (4)
	HF_t	Non_HF_t	*p*-value of difference	HF_t	Non_HF_t	*p*-value of difference
$Alpha_t$	0.080***	0.006				
	(4.90)	(0.44)	0.00			
Idio. vol_t				0.109***	0.018	
				(4.99)	(1.12)	0.00
$Ln(Book/Market)_{t-1}$	0.026**	0.079***		0.027**	0.079***	
	(1.99)	(7.73)	0.00	(2.02)	(7.95)	0.00
$Ln(Market\ Cap)_{t-1}$	0.179***	0.515***		0.179***	0.517***	
	(11.30)	(24.08)	0.00	(11.45)	(24.34)	0.00
$Ln(Dividend\ yield)_{t-1}$	-0.140***	-0.195***		-0.135***	-0.193***	
	(-10.92)	(-15.50)	0.00	(-10.09)	(-14.88)	0.00
$Ln(Age)_{t-1}$	-0.063***	0.066***		-0.061***	0.067***	
	(-4.15)	(6.57)	0.00	(-4.07)	(6.84)	0.00
$Ln(Price)_{t-1}$	-0.073***	0.125***		-0.065***	0.127***	
	(-5.09)	(7.89)	0.00	(-4.13)	(7.94)	0.00
S&P500 $dummy_{t-1}$	-0.227***	-0.162***		-0.226***	-0.164***	
	(-5.12)	(-3.49)	0.17	(-5.13)	(-3.56)	0.18
Constant	-0.032	0.108***		0.140***	0.123***	
	(-1.08)	(3.90)		(9.46)	(7.19)	
Adj. R-squared	0.139	0.398		0.143	0.399	

Table 8, continued.

Panel B: Dependent variable = Change in HF (Non-HF) ownership

	(1)	(2)	(1) – (2)	(3)	(4)	(3) – (4)
	ΔHF_t	ΔNon_HF_t	*p*-value of difference	ΔHF_t	ΔNon_HF_t	*p*-value of difference
$Alpha_t$	0.159***	0.045*				
	(6.97)	(1.96)	0.00			
Idio. vol_t				0.194***	0.025	
				(7.10)	(0.89)	0.00
$Ln(Book/Market)_{t-1}$	0.008	-0.064***		0.010	-0.066***	
	(0.71)	(-4.69)	0.00	(0.81)	(-4.87)	0.00
$Ln(Market Cap)_{t-1}$	0.054***	0.047**		0.053***	0.043**	
	(2.72)	(2.20)	0.81	(2.74)	(2.00)	0.73
$Ln(Dividend yield)_{t-1}$	-0.004	-0.047***		-0.001	-0.052***	
	(-0.29)	(-4.01)	0.02	(-0.06)	(-4.28)	0.01
$Ln(Age)_{t-1}$	0.039**	-0.065***		0.039**	-0.065***	
	(2.52)	(-3.88)	0.00	(2.52)	(-3.95)	0.00
$Ln(Price)_{t-1}$	-0.030*	-0.065***		-0.020	-0.075***	
	(-1.81)	(-3.64)	0.14	(-1.15)	(-4.08)	0.03
S&P500 $dummy_{t-1}$	-0.023	-0.026		-0.024	-0.021	
	(-0.51)	(-0.54)	0.97	(-0.52)	(-0.44)	0.97
Constant	-0.191***	0.132***		0.139***	0.221***	
	(-4.71)	(4.03)		(6.04)	(8.41)	
Adj. *R*-squared	0.091	0.112		0.093	0.113	

Table 9 Regressions of Hedge Fund Ownership on Alpha- and Beta-Components of Returns for Positive Alpha Stocks

Panel A reports the results from the Fama-MacBeth cross-sectional regressions of hedge fund ownership (both level and change) and non-hedge-fund ownership on one-quarter lagged alpha and benchmark-matched return. Panel B reports the results from the Fama-MacBeth cross-sectional regressions of hedge fund ownership (both level and change) and non-hedge-fund ownership on contemporaneous alpha and benchmark-matched return. The control variables are lagged values of 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, and the corresponding benchmark-match stock return is calculated by subtracting alpha from the stock return. For a stock to be included in the analysis, we require its *t*-statistic associated with the lagged alpha greater than 1.65 in the quarter (i.e., the stock has a positive alpha as judged by the Fama-French-Carhart four-factor model). All the variables except dummy variables are standardized each quarter based on the full sample. *t*-statistics calculated using Newey-West standard errors are in parentheses. The sample period is from 1981 to 2012. ***, **, * denote statistically significance at 1%, 5%, and 10% levels, respectively.

Table 9, continued.

	Panel A: Results from one-quarter lagged alpha				Panel B: Results from contemporaneous alpha			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	HF_t	Non_HF_t	ΔHF_t	ΔNon_HF_t	HF_t	Non_HF_t	ΔHF_t	ΔNon_HF_t
$Alpha_{t-1}$	0.080***	-0.026*	0.032*	0.008				
	(4.48)	(-1.72)	(1.74)	(0.45)				
$Bench\text{-}matched\text{-}ret_{t-1}$	0.014	0.002	0.006	0.047***				
	(1.25)	(0.29)	(0.48)	(3.84)				
$Alpha_t$					0.080***	-0.003	0.167***	0.017
					(4.77)	(-0.23)	(6.61)	(0.70)
$Bench\text{-}matched\text{-}ret_t$					0.009	0.008	0.012	0.063***
					(0.77)	(0.92)	(0.95)	(3.87)
$Ln(Book/Market)_{t-1}$	0.054***	0.092***	0.000	-0.026	0.033**	0.081***	0.016	-0.060***
	(5.20)	(7.68)	(0.05)	(-1.60)	(2.41)	(7.91)	(1.33)	(-4.09)
$Ln(Market\ Cap)_{t-1}$	0.183***	0.531***	-0.002	-0.026	0.176***	0.503***	0.054***	0.040*
	(10.23)	(24.64)	(-0.12)	(-1.07)	(11.32)	(24.32)	(2.65)	(1.89)
$Ln(Dividend\ yield)_{t-1}$	-0.137***	-0.188***	0.005	-0.012	-0.137***	-0.193***	-0.007	-0.045***
	(-9.88)	(-14.03)	(0.42)	(-1.11)	(-10.53)	(-15.92)	(-0.46)	(-3.84)
$Ln(Age)_{t-1}$	-0.064***	0.053***	0.013	-0.102***	-0.060***	0.068***	0.035**	-0.068***
	(-4.41)	(5.08)	(1.16)	(-6.71)	(-4.06)	(6.69)	(2.31)	(-4.16)
$Ln(Price)_{t-1}$	-0.052***	0.105***	-0.009	-0.085***	-0.074***	0.124***	-0.031*	-0.069***
	(-3.52)	(6.39)	(-0.57)	(-4.30)	(-5.30)	(8.07)	(-1.94)	(-3.81)
$S\&P500\ dummy_{t-1}$	-0.244***	-0.173***	-0.003	0.031	-0.229***	-0.148***	-0.016	-0.027
	(-5.35)	(-3.69)	(-0.07)	(0.66)	(-5.53)	(-3.19)	(-0.35)	(-0.55)
Constant	-0.043	0.099***	-0.051	0.114***	-0.023	0.121***	-0.197***	0.189***
	(-1.42)	(3.55)	(-1.49)	(3.39)	(-0.76)	(4.23)	(-4.67)	(5.40)
Adj. R-squared	0.155	0.407	0.086	0.122	0.156	0.411	0.112	0.133

Table 10 Regression Results from the DGTW Alpha

This table reports the results from the Fama-MacBeth cross-sectional regressions of hedge fund ownership (both level and change) and non-hedge-fund ownership on one-quarter lagged alpha, with stock alpha computed using the Daniel-Grinblatt-Titman-Wermers (DGTW, 1997) measure. For each stock in each quarter, the DGTW alpha is calculated as the return difference between the stock and a portfolio of stocks that have comparable characteristics in size, book-to-market ratio, and past stock returns. The reported results are from the Fama-MacBeth cross-sectional regressions. 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 each quarter, we use stocks with top 5% largest alphas in the test. All the variables except dummy variables are standardized each quarter based on the full sample. *t*-statistics calculated using Newey-West standard errors are in parentheses. The sample period is from 1981 to 2012. ***, **, * denote statistically significance at 1%, 5%, and 10% levels, respectively.

Table 10, continued.

	Panel A: Results from one-quarter lagged DGTW alpha				Panel B: Results from contemporaneous DGTW alpha			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	HF_t	Non_HF_t	ΔHF_t	ΔNon_HF_t	HF_t	Non_HF_t	ΔHF_t	ΔNon_HF_t
$DGTW\_Alpha_{t-1}$	0.032***	-0.043***	0.047***	0.013				
	(2.98)	(-4.50)	(4.00)	(1.54)				
$DGTW\_Alpha_t$					0.037***	-0.038***	0.112***	0.023
					(3.15)	(-4.27)	(5.66)	(1.08)
$Ln(Book/Market)_{t-1}$	0.059***	0.128***	0.029**	-0.025***	0.025*	0.112***	0.029*	-0.096***
	(5.04)	(11.03)	(2.27)	(-2.60)	(1.96)	(11.62)	(1.88)	(-6.29)
$Ln(Market\ Cap)_{t-1}$	0.321***	0.714***	-0.011	-0.041	0.331***	0.706***	0.140***	0.060*
	(10.66)	(35.42)	(-0.51)	(-0.78)	(12.03)	(35.32)	(5.26)	(1.89)
$Ln(Dividend\ yield)_{t-1}$	-0.155***	-0.147***	-0.007	-0.016**	-0.139***	-0.149***	0.034	-0.049***
	(-12.36)	(-9.51)	(-0.44)	(-2.30)	(-9.34)	(-8.74)	(1.62)	(-3.00)
$Ln(Age)_{t-1}$	-0.080***	0.003	-0.018	-0.015	-0.069***	0.010	0.006	-0.056***
	(-5.57)	(0.34)	(-1.38)	(-1.54)	(-5.03)	(1.00)	(0.35)	(-3.42)
$Ln(Price)_{t-1}$	-0.067***	0.104***	-0.000	-0.046***	-0.089***	0.109***	-0.078***	-0.142***
	(-3.55)	(7.49)	(-0.02)	(-3.63)	(-5.86)	(8.35)	(-4.03)	(-7.50)
$S\&P500\ dummy_{t-1}$	-0.424***	-0.291***	-0.062	0.017	-0.367***	-0.274***	-0.084*	-0.029
	(-7.82)	(-4.45)	(-1.28)	(0.50)	(-7.64)	(-4.50)	(-1.73)	(-0.44)
Constant	0.178***	0.234***	-0.044	0.029	0.187***	0.279***	0.010	0.075**
	(6.57)	(9.21)	(-1.40)	(1.08)	(6.54)	(10.62)	(0.24)	(2.13)
Adj. *R*-squared	0.104	0.422	0.058	0.077	0.108	0.424	0.076	0.101

Table 11 Out-of-Sample Performance of Portfolios Sorted by Hedge Fund (Non-Hedge-Fund) Ownership

This table presents the "out-of-sample" performance of two equal-weighted portfolios: the first investing in positive-alpha stocks with lower-than-median hedge fund ownership, and the second investing in positive-alpha stocks with higher-than-median hedge fund ownership. In each quarter *t*, we first identify positive-alpha stocks as those with a *t*-value of their alpha greater than 1.65. Then, we sort such stocks into two equal-weighted portfolios based on their hedge fund ownership in quarter *t*+1. The portfolios are held for the next three months before rebalancing. With the monthly time-series returns from the two portfolios, we calculate various measures of investment performance. For comparison purposes, we construct two similar portfolios based on non-hedge-fund ownership. *t*-statistics calculated using Newey-West standard errors are in parentheses. The monthly return series for the portfolios is from July 1981 to March 2013.

Panel A: Summary statistics of portfolio returns (returns are in percent per month)

	Portfolios based on HF ownership		Portfolios based on Non-HF ownership	
	Low_portfolio	High_portfolio	Low_portfolio	High_portfolio
Mean return	1.15	1.64	1.35	1.42
Median return	1.66	2.09	1.87	1.81
Standard dev.	5.28	6.49	5.58	6.19
Sharpe ratio	0.15	0.19	0.18	0.17
Information ratio	0.36	0.59	0.44	0.49

Panel B: Regression results from the Fama-French-Carhart four-factor model

	Portfolios based on HF ownership			Portfolios based on Non-HF ownership		
	Low_portf.	High_portf.	High-minus-Low	Low_portf.	High_portf.	High-minus-Low
Alpha	0.040	0.479	0.439	0.206	0.297	0.091
	(0.30)	(3.82)	(3.09)	(1.47)	(2.24)	(0.56)
Rm-Rf	0.979	1.120	0.138	0.964	1.130	0.166
	(22.90)	(35.20)	(2.76)	(22.90)	(36.10)	(3.49)
SMB	0.508	0.761	0.252	0.707	0.567	-0.140
	(6.52)	(16.40)	(3.43)	(10.80)	(10.90)	(-2.55)
HML	0.218	-0.065	-0.284	0.164	-0.002	-0.165
	(3.62)	(-1.22)	(-4.74)	(2.73)	(-0.03)	(-2.13)
MOM	0.040	0.103	0.063	0.109	0.034	-0.075
	(0.75)	(2.84)	(1.22)	(1.98)	(0.89)	(-1.33)
Adj. R^2	0.83	0.89	0.30	0.84	0.88	0.13

Table 12 Out-of-Sample Performance of Portfolios Sorted by Change in Hedge Fund (Non-Hedge-Fund) Ownership

This table presents the "out-of-sample" performance of two equal-weighted portfolios: the first investing in positive-alpha stocks with lower-than-median change in hedge fund ownership, and the second investing in positive-alpha stocks with higher-than-median change in hedge fund ownership. In each quarter *t*, we first identify positive-alpha stocks as those with a *t*-value of their alpha greater than 1.65. Then, we sort such stocks into two equal-weighted portfolios based on their change in hedge fund ownership (ΔHF_ownership) in quarter *t*+1. The portfolios are held for the next three months before rebalancing. With the monthly time-series returns from the two portfolios, we calculate various measures of investment performance. For comparison purposes, we construct two similar portfolios based on change in non-hedge-fund ownership. *t*-statistics calculated using Newey-West standard errors are in parentheses. The monthly return series for the portfolios is from July 1981 to March 2013.

Panel A: Summary statistics of portfolio returns (returns are in percent per month)

	Portfolios based on ΔHF_ownership		Portfolios based on ΔNon_HF_ownership	
	Low_portfolio	High_portfolio	Low_portfolio	High_portfolio
Mean return	1.23	1.53	1.34	1.43
Median return	1.58	2.14	1.87	1.82
Standard dev.	5.77	5.90	5.42	6.23
Sharpe ratio	0.15	0.20	0.18	0.17
Information ratio	0.40	0.57	0.45	0.54

Panel B: Regression results from the Fama-French-Carhart four-factor model

	Portfolios based on ΔHF_ownership			Portfolios based on ΔNon_HF_ownership		
	Low_portf.	High_portf.	High-minus-Low	Low_portf.	High_portf.	High-minus-Low
Alpha	0.107	0.387	0.281	0.260	0.244	-0.016
	(0.76)	(3.34)	(2.11)	(2.04)	(2.06)	(-0.14)
Rm-Rf	1.030	1.070	0.036	0.988	1.110	0.119
	(27.40)	(38.30)	(1.06)	(28.70)	(39.80)	(4.19)
SMB	0.643	0.624	-0.019	0.547	0.722	0.175
	(11.40)	(10.90)	(-0.44)	(7.91)	(16.20)	(3.42)
HML	0.112	0.044	-0.0689	0.148	0.008	-0.140
	(1.87)	(0.89)	(-1.30)	(2.72)	(0.14)	(-2.57)
MOM	0.047	0.096	0.049	0.015	0.124	0.109
	(0.90)	(2.77)	(1.11)	(0.36)	(3.32)	(3.55)
Adj. R^2	0.86	0.88	0.01	0.85	0.90	0.23

Table 13 Logit Regression of Alpha Dissipation on Institutional Ownership

This table presents the results from logit regressions of alpha dissipation on the level and change in stock ownership by hedge funds and non-hedge funds. For each stock in each quarter *t*, *D* (*alpha dissipation*)$_t$ is a dummy variable that equals 1 if the stock was a positive-alpha share in quarter *t*-1 but not anymore in quarter *t*, and 0 otherwise. An odds ratio greater (smaller) than 1 indicates the independent variable is positively (negatively) associated with the dependent variable. 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. All the variables except dummy variables are standardized each quarter. Quarter dummies are included in the regression. Standard errors are clustered at the stock level. The sample period is from 1981 to 2012. ***, **, * denote statistically significance at 1%, 5%, and 10% levels, respectively.

Dependent variable = *D(Alpha dissipation)*$_t$						
	(1)		(2)		(3)	
	Odds Ratio	*z*-Score	Odds Ratio	*z*-Score	Odds Ratio	*z*-Score
HF ownership$_{t-1}$	1.060***	2.88			1.068***	3.29
Non-HF ownership$_{t-1}$	0.871***	-3.31			0.872***	-3.38
ΔHF_ownership$_t$			1.057*	1.84	1.063**	2.24
ΔNon_HF_ownership$_t$			1.024	0.63	1.011	0.27
Ln(Book/Market)$_{t-1}$	0.788***	-7.62	0.780***	-7.93	0.788***	-7.62
Ln(Market Cap)$_{t-1}$	1.218***	3.59	1.138**	2.41	1.216***	3.57
Ln(Dividend yield)$_{t-1}$	1.135***	3.50	1.161***	4.34	1.138***	3.57
Ln(Age)$_{t-1}$	1.028	0.78	1.011	0.32	1.029	0.81
Ln(Price)$_{t-1}$	1.061	1.23	1.041	0.83	1.063	1.26
S&P500 dummy$_{t-1}$	0.608***	-4.36	0.618***	-4.24	0.610***	-4.33
Quarter dummies	Yes		Yes		Yes	
Stock-quarter obs.	386,584		386,584		386,584	
Pseudo *R*-squared	0.027		0.026		0.028	

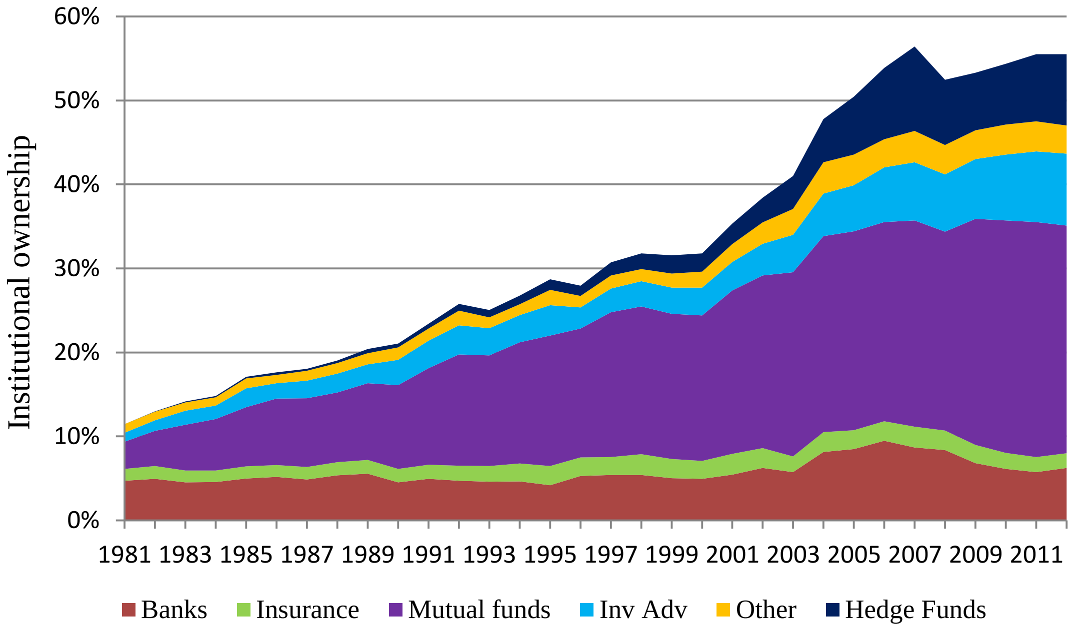

Figure 1: Evolution of stock ownership by institutional investors

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 2012.

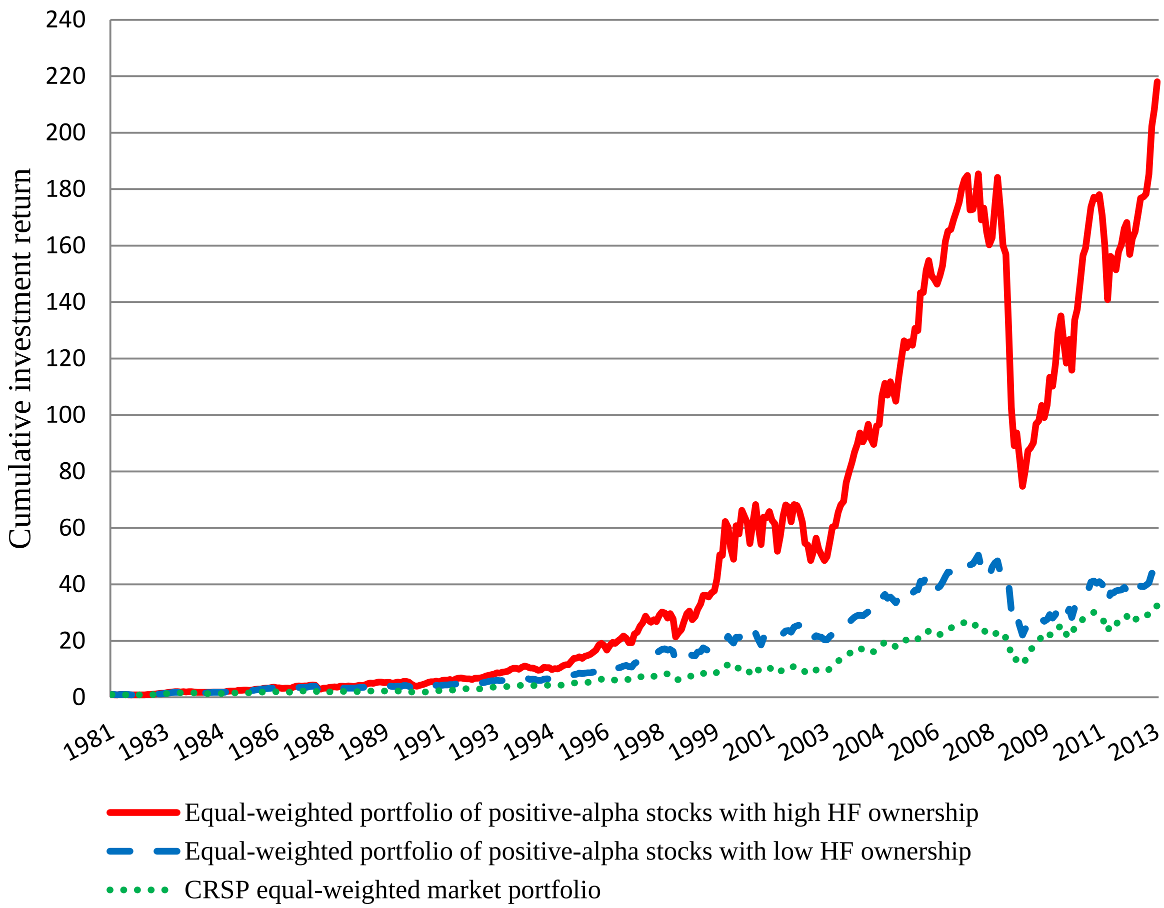

Figure 2: Cumulative returns on equal-weighted portfolios of positive-alpha stocks with high and low hedge fund ownership

This figure plots cumulative monthly returns on two equal-weighted portfolios of positive-alpha stocks with high and low hedge fund ownership, respectively. In each quarter *t* starting from 1981Q1, we identify positive-alpha stocks as those with a *t*-value of their alpha greater than 1.65. Then, we sort such stocks into two equal-weighted portfolios based on their hedge fund ownership in quarter *t*+1. The portfolios are held for the following three months before rebalancing. For comparison, we also plot the cumulative monthly returns on the CRSP equal-weighted portfolio of all stocks. The sample period for the portfolio returns is from July 1981 to March 2013.

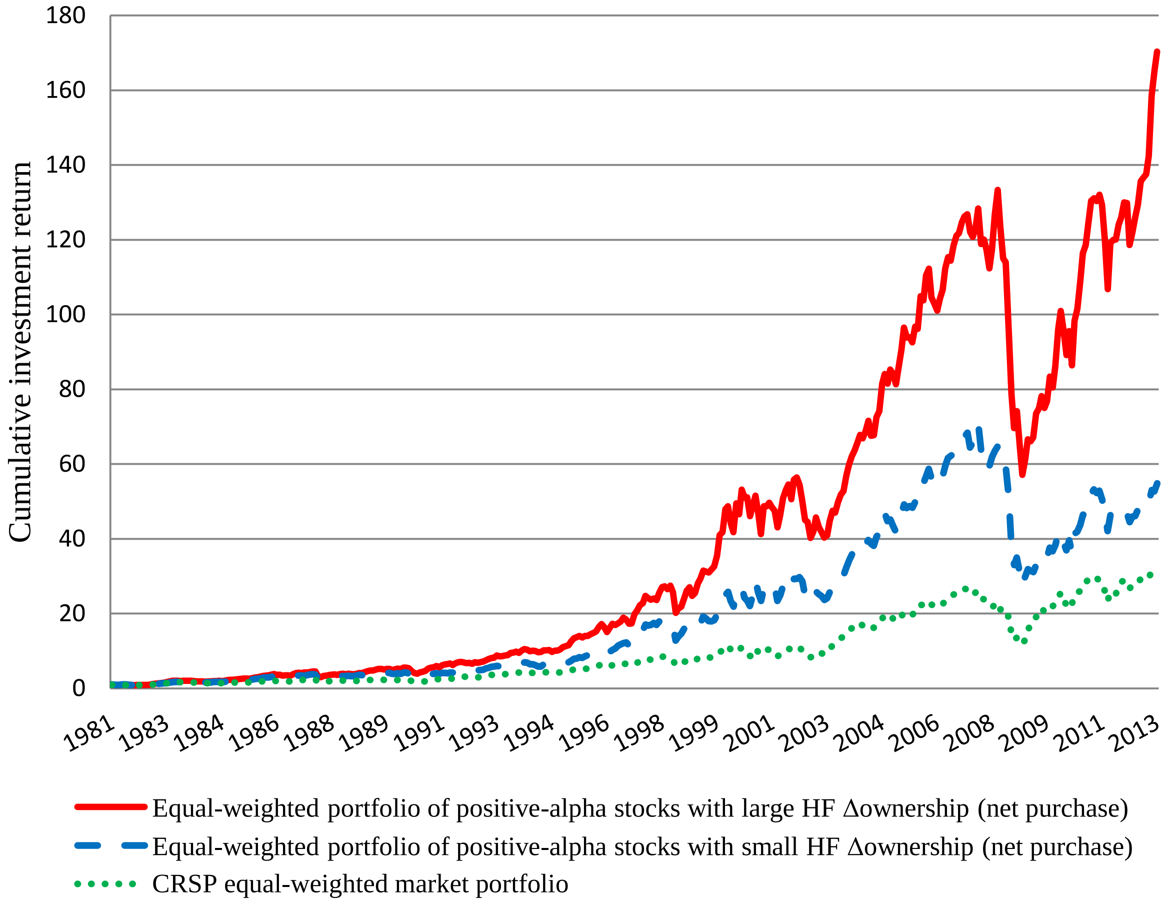

Figure 3: Cumulative returns on equal-weighted portfolios of positive-alpha stocks with large and small change in hedge fund ownership (Δownership)

This figure plots cumulative monthly returns on two equal-weighted portfolios of positive-alpha stocks with large and small change in hedge fund ownership (**Δ**ownership), respectively. In each quarter *t* starting from 1981Q1, we identify positive-alpha stocks as those with a *t*-value of their alpha greater than 1.65. Then, we sort such stocks into two equal-weighted portfolios based on their changes in hedge fund ownership in quarter *t*+1. The portfolios are held for the following three months before rebalancing. For comparison, we also plot the cumulative monthly returns on the CRSP equal-weighted portfolio of all stocks. The sample period for the portfolio returns is from July 1981 to March 2013.