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Institutional Investors: Arbitrageurs or Rational Trend Chasers

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Abstract

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This paper studies the relationship between institutional investor holdings and misvalued stocks over the last three decades in the U.S. equity market. Using multiple proxies of stock mispricings, I find that institutional investors overweight overvalued and underweight undervalued stocks in their portfolio, taking the market portfolio as a benchmark. Cross-sectionally, institutional investors hold more overvalued stocks than undervalued stocks. The time series studies show that institutional ownership of overvalued portfolios increases as the portfolios' overvaluation degree increases. Institutional investor riding stock misvaluation is neither driven by the fund flows from individual investors into institutions, nor industry-specific. Consistent with the agency problem explanation, investment companies and independent investment advisors have a higher tendency to ride stock misvaluation than the other institutions. My findings challenge the models which view individual investors as noise traders and disregard the role of institutional investors in stock market misvaluation.

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Dedication

I dedicate my dissertation work to my family. A special feeling of gratitude to my loving parents, Youying Xiao and Juxin Zeng whose words of encouragement and push for tenacity ring in my ears. My wife Qian Deng and my son Ethan Zeng have never left my side and are very special.

Chapter 1

Introduction

The finance literature assumes that the stock market is composed of two broad types of investors: arbitrageurs and noise traders¹. Noise traders trade for non-information-based reasons and are subject to systematic biases on stocks return expectations. In contrast, arbitrageurs form fully rational expectations and correct stock mispricings caused by noise traders. The existence of noise traders provides subsidy for arbitrageurs to cover their information production cost [38]. In reality, participants in the stock market include individual retail investors and institutional investors. The literature regards behavioral individual investors as noise traders and sophisticated institutional investors as informed arbitrageurs, which leads to a question. Why does stock misvaluation still persist in a stock market which institutional investors dominate in terms of both market share and trading volume? In this paper, I investigate institutional holdings of mispriced stocks in the U.S. equity market to better understand the role of institutions in stock market misvaluation.

Although the efficient market hypothesis precludes the existence of long-term stock misvaluation, the presence of mispriced stocks has been well documented in previous literature. For individual stocks, some famous examples are the mispricing of carve-outs when 3COM spun off its Palm unit in March of 2000; the dual-listed stock price discrepancies for Infosys on March 7, 2000; and price gaps between Royal Dutch and Shell from 1907 to 2005. Other

¹Other names for arbitrageurs are rational speculators and smart money. Noise traders are also known as behavioral traders, liquidity traders, irrational investors and dumb money.

examples of stock market-level misvaluation are the Japanese stock market bubble in the late 1980's, and the Dot-com bubble in the late 1990's and the real estate bubble in 2007. Indeed, there is a long debate on the existence of stock bubbles in previous literature². However a common understanding that stock prices may deviate from intrinsic value at least in the short-run has been reached.

Why do arbitrageurs fail to play their role in driving stock prices back to intrinsic value? Among all the explanations on the failure of arbitrage, three are accepted by most researchers. The first is that both fundamental risk and noise trader risk cause the unpredictability of future returns on mispriced stocks [13, 52, 50]. Secondly, stock misvaluation can only be corrected if arbitrageurs collectively trade against the misvaluation. But the synchronization among arbitrageurs is very difficult in practice [1, 2]. Thirdly, heterogeneous investor opinions and short sale constraints limit the arbitrage so that stock prices only reflect good information [51, 26, 44]. However these theories may not fully explain the persistence of stock misvaluation in the U.S. stock market.

In 1950, 90% of U.S. corporate equities were held by individual investors [3]. Institutions³ might not have sufficient capital to correct stock mispricing promptly. Gradually, the U.S. stock market has become more institutionalized. According to Gompers and Metrick [34], the largest one hundred institutions controlled more than half of the market value of U.S. publicly traded equities in 1996. Ferreira and Matos [30] also report that the institutional stock holdings accounted for 65.7% of the U.S. stock market value in 2005, 59.6% if held domestically. Previous empirical literature shows that institutions are better informed and less likely to be affected by irrationality than individual investors [36, 11, 14]. If institutions trade as arbitrageurs, they should be able to win the battle against noise traders. Recent empirical evidence also documents institutional herding, which raises the doubts about the real synchronization risk for institutions. At last, Battalio and Schultz [12] argue that during

²For example, Cochrane [24] argues that internet stocks are in short of supply during the boom of "Dot-com bubble" because usually a lock-up period after the IPO of tech companies limits the shares of internet firm stocks traded in the stock market. The limited outstanding shares of internet stocks provide convenience yield for investors to trade the floating shares, which explains why internet stock prices are above their fundamental value.

³Throughout the manuscript, I use these three terms "institution", "institutional investor" and "fund manager" interchangeably.

the Dot-com bubble period, investors are able to synthetically short overpriced internet stocks using stock options but they choose not to do so. Short sale constraints may not prevent institutional investors from trading against stock misvaluation because they are the major traders in the derivative market. Despite the growth of institutional holdings in the U.S. stock market, it is uncertain whether or not average institutional investors trade against stock misvaluation.

Based on the above phenomenon, I address three related research questions. At first I examine which stocks are mispriced based on asset pricing models during my sample period 1980-2010. Assuming institutional investors are aware of stock misvaluation, my second question investigates whether institutional investors exploit these misvaluation opportunities. Do they hold fewer overvalued stocks than undervalued stocks? Or do they ride stock misvaluation and adjust their positions of mispriced stocks before the price correction? My third question examines which type of institutions has a higher tendency to ride stock misvaluation than the others?

Using all CRSP stocks over 1980-2010, I identify mispriced stocks using five methods. I assume that stock misvaluation will always disappear through time, due to either exogenous or endogenous reasons. Therefore in the long run, overvalued stocks have negative abnormal returns and undervalued stocks have positive abnormal returns. My first method to detect stock misvaluation is the rolling regression based on factor models. I regress individual stock monthly returns on a five factor model which includes the Fama and French [29] three factors, the Carhart [22] momentum factor and the Pastor and Stambaugh [55] liquidity factor. The regressions are on a five-year window and rolled over my whole sample period. The factor model *alphas* of individual stocks can be taken as a measure of misvaluation at the stock-level. Stocks with significantly negative (positive) *alphas* are overvalued (undervalued) during the five-year windows.⁴

The second method follows Brunnermeier and Nagel [17] and assigns stocks into quintile or decile portfolios each month based on their valuation ratios (Price-to-Sales ratio

⁴The Fama and French [29] three factor model and the Carhart [22] four factor model are tested as well. I also replace five-year rolling windows by three-year rolling windows. My main findings are robust to these specifications.

(P/S) and Price-to-Earnings ratio (P/E)⁵. I calculate equal-weighted and value-weighted monthly returns on these portfolios, and fit the five factor model to monthly portfolio returns. The portfolios composed of the highest (lowest) valuation ratio stocks have significantly negative (positive) *alphas*, suggesting that they are indeed overvalued (undervalued) on average. I also record portfolio five-year rolling *alphas*, which can be taken as the time-series measurement for the degree of misvaluation.

In the third method, I sort all individual stocks into quintile portfolios each month by a dispersion of opinion proxy in the previous month. Then I divide each quintile portfolio further into five groups based on the rank of each stock's short sale constraint proxy in the previous month. Miller [51] shows that stocks with high dispersion of opinions and high short sale constraints are likely to be overvalued, and Boehmer et al. [15] find empirical evidence to support Miller's theory. Consistent with these studies, I found significantly negative (positive) five factor model *alpha* for the portfolio with the highest (lowest) dispersion of opinions and the highest (lowest) short sale constraints.

My first three methods focus on stock returns. They are all based on factor models and historical information of stocks. The next two methods investigate misvaluation at the price-level. In the fourth method, I use a dividend discount model with unobserved bubble terms to estimate the time-series misvaluation for S&P500 Index and high valuation ratio portfolios [For details, see 20, 66]. The unobserved bubble terms are estimated by Kalman filter with a state-space model. The fifth method I use is based on an earnings discount model. Individual stock's fair value at time t is estimated by discounting the stock's next five year quarterly earnings and a terminal value. I assign each stock into Fama-French 49 industries. The terminal value is assumed to be the product of the stock five-year end earnings and the stock's industry average P/E ratio at that time. The discount rate is defined as the industry average stock return over each quarter. If the difference between a stock's market value and the estimated fair value is positive (negative), then this stock is likely to be overvalued (undervalued) at time t .

After identifying mispriced stocks and their degree of misvaluation, I investigate in-

⁵Other widely used valuation ratios *Price/Book* (P/B), *Price/Cash Flow* (P/CF) and *Price/Earnings Before Interest, Taxes, Depreciation, and Amortization* ($P/EBITDA$) are checked in robustness tests.

stitutional holdings of these mispriced stocks. Following the previous literature, I define institutional holding measures using the Thomson Reuters 13F database. Institutional investors do not appear to underweigh (overweigh) overvalued (undervalued) stocks in their portfolios when using the market portfolio as a benchmark. Furthermore, the stocks with lowest decile positive P/E ratios have a higher weight in the market portfolio than in the aggregate institutional portfolio. And institutional investors also dramatically overweigh negative valuation ratio stocks in their portfolios relative to the market portfolio, especially during the Dot-com bubble period, consistent with Brunnermeier and Nagel [17]. Intuitively, the negative valuation ratio stocks are more overvalued than stocks with the highest positive valuation ratio. I find that approximately half of the stocks in Brunnermeier and Nagel [17]’s overvalued portfolio (high quintile P/S stocks) have negative P/E , P/CF or $P/EBITDA$ ratios, indicating that the aggregate institutional investor not only overweighs stocks with high positive valuation ratios but also stocks with negative valuation ratios in the institutional portfolio.

Similar results are also found when I use the five factor model *alpha* as the misvaluation measure. The weights of stocks with significantly negative *alphas* on the aggregate institutional portfolio are very close to their weights on the market portfolio over my whole sample period, suggesting that institutional investors tend to ride stock misvaluation instead of trading against it. Next I compare institutional holdings of overvalued stocks and undervalued stocks cross-sectionally. Using all misvaluation measures, the time-series mean of cross-sectional average of institutional ownership is higher for overvalued stocks than for undervalued stocks. Overall, the tabulated statistics show that institutions do not correct misvaluation since they hold more overvalued stocks than undervalued stocks.

Using the cross-sectional regressions, I show that institutional investors hold more negative *alpha* stocks than positive *alpha* stocks, controlling for other stock characteristics. Consistent with the *alpha* measure, institutional holdings are higher among overvalued stocks than undervalued stocks cross-sectionally when I use the misvaluation measure estimated by the earnings discount model. Additionally, the tendency to invest on overvalued stocks differs across institution types. I find that investment companies and independent investment advisors have a higher tendency to hold overvalued stocks than the other institutions

do.

Time-series tests further show that institutions increase their holdings of the overvalued stocks when the overvaluation continues to grow. The time series relationship between institutional holdings of overpriced portfolios and the overpriced portfolios' rolling *alphas* is negative, indicating that institutional investors ride stock misvaluation instead of trading against it. Similar results are also found when I replace *alpha* with the estimated bubble terms by dividend discount model. For both the S&P500 Index and the top quintile valuation ratio portfolios, institutional holdings are positively correlated with the size of bubbles.

Besides my main results, I also find that institutional investor riding stock misvaluation can not be explained by the inflow of funds from individual investors. Institutions do not have a higher tendency to invest on overvalued stocks during the quarters when fund inflows into institutions are higher. And my results are not driven by the Dot-com bubble period and the real estate bubble period either. I find qualitatively similar results for the sample period 1980-1994. At last, my results are firm-specific, not industry-specific. I find that institutions overinvest on overvalued stocks for 36 out of the 49 Fama-French industries. The rest of the 13 industries are mainly traditional industries such as Mining and Defense. Institutions show no significant preference on overvalued and undervalued stocks for 11 of them.

In summary, this paper challenges previous theories that view individual investors as noise traders and institutional investors as rational arbitrageurs. On average institutional investors ride stock misvaluation until the price correction. We cannot disregard the role of institutional trading on stock misvaluation and use individual investor's irrationality as the only explanation for stock misvaluation. Kelley and Tetlock [48] find evidence that the aggregate individual investor is "wise" and the net retail buying can predict future stock returns in their sample from February 2006 to December 2007. Riding stock misvaluation does not mean that institutional investors lose money. On the contrary, institutional investors may gain more profits when they correctly follow the pulse of stock misvaluation and exit before the price correction.

The remainder of the paper is organized as follows. The next chapter reviews the

related literature. Chapter 3 develops the hypothesis. Chapter 4 describes the data sample and variable definitions. Chapter 5 investigates stock misvaluation and forms overvalued (undervalued) stock portfolios. In Chapter 5, I show whether institutional investors correct stock misvaluation or ride stock misvaluation wave. Chapter 6 includes a robustness check of the results, and Chapter 7 concludes.

Chapter 2

Literature Review

Overtime, institutions have dominated the U.S. stock market in terms of both ownership and trading volume [See, e.g., 3, 34, 36, 30, 47]. Because institutional investors and individual investors differ in their demand for stock characteristics and their trading strategies, the growth of institutional ownership in the stock market helps to explain some recent changes on stock return behavior. For example, Kamara [45] finds that the decrease of Monday seasonality in stock returns is positively related the ratio of institutional to individual trading volume. Gompers and Metrick [34] indicate that upward shifts on institutional demand curve combined with institutional investors' preference on large capitalization stocks can partly explain the disappearance of equity size premium since 1980. Extant literature has also studied the relationship between institutional trading and stock misvaluation, one of the most interesting anomalies in the stock market. However, to the best of my knowledge, this paper is the first attempt to empirically explore the relationship between institutional holdings and stock misvaluation measures estimated by asset pricing models.

This paper is most closely related to Brunnermeier and Nagel [17] who study hedge fund holdings of internet stocks during the Dot-com bubble period and conclude that hedge funds ride the up-trend of the Dot-com bubble and avoid loss by selling internet stocks before the bubble bursts. My paper extends their findings to all U.S publicly traded stocks and all institutional investors over a sample period 1980-2010. Furthermore, I use asset pricing models to identify mispriced stocks and the degree of misvaluation while Brunnermeier and

Nagel [17] use the top quintile Price-to-Sales ratio to classify overpriced stocks. Admittedly, any empirical mispricing test is in fact a joint test of stock misvaluation and the efficacy of the model used for defining stock fundamental value. Both Camerer [18] and Gurkaynak [39] provide excellent surveys on econometric tests of stock bubbles. They conclude that econometric detection of asset price misvaluation cannot be achieved with a satisfactory degree of certainty. Therefore, I identify mispricings using five different metrics on both stock return and price levels, so that my findings are not sensitive to one model mis-specification of stock intrinsic value.

My work is also related to the theoretical literature on the agency problem of delegated portfolio management that may lead to stock misvaluation. Shleifer and Vishny [59] indicate that most of arbitragers in the market are professional investors who manage fund from other wealthy individual investors, banks and endowments. Due to the existence of agency problems, professional investors may forgo some arbitrage opportunities that may incur short-term losses but have long-term positive returns. In their model, the limited effectiveness of professional investors as rational arbitrageurs reduces market efficiency. Among other theoretical works, Allen and Gorton [5] show that due to information asymmetry, fund managers have incentives to churn assets in order to deceive their less informed clients. Furthermore, fund managers may intentionally invest on overpriced stocks even though they may lose clients' money for not exiting before the price correction. Dow and Gorton [27] argue that conflicts of interest between institutional investors and their clients may force fund managers engage in uninformed noise trading, because fund managers have incentives to pretend that they are informed traders. Allen and Gale [4] also stress that investors may use borrowed money to invest on risky assets and bid up asset prices because defaulting is always their last resort. Goldman and Slezak [33] indicate that when it takes longer to reveal fund managers' private information than their tenure, fund managers lose incentive to trade on long-term information. This may cause rational prolonged stock mispricing. Abreu and Brunnermeier [1, 2] argue that the synchronization risk delays rational arbitrage and the competition among institutional investors may force fund managers to invest on overvalued assets with high past returns. The "keeping up with joneses" trading behavior may lead to excess volatility and market fragility. Hong et al. [42] show that because of

future career concerns, even well-intentioned professional investment advisors may overstate their estimates on new technology stock returns as a positive signal so that more advisees will follow them in the future.

Besides the above theoretical models, empirical studies show mixed evidence about the role of institutional investors on stock misvaluation. Lakonishok et al. [49] study 768 tax-exempt (mostly pension) funds and find little evidence that these funds act as positive-feedback traders or follow each other into and out of the same stocks. But Greenwood and Nagel [35] find that mutual fund managers with younger age invest more on technology stocks than their older colleagues. They argue that the growth of inexperienced investor's participation on the stock market could have been a driving factor of Dot-com bubble. Recent studies on institutional momentum trading and herding [See, e.g., 37, 63, 10, 60, 62, 61] also suggest that institutional trading may lead to stock misvaluation. And Grinblatt et al. [37] find that institutions who engage in momentum trading perform better than other institutions, indicating that institutional investors have incentive to ride stock misvaluation wave.

Chapter 3

Hypothesis

Motivated by the growth of institutional ownership in the stock market, previous literature has studied if the role of institutions in improving stock market efficiency. However there is no consensus as to whether institutional investors drive stock prices back to or away from fundamental value. The competing theories and empirical evidence can be categorized into three groups: rational arbitrageur, destabilizing trend chaser, and neutral on average.

3.1 Rational Arbitrageur

According to the traditional view, institutional investors are rational arbitrageurs in the stock market. They explore any stock misvaluation opportunities and drive stock prices closer to intrinsic value. In general, institutional investors have long history of investment experience and are specialized in investing on certain industry stocks. Compared with individual investors, institutions have more resources and are better informed. Furthermore aggregate trading and utilizing the collective financial information lead to economies of scale for institutional investors, which greatly lower their transaction costs. This traditional view predicts that institutions are more likely to sell stocks when they are overvalued and to buy stocks when they are undervalued.

3.2 Destabilizing Trend Chaser

An opposite view on institutional investors is that they destabilize stock prices and push stock prices away from the fundamental value. Institutional investors have much larger holdings than individual investors. If institutions herd, their trading has a much stronger effect on stock prices than individual investors' trading does. However, institutional herding does not necessarily destabilize stock prices unless they ride stock misvaluation. Only if institutional investors ignore stock fundamental value and just mimic each other's trades due to information asymmetry and agency problems, the institutional herding will push stock prices away from the fundamentals. For example: information cascades, fads, and reputational herding.

Besides, previous empirical studies document momentum trading initiated by institutional investors. Following positive feedback trading strategies, institutional investors may chase stock return trend and buy (sell) stocks after their prices rise (fall). Kaniel et al. [47] find evidence that institutions are positive feedback traders on average, while individual investors tend to trade as negative feedback traders and provide liquidity for institutional demand. Furthermore institutional investors often use stop loss orders that may force them to sell stocks after a certain level of losses, regardless of institution's expectation on stock future returns. Before the price correction, institutional investors are better off selling out near the peak or buying near the bottom than just trading against the trend. Even though in the long run institutions drive stock prices back to fundamentals, trend chasing by institutional investors still destabilize stock prices in the short term and intermediate term.

3.3 Neutral on Average

The third view on institutional investors is neutral. Because institutions are heterogeneous, their trades may offset each other. As long as the majority institutional demand and supply cancel each other out, institutional trading does not change stock return characteristics. Therefore, there is no relationship between institutional trading and stock misvalua-

tion.

Based on these three views, I state my main hypothesis as below:

- **Hypothesis (H0):** *Institutional investors are rational arbitrageurs on average. Their aggregate trading drives stock prices back to fundamentals*
- **Hypothesis (H1a):** *Institutional investors are trend chasers on average. They ride stock misvaluation wave instead of trading against it.*
- **Hypothesis (H1a):** *Institutional trading cancels each other out and has no net effect on stock prices.*

Chapter 4

Data and Variable Description

In this chapter, I introduce my data sources and variable definitions.

4.1 Data Sources

My sample is collected from several data sources: (i) The institutional investor stock holdings and institution types are from CDA-Spectrum which arises from institutional investors' 13F filings. (ii) Stock prices, shares outstanding, and dividends are taken from the Center for Research in Security Prices (CRSP) daily and monthly tapes for all NYSE, AMEX, and NASDAQ stocks. (iii) Firms' accounting data are collected from the CRSP/COMPUSTAT Merged Database. Stock short interest and S&P500 constituents are collected from COMPUSTAT monthly file. (iv) Data on financial analysts' earnings forecasts are retrieved from Institutional Brokers Estimate System (I/B/E/S). (v) Data for the Fama-French three factors, the Carhart momentum factor and the Pastor-Stambaugh liquidity factor are from Wharton Research Data Service (WRDS). (vi) The consumer price index (CPI), and S&P500 index price and dividends data are collected from Robert Shiller's website. (vii) Fama and French 49 industry portfolio returns are downloaded from Kenneth R. French's website. Because institutional ownership data in CDA/Spectrum can only be traced from 1980, my main sample period is from 1980 to 2010.

4.2 Variable Definitions

In this subsection, I describe how institutional ownership measurements are constructed. Following previous literature on institutional investors, I define the institutional holding measure at the end of quarter t and their herding measures over quarter t .

Measurement 1:

$$IO_{i,t} = \sum_{j=1}^N \frac{\text{Shares}_{j,i,t}}{\text{Shares Outstanding}_{i,t}}$$

Following Gompers and Metrick [34], I define my main institutional holding measurement $IO_{i,t}$ as a percentage level of institutional ownership of stock i at the end of quarter t . N is the number of institutional investors who hold stock i at the end of quarter t . $\text{Shares}_{j,i,t}$ is the number of stock i shares held by institution j at the end of quarter t . And $\text{Shares Outstanding}_{i,t}$ is the total shares outstanding of stock i at the end of quarter t . If stock i in CRSP is not held by any institution at the end of quarter t , then $IO_{i,t}$ is set to be zero.¹ $IO_{i,t}$ is a cumulative institutional holding measure which is determined by the aggregate institutional trading before the end of quarter t . Cross-sectionally, the variation of $IO_{i,t}$ indicates institution's preference for stocks with different characteristics. The time series of $IO_{i,t}$ reveals the change of institutional holdings of stock i with respect to the changes of stock i 's characteristics.²

Measurement 2:

$$HM_{i,t} = |p_{i,t} - E[p_{i,t}]| - E[|p_{i,t} - E[p_{i,t}]|]$$

$$BHM_{i,t} = HM_{i,t} | p_{i,t} > E[p_{i,t}]$$

$$SHM_{i,t} = HM_{i,t} | p_{i,t} < E[p_{i,t}]$$

¹Because holdings that are less than \$200,000 or 10,000 shares will not be reported. There is a small downward bias to $IO_{i,t}$ measurement, especially for small stocks. And we would expect a weak positive relationship between IO and size due to this bias alone.

²In the untabulated tests, other institutional trading measures such as the net dollar amount of institutional purchase divided by total dollar amount of institutional trading for stock i over quarter t Lakonishok et al. [49]; standardized shares purchased by institutions Sias [60]; the change in the number of institutions holding stock i over quarter t Jiang [43] are studied. Qualitatively similar results are generated.

$$p_{i,t} = \frac{\text{Number of Institutions Buying}_{i,t}}{\text{Number of Institutions Buying}_{i,t} + \text{Number of Institutions Selling}_{i,t}}$$

Lakonishok et al. [49] and Wermers [63] use $HM_{i,t}$ to investigate institutional investor herding. This measure captures whether a disproportionate number of institutions are buying or selling stock i over quarter t . $p_{i,t}$ is defined as the proportion of active traders on stock i who are buyers. $E[p_{i,t}]$ is the expected proportion of institution buying stock i over quarter t relative to the total number of active institutions. It is estimated as the ratio of number to institutional purchases to the total number of institutional active trades at time t . $E[|p_{i,t} - E[p_{i,t}]|]$ is an adjustment factor which allows for random variation around the expected proportion of buyers under the null hypothesis of independent trading decisions by institutions.³ $HM_{i,t}$ captures the tendency of a given subgroup of institutions to trade stock i over quarter t together and in the same direction, which is more frequent than would be expected by trading randomly and independently.

Based on $HM_{i,t}$, I define two conditional institution trading measures: $BHM_{i,t}$ and $SHM_{i,t}$ [63, 37]. $BHM_{i,t}$ ($SHM_{i,t}$) is the conditional buy-herding (sell-herding) measurement for stock i at the end of quarter t .⁴ These two conditional measures separate institution herding into stocks and out of stocks. That is, a large $BHM_{i,t}$ ($SHM_{i,t}$) suggests that the number of net buyers (sellers) of stock i over quarter t are greater than the expected average.

³Subtracting this adjustment factor addresses the concern that stocks that are not actively traded lead to a positive difference between $p_{i,t}$ and $E[p_{i,t}]$ even if each institution trades independently. The adjustment factor decreases with the number of institutions trading in the stock. It is easy to calculate the adjustment factor numerically given that the number of institution buying follows a Binomial distribution with probability $E[p_{i,t}]$ of success and the total number of active institutions. Please find the detail information about this measure in Lakonishok et al. [49] and Wermers [63].

⁴The adjustment factors in $BHM_{i,t}$ and $SHM_{i,t}$ are recalculated conditional on $p_{i,t} > E[p_{i,t}]$ or $p_{i,t} < E[p_{i,t}]$. That is, I separate all stock-quarters into buy-herding sub-sample or sell-herding sub-sample, then calculate $BHM_{i,t}$ and $SHM_{i,t}$ separately in two sub-samples.

Chapter 5

Results

5.1 The Growth of Institutional Holdings

Previous literature on institutional investors documents that the institutional ownership of stock market increases gradually and has a time trend. Figure 1 displays the time-series plots of institutional holdings and the number of institutions at the end of every year from 1980 to 2010. Figure 1.1 presents the institutional holding scope relative to the total stock market value. Following Gompers and Metrick [34], the percentages of market value held by all institutions, the 100 largest institutions, the 10 largest institutions, and the largest institution covered in 13F database at the end of each year are presented. Institutional holdings increased steadily over the past 30 years and the growth in the largest institutions accounted for most of the total institutional holding growth. In December 1980, the largest 100 institutions owned slightly above 20% of the stock market. While in December 2005, the market share of top 100 institutional holdings exceeded 50% of the total stock market value. Figure 1.2 plots institutional holdings by institution types: Bank, Insurance Company, Investment Company (mutual fund), Independent Investment Advisor (including hedge fund) and All Others(endowment, pension, and foundation). Because institution type codes are not accurate after 1998 in 13F database, the time span of Figure 1.2 is only from 1980 to 1997. Over this particular period, investment companies and independent investment advisors remarkably increased their holdings relative to the other three types of

institutions. Figure 1.3 tracks the number of institutions in my sample. The total number of institutions quintupled over the last 30 years and approached to 3,000 recently.

Table F.1 reports the summary statistics for institutional holdings and stocks covered in my sample. Panel A of Table F.1 shows that the total stock market value grew more than 1,000 percent from 1980 to 2010. During the same time period, the dollar amount of institutional holdings grew approximately 2,000 percent from \$460 billion to \$10,058 billion. As a result, institutional holdings accounted for almost 70% of total stock market value in December 2010, nearly doubled from 35% in December 1980. After 1995 institutions controlled more than half of the stock market, and in recent years they eventually became the dominating participants in the stock market. Panel B of Table F.1 reports average number of institutions and stocks covered in my sample. On average, my sample contains 4,604 stocks and 1,426 institutions each quarter. And the time-series mean of cross-sectional average of institutional holdings indicates that a representative institution holds 219 stocks in a portfolio with \$2.5 billion market value. Panel C of Table F.1 reports the summary statistics for the number of institutional owners per stock at the end of each year. All the stocks included in Panel C have at least one institutional owner. The average number of institutional owners for one stock has increased from 27 in December 1980 to 156 in December 2010.

Overall, institutional investors as a group dominate the U.S stock market. The largest institutions exercise discretionary control of most institutional holdings. Thus sophisticated institutional investors have the market power to correct stock misvaluation collectively. Furthermore, the synchronization among institutions should become easier if the institutional holdings are concentrating on the top 100 institutions.

5.2 Five Measures of Stock Misvaluation

According to the efficient market theory, stock prices are informationally efficient. So no investor can consistently achieve risk adjusted returns above the average market returns, given all information available at the time the investment is made. Grossman and Stiglitz [38] recognized that if the stock market is extremely efficient, then investors would lose

incentive to collect and analyze information. They argue that stock market frictions, such as transaction costs and asymmetric information, limit the stock market efficiency. Recent research on stock overvaluation also indicates that the aggregate effect of differences of opinions and short sale constraints may lead to stock overvaluation. This paper focuses on the question of whether institutional investors correct or ride stock misvaluation. So the first step is to identify stock candidates that are most likely to be overvalued or undervalued during my sample period. Admittedly, stock fundamental value is never observed to investors and any test of misvaluation suffers from the joint hypothesis problem that either the asset pricing model is incorrect or the stock is mispriced. Therefore, five generalized metrics extensively used in the previous literature for identifying mispriced stocks are applied in this study.

5.2.1 Factor Asset Pricing Models

The first method is to fit individual stock monthly returns to factor asset pricing models directly. Stocks with significantly negative *alphas* are undervalued and stocks with significantly positive *alphas* are overvalued. I use the five factor model which arguments the Carhart [22] four factor model by the Pastor and Stambaugh [55] liquidity factor in my main analysis, and the Carhart [22] four factor model as a supplementary test¹.

$$R_{p,t} - R_{f,t} = \alpha_p + \beta_p(R_{m,t} - R_{f,t}) + s_pSMB_t + h_pHML_t + u_pUMD_t + l_pL_t + \epsilon_{p,t} \quad (5.1)$$

$$R_{p,t} - R_{f,t} = \alpha_p + \beta_p(R_{m,t} - R_{f,t}) + s_pSMB_t + h_pHML_t + u_pUMD_t + \epsilon_{p,t} \quad (5.2)$$

Both five-year and three-year rolling windows are checked over the sample period from January 1980 to December 2010. I record individual stocks with significant non-zero *alphas* and take them as mispriced stocks. The significance level I choose is 10% at each tail.

Table F.2 reports the summary statistics of the number of non-zero *alpha* stocks. Panel A shows that on average there are 106 stocks with significantly negative *alpha* and 220 stocks with significantly positive *alpha* if monthly stock returns are fitted to the five factor model

¹In an untabulated test, monthly stock returns are fitted to the Fama and French [29] three factor model and slightly more significant non-zero *alpha* stocks can be found.

with a five-year rolling window. Panel B shows that on average there are 104 stocks with significantly negative α and 217 stocks with significantly positive α at each month end if monthly stock returns are fitted to the Carhart four factor model with a five-year rolling window. And Panel C shows that on average there are 169 stocks with significantly negative α and 474 stocks with significantly positive α if monthly stock returns are fitted to the five factor model with a three-year rolling window.

5.2.2 Valuation Ratios

Brunnermeier and Nagel [17] and Greenwood and Nagel [35] use Price-to-Sales (P/S) ratio to identify overvalued internet stocks during the Dot-com bubble period. They find that this measure captures technology industry stocks which are extremely overvalued. In the second method, I choose Price-to-Sales ratio (P/S) and Price-to-Earnings ratio (P/E) as the main valuation ratio identifier. And three other widely used valuation ratios are applied as robustness checks: Price-to-Book ratio (P/B); Price-to-Cash Flow ratio (P/CF); and Price-to-Earnings Before Interest, Taxes, Depreciation and Amortization ($P/EBITDA$). Each month, all stocks are sorted into quintile or decile portfolios based on the level of previous month end valuation ratios. Stocks in the top (bottom) quintile or decile portfolios have the highest (lowest) valuation ratios and are most likely to be overvalued (undervalued). Both the equally-weighted (EW) and value-weighted (VW) monthly returns for these portfolios are calculated. Then I estimate the five-factor model α s for these portfolios.²

Table F.3 presents the regression results. The intercept term α_p represents the abnormal returns estimated by the five factor model, which is a long-term average misvaluation measure. The first row of Panel A shows that for all the valuation ratios, the five factor model α s are all significantly negative for top quintile portfolios, indicating that stocks with the highest valuation ratios are indeed overvalued. The second row of Panel A shows that for P/S and P/B ratios, the five factor model α s are significantly positive

²There is a general agreement by most researchers that internet stocks in the Dot-com bubble period are overvalued. So it is reasonable for Brunnermeier and Nagel [17] to use high P/S ratio to identify overpriced stocks during this period. However, whether the high P/S ratio stocks over my sample period is overvalued remains uncertain. The factor model α is a more rigorous misvaluation measurement than the valuation ratios. In untabulated tests, I find the similar results using the Carhart [22] four-factor model and the Fama and French [29] three factor model.

for bottom quintile portfolios, suggesting that stocks with the lowest P/S or P/B ratios are indeed undervalued. However, *alphas* for bottom quintile portfolios sorted by P/E , P/CF , $P/EBITDA$ ratios are significantly negative. These results are driven by the fact that firms with negative earnings or cash flows are included in the bottom quintile portfolio. Stocks with negative valuation ratios should be taken as the most overvalued. Therefore it is not surprising that significantly negative *alphas* are found for these three bottom quintile portfolios.

I use two methods to mitigate the negative valuation ratio issue. The first one is to exclude the observations with negative valuation ratios from the sample. The third and fourth rows of Panel A report the *alphas* of Quintile 5 and Quintile 1 portfolios formed by sorting stocks with only positive valuation ratios. The alternative method is to adjust the negative valuation ratios so that stocks with negative valuation ratios are assigned into top valuation ratio portfolios.³ The fifth and sixth rows of Panel A report the *alphas* of Quintile 5 and Quintile 1 portfolios formed by sorting stocks according to their adjusted valuation ratios. After using these two mitigation methods to sort stocks, Quintile 5 (1) portfolios have significantly negative (positive) *alphas*, suggesting that stocks in Quintile 5 (1) portfolio are overvalued (undervalued). Panel B and Panel C of Table F.3 show the *alphas* of ten decile portfolios formed by sorting positive valuation ratios and adjusted valuation ratios. The results indicate a clear pattern that estimated five factor model *alphas* decrease almost monotonically from significantly positive in Decile 1 portfolios to significantly negative in Decile 10 portfolios.

5.2.3 Misvaluation Driven by Differences of Opinions and Short Sale Constraints

Miller [51] shows that heterogenous expectations across investors may lead to stock overvaluation if short sale constraints on overvalued stocks prevent investors with negative information from getting access to the stock market. Motivated by Miller’s theory, both theoretical [See, e.g., 23, 57] and empirical studies [See, e.g., 26, 50, 54, 15] conclude

³I use the following transformation to mitigate the negative valuation ratio issue. If an observation has negative $P/E_{i,t}$, I replace this negative $P/E_{i,t}$ with $Max_i\{P/E_{i,t}\}$ minus $P/E_{i,t}$.

that differences of investor opinions and short sale constraints together can cause stock overvaluation or bubbles. Therefore, my third method to identify overvalued stocks is a two-dimensional criterion which includes one proxy variable for differences of opinions and one proxy variable for short sale constraints.

The ideal measure of stock short sale constraints is stock short sale rebate rate which is not available in public database so far [44, 15]. However Boehmer et al. [15] document a positive relationship between short sale rebate fee and short interest (SI) for the same stocks.⁴ So I use SI as the proxy variable for short sale constraints in my main analysis. The arguably best proxy for differences of investor opinions is the standard deviation of I/B/E/S analyst earnings forecast [26]. But this proxy is only available for stocks covered by at least 2 analysts, which may cause sample bias against small firm stocks with little analyst coverage. Following Boehmer et al. [15], I use the regression model below to estimate a unitary $Dispersion_{i,t}$ proxy variable:

$$\begin{aligned} Dispersion_{i,t} = & Constant + \beta_1 SIGMA_{i,t} + \beta_2 SIGMA_{i,t}^2 + \beta_3 TURNOVER_{i,t} \\ & + \beta_4 TURNOVER_{i,t}^2 + \epsilon_{i,t} \end{aligned} \quad (5.3)$$

where $Dispersion_{i,t}$ is the standard deviation of I/B/E/S analyst earnings forecast normalized by the mean of earnings forecast. $SIGMA_{i,t}$ is the standard deviation of the error term in the $CAPM$ model, estimated over a three-month window for stock i 's daily returns before time t ; and $TURNOVER_{i,t}$ is the trading volume normalized by shares outstanding of stock i over the previous three months. Equation 5.2.3 is estimated for stocks covered by at least two analysts. Then the regression coefficients are used to calculate the $Dispersion_{i,t}$ proxy for all the stocks with available $SIGMA_{i,t}$ and $TURNOVER_{i,t}$ data.

Due to the non-stationarity in the $SIGMA_{i,t}$ and $TURNOVER_{i,t}$, I follow Boehmer et al. [15] and sort all the stocks into twenty groups by their actual $Dispersion_{i,t}$, $SIGMA_{i,t}$ and $TURNOVER_{i,t}$ value at each month. Then I use the rank of the group which stock i is

⁴Boehmer et al. [15] also use stock option status as a supplementary variable to estimate stock short sale rebate fee. The option status data in my sample is only available after 1998, so I only include option status variable in my robustness tests. Boehmer et al. [15] find that SI has significantly higher explanatory power than option status variable and excluding option status variable does not qualitatively affect the results.

assigned to as the value of the variables in the regression . So all $Dispersion_{i,t}$, $SIGMA_{i,t}$ and $TURNOVER_{i,t}$ take discrete values from 1 to 20 in regression 5.2.3. The actual values of the variables are also tested in regression 5.2.3 as a robustness check.

Next, I sort all stocks by estimated $Dispersion_{i,t}$ proxy into five quintile portfolios at each month. I further divide each quintile portfolio into five sub-groups by using $SI_{i,t}$. The stocks in the portfolio Quintile 5 & Quintile 5 (Q5&Q5) with the highest $Dispersion_{i,t}$ and $SI_{i,t}$ are most likely to be overvalued. Then I calculate monthly returns for the portfolio Q5&Q5 and fit the returns to the five factor model. For comparison, I repeat the same analysis for portfolio Quintile 1 & Quintile 1 (Q1&Q1) with the lowest $Dispersion_{i,t}$ and $SI_{i,t}$ ranks. Both equally-weighted and value-weighted portfolio returns are tested. And because the number of stocks in the portfolio varies from month to month, I use both ordinary least squares (OLS) and weighted least squares (WLS) in my analysis. The weights in the WLS regressions are the number of stocks in portfolios every month.

Table F.4 shows that the five factor model *alphas* for portfolio Q5&Q5 are all significantly negative, indicating that the stocks with the highest $Dispersion_{i,t}$ and $SI_{i,t}$ are indeed overvalued on average. And the five factor model *alphas* for portfolio Q1&Q1 are significantly positive if the equally weighted monthly returns are tested, suggesting that stocks with the lowest $Dispersion_{i,t}$ and $SI_{i,t}$ are undervalued on average. However the five factor model *alphas* for portfolio Q1&Q1 are not significant if the value weighted monthly returns are used, suggesting that the undervalued stocks in Q1&Q1 portfolios are mostly small firm stocks.⁵

5.2.4 Asset Bubble Tests Based on a Dividend Discount Model

Most stock bubble tests in previous literature are based on dividend discount models [For details, see 18, 39], in which stock prices are represented as the summation of discounted future dividends. To empirically apply these models, there must be consecutive historical dividend cash flows which are not always available at individual stock level. So most of the empirical tests of stock bubbles focus only on S&P 500 Index or NASDAQ Index. In my

⁵All results are robust if monthly portfolio returns are fitted to the Carhart [22] four factor model or the Fama and French [29] three factor model

for the method, I apply one dividend discount model [66] which can generate a time-series of bubble terms.

In a standard representative agent's utility maximization problem:

$$\text{Max}_x \mathbb{E}_t \left\{ \sum_{i=0}^{\infty} \beta^i u(c_{t+i}) \right\} \quad (5.4)$$

$$\text{subject to } c_{t+i} = w_{t+i} + (P_{t+i} + D_{t+i-1})S_{t+i} - P_{t+i}S_{t+i+1} \quad (5.5)$$

where β is the time discount factor over one period; c_t is the consumption at time t ; S_t is the number of stock shares held at time t ; P_t is the stock price at time t ; D_{t-1} is the dividend per share from time $t-1$ to time t .

Solving this optimization problem, stock price P_t can be represented as

$$P_t = \frac{1}{1+R} [\mathbb{E}_t(P_{t+1}) + D_t] \quad (5.6)$$

where R is the required rate of return. Following Campbell and Shiller [20], the realized log gross return r on a portfolio held from the beginning of time t to the beginning of time $t+1$ can be approximately written as⁶

$$r_t = \kappa + \rho p_{t+1} + (1-\rho)d_t - p_t \quad (5.7)$$

Taking expectation at time t and solving for log price p_t

$$p_t = \kappa + \rho \mathbb{E}_t p_{t+1} + (1-\rho)d_t - r_t \quad (5.8)$$

⁶See Appendix E for details.

Solve p_t by forward induction, the non-bubble solution p_t^f and bubble solution p_t are:

$$p_t^f = \frac{\kappa - r}{1 - \rho} + (1 - \rho) \sum_{i=0}^{\infty} \rho^i \mathbb{E}_t(d_{t+i}) \quad (5.9)$$

$$p_t = p_t^f + b_t \quad (5.10)$$

$$\text{where } \mathbb{E}_t(b_{t+i}) = \frac{1}{\rho^i} b_t \text{ for } i = 1, 2, \dots \quad (5.11)$$

An important advantage of this bubble model is that it generates a time series of bubble term b_t . The main focus of this paper is to establish a robust link between institutional investor holdings and stock misvaluation. With the time series of b_t , the relationship between the size of stock bubbles and institutional holdings can be empirically investigated. Because the bubble term b_t is unobservable to investors, Wu [66] proposes that a state-space model with Kalman filter⁷ can be applied to estimate b_t in this model. Following Wu [66], I assume that the log dividend series d_t follows an $ARIMA(h, 1, 0)$ process, therefore the change of the log dividend follows an $AR(h)$ process:

$$\Delta d_t = \mu + \sum_{j=1}^h \phi \Delta d_{t-j} + e_t \quad (5.12)$$

where e_t is an i.i.d $N(0, \sigma_e^2)$ and the autoregressive order h is to be determined by actual stock dividend data. Rewrite the above equation into matrix form:

$$W_t = U + AW_{t-1} + \zeta_t \quad (5.13)$$

where $W_t' = (\Delta d_t \quad \Delta d_{t-1} \quad \dots \quad \Delta d_{t-h+1})$, $U' = (\mu \quad 0 \quad \dots \quad 0)$, and $\zeta_t' = (\delta_t \quad 0 \quad \dots \quad 0)$

⁷Kalman filter, named after Rudolf E. Kalman, is a recursive procedure for computing the estimator of the unobserved component or the state vector at time t based on available information at time t .

are all $h \times 1$ column vectors and

$$A_{h,h} = \begin{pmatrix} \phi_1 & \phi_2 & \phi_3 & \cdots & \phi_{h-1} & \phi_h \\ 1 & 0 & 0 & \cdots & 0 & 0 \\ 0 & 1 & 0 & \cdots & 0 & 0 \\ \vdots & \vdots & \vdots & \ddots & 0 & 0 \\ 0 & 0 & 0 & \cdots & 1 & 0 \end{pmatrix} \quad (5.14)$$

Taking the first order difference of the bubble equation,

$$\Delta p_t = p_t - p_{t-1} = (1 - \rho) \sum_{i=0}^{\infty} \rho^i [\mathbb{E}_t(d_{t+i}) - \mathbb{E}_{t-1}(d_{t+i-1})] + \Delta b_t = \Delta p_t^f + \Delta b_t \quad (5.15)$$

Following Campbell and Shiller [19], Δp_t can be solved as

$$\Delta p_t = \Delta d_t + M \Delta W_t + \Delta b_t \quad (5.16)$$

$$\text{where } M_{1,h} = gA(I_{h,h} - A)^{-1}[I_{h,h} - (1 - \rho)(I_{h,h} - \rho A)^{-1}] \quad (5.17)$$

$$g_{1,h} = \begin{pmatrix} 1 & 0 & 0 & \cdots & 0 \end{pmatrix} \quad (5.18)$$

And assuming the bubble process is linear, equation (5.11) implies that

$$b_t = \frac{1}{\rho} b_{t-1} + \eta_t \quad (5.19)$$

Equation (5.13), (5.16), (5.19) can be rewritten into a state space form. And stock bubble term b_t can be estimated as an unobserved state variable by Kalman filter.⁸ Before applying this model in my sample, I replicate Wu [66]'s main results and test stock bubbles in S&P500 index for a sample period from 1871 to 2011. Nominal S&P500 index price and dividend series along with the Consumer Price Index (CPI) data are downloaded from Robert Shiller's website. Consistent with Wu [66], I look for the best $ARIMA(h, d, q)$ model coefficients for the natural log of real S&P500 dividend. Based on Akaike information criterion (AIC), I find that the $ARIMA(2, 1, 0)$ model fits dividend data the best. The ratios of the estimated

⁸The details of Kalman filter estimation are included in Appendix F.

bubbles to the actual stock prices are plotted in Figure F.2.⁹ The Bubble/Price ratios in Figure F.2 are similar to the findings in Wu [66].

Next I use the above model to estimate bubble series for the portfolios with the highest valuation ratios. Because my sample period is from 1980 to 2010 and institutional ownership data is at quarterly frequency, the quarterly deflated log nominal portfolio returns and dividend returns are applied in my estimation. The Dicky-Fuller unit root test suggests that there is a unit root in the quarterly portfolio dividends. And $ARIMA(4, 1, 0)$ model has the lowest AIC for fitting the quarterly dividend data. All the estimated b_t at each quarterly end are recorded for the further analysis of the time series relationship between institutional ownership and the degree of stock overvaluation.

5.2.5 Stock Fair Value Estimated by an Earnings Discounted Model

Dividend discount models are very conservative equity valuation models. Some companies never pay dividend as a matter of principle. DeAngelo et al. [25] find that the number of dividend paying firms decreases overtime, though the total dollar value of stock dividend payments keeps increasing. Dividend discount models may work well for indexes or portfolios including lots of stocks, but not for every individual stock. An earnings discount model can serve as an alternative if we assume that investor payout per share is equivalent to the earnings per share (EPS). I estimate the fair value of stock i at the end of quarter t as:

$$FV_{i,t} = Earnings_{i,t} + \sum_{j=t+1}^{t+19} \frac{Earnings_{i,j}}{\prod_{k=t+1}^j (1 + R_{i,k})} + \frac{TV_{i,t+19}}{\prod_{k=t+1}^{t+19} (1 + R_{i,k})} \quad (5.20)$$

$$TV_{i,t+19} = Earnings_{i,t+19} * \frac{\sum_{n=1}^N \frac{P}{E_n}}{N} \quad (5.21)$$

where $FV_{i,t}$ is the fair value of stock i at quarter t , $Earnings_{i,t}$ is the total earnings of stock i at quarter t , $TV_{i,t+19}$ is the terminal value of stock i at quarter $t + 19$. I assign all stocks in my sample into 49 Fama-French industries at each quarter, and $TV_{i,t+19}$ is calculated as

⁹The parameters are estimated by using the maximum likelihood estimation(MLE) and conducted in GAUSS system. The nonlinear optimization in GAUSS program is realized by using OPTMUM procedure. The standard errors of parameter estimators are calculated as the square roots of estimated Hessian matrix. Kalman filter is applied for iterations.

the product of stock i 's earnings at time $t + 19$ and the average P/E ratio of all stocks in stock i 's industry at that time. To account for the cross-sectional and time-series variations in the discount rates, $R_{i,t}$ is estimated by the CAPM model with daily stock returns over quarter t .

After estimating $FV_{i,t}$, I calculate an individual stock's standardized misvaluation measurement $SDM_{i,t}$ using the following definition:

$$SDM_{i,t} = \frac{MV_{i,t} - FV_{i,t}}{FV_{i,t}} \quad (5.22)$$

Stocks with high $SDM_{i,t}$ are relatively overvalued and stocks with low $SDM_{i,t}$ are relatively undervalued.

Overall, I use five methods to identify misvalued stocks in my sample. While the joint hypothesis problem can never be fixed, I believe that factor asset pricing models, valuation ratio portfolios, short sale constraints combined with dispersions of opinions, the dividend discounted model and the earnings discounted model together may provide robust evidence that stock misvaluation persists during the past three decades. Despite the fact that institutional investors have controlled the major portion of the stock market, stock misvaluation still persists over time. In the next section, I will investigate the institutional holdings of these misvalued stocks.

5.3 Institutional Holdings of Misvalued Stocks: Preliminary Statistics

In this section, I present the preliminary statistics of institutional holdings of misvalued stocks. If institutional investors act as arbitrageurs, they will buy undervalued stocks and sell overvalued stocks. As a result, institutional holdings of overvalued stocks should be lower than their holdings of undervalued stocks.

5.3.1 Institutional Ownership and Stock *Alpha*

At first, I form portfolios using *alphas* estimated by the five factor model with rolling five-year windows. Each month, the overvalued portfolio includes all the stocks with significantly negative *alpha* and the undervalued portfolio includes all the stocks with significantly positive *alpha*. In Figure F.3, I compare the weights of these misvalued stocks on the aggregate institutional investor portfolio to the weights of these misvalued stocks on the market portfolio. The top Panel of Figure F.3 shows that institutional investors invest more (less) on the significantly negative *alpha* stocks when the weights of these overvalued stocks on the market portfolio increase (decrease). Furthermore, there is no evidence that the aggregate institutional investor underweighs these overvalued stocks in his portfolio by using the market portfolio as a benchmark. Similarly, the bottom panel of Figure F.3 shows that institutional investors do not overweigh undervalued stocks in their portfolio relative to the market portfolio either. We can only observe a slightly positive gap between the undervalued stock weights on the aggregate institutional investor's portfolio and the weights on the market portfolio during the period between 1985 and 1995.

Next, I compare institutional holdings of stocks with significantly positive *alpha* to institutional holdings of stocks with significantly negative *alpha*. Previous literature shows that institutional ownership increases with firm size and large firm stocks have been outperformed small firm stocks since 1980 [34]. Therefore I divide all stocks into 5 quintile groups by their market value at each quarter. In each quintile group, I calculate the time-series mean of cross-sectional average of institutional ownership *IO* for significantly positive *alpha* stocks and significantly negative *alpha* stocks. *Alphas* are estimated by using the five factor model with rolling five-year windows, the four factor model with rolling five-year windows, and the five factor model with rolling three-year windows. Panel A of Table F.5 shows that institutional investors hold more significantly negative *alpha* (overvalued) stocks than significantly positive *alpha* (undervalued) stocks in the first four quintile groups. Only in the group including the largest stocks, I find the contrary results.

5.3.2 Institutional Ownership and Stock Valuation Ratios

Following Brunnermeier and Nagel [17], I assume all institutions as one giant institutional investor. Then I assign stocks into ten decile portfolios separately by five valuation ratios: P/S, P/E, P/CF, P/EBITDA and P/B. Stocks with negative valuation ratios at a given quarter are excluded at that quarter. I calculate total market value of the aggregate institutional investor's portfolio by summing up all institutional holdings at the end of each quarter. Market value of the aggregate institutional investor's holdings of top decile valuation ratio portfolios and bottom decile valuation ratio portfolios are also calculated at the end of each quarter. The weights of overvalued (undervalued) decile portfolio on the institutional investor's portfolio can be derived by the above information. As benchmarks, the quarterly weights of top and bottom decile valuation ratio portfolios on the market portfolio are also calculated.

As shown in Figure F.4, the red dotted lines represent the time-series weights of top or bottom decile portfolio stocks on the aggregate institutional investor's portfolio. And the blue solid lines represent the time-series weights of top or bottom decile portfolio stocks on the market portfolio. If the aggregate institutional investor keeps buying undervalued stocks and selling overvalued stocks, the red dotted lines should be above (below) the blue solid lines with a significant gap for all bottom (top) decile portfolio figures. However, the graphs on the left column of Figure F.4 show that the aggregate institutional investor does not overweigh undervalued stocks in its portfolio compared to the market portfolio. The graphs on the right column of Figure F.4 show that the aggregate institutional investor does not underweigh overvalued stocks in its portfolios compared to the market portfolio either. In fact, both red and blue lines move concurrently over time on all sub-figures. When overvalued stock portfolio weights in the market portfolio increase, the aggregate institutional investor also increases the weights of overvalued stocks in its portfolio. These results suggest that the aggregate institutional investor rides stock overvaluation and undervaluation wave instead of trading against the wave.

Figure F.5 is similar to Figure F.4, except that the negative valuation ratio are transformed to be positive and have a higher rank than the highest positive valuation ratio stocks

when sorting all stocks into decile portfolios. Because P/S and P/B ratios are all positive, I only report the figures for portfolios sorted by P/E , P/CF and $P/EBITDA$ ratios. Most of the stocks in the decile 10 portfolios have negative valuation ratios, and all the stocks in the decile 1 portfolios have positive valuation ratios. The most striking fact is that the red dotted lines are significantly below the blue solid lines on the left column of Figure F.5, suggesting that the aggregate institutional investor consistently underweights decile 1 (undervalued) portfolio stocks in its portfolio. And on the right column of Figure F.5, the red dotted lines are significantly above the blue solid lines, suggesting that the aggregate institutional investor consistently overweights decile 10 (overvalued) portfolio stocks in its portfolio.

During the Dot-com bubble period, institutional investors radically overinvested on negative valuation ratio stocks. This finding is consistent with Brunnermeier and Nagel [17] who find that hedge fund generally overweights technology stocks in their portfolios and most of the technology stocks do not even have positive earnings. Brunnermeier and Nagel [17] use top quintile P/S ratio to classify overpriced internet stocks. During their sample period from March 1998 to December 2000, 53% of top quintile P/S ratio stocks have negative P/E ratios; 48% of top quintile P/S ratio stocks have negative P/CF ratios; and 45% of top quintile P/S ratio stocks have negative $P/EBITDA$ ratios. These results show that Brunnermeier and Nagel [17]'s findings may be mainly driven by the negative valuation ratio stocks.

The preliminary summary statistics also show the similar results. Panel B of Table F.5 presents the time series mean of cross-sectional average of institutional holding measurements on portfolios formed by valuation ratios. The observations with negative valuation ratios are excluded. Comparing the institutional holding measurements on top quintile valuation ratio portfolios with bottom quintile valuation ratio portfolios, I find that institutions do not hold more undervalued stocks than overvalued stocks on average.

In Panel C of Table F.5, the valuation ratios have been transformed so that stock observations with negative valuation ratios have higher rank than stock observations with positive valuation ratios when sorting stocks into quintile. I also do not find evidence that institutions hold more undervalued stocks than overvalued stocks. Panel D of Table F.5

reports the time-series mean of cross-sectional average of institutional holding measures for top decile and bottom decile valuation ratio portfolios. I exclude all the stock observations with negative valuation ratios. Institutional investors have a higher tendency to hold stocks in the top decile valuation ratio portfolios than the bottom decile valuation ratio portfolios.¹⁰

5.3.3 Institutional Ownership of Misvalued Stocks Identified by Dispersion of Opinions and Short Sale Constraints

In Panel E of Table F.5, I present the time series mean of cross-sectional average of institutional ownership on stock portfolios formed by dispersion of opinion proxy and short sale constraint proxy. My previous tests have shown that stocks with the highest (lowest) dispersion of opinion and the highest (lowest) short-sale constraints tend to be overvalued. But I do not find evidence that institutional investors hold less shares in portfolio D10&D10 than D1&D1. D10&D10 represents top decile dispersion of opinions and top decile short sale constraints. D1&D1 represents bottom decile dispersion of opinions and bottom decile short sale constraints.

5.3.4 Institutional Ownership of Misvalued Stocks Identified by the Earnings Discount Model

In Panel F of Table F.5, I compare institutional holdings of stocks whose market value are greater than their estimated fair value and institutional holdings of stocks whose market value are lower than their estimated fair value. The time-series means of cross-sectional average of institutional ownership are reported. The first two columns of Panel F show that institutional investors hold slightly more stocks whose market value is above its estimated fair value than stocks whose market value is below its estimated fair value. Then I sort all stocks by their *SDM* into 20 groups at each quarter. The third and fourth columns of Panel F show that institutional ownership is higher on stocks with the highest 5% *SDM* (overvalued) than stocks with the lowest 5% *SDM* (undervalued).

¹⁰In an unreported table, I use the cross-sectional median of institutional holding measures and find qualitatively similar results.

In sum, the preliminary summary statistics show that there is no evidence that institutions put more weights on undervalued stocks than overvalued stocks.

5.4 Cross-Sectional Studies on Institutional Holdings and the Degree of Misvaluation

In this subsection, I investigate the relationship between institutional holdings and individual stock misvaluation using multivariate cross-sectional regressions. At each quarter end in my sample from 1980 to 2010, I estimate the cross-sectional regression specified as:

$$IO_i = C_{i,t} + \alpha_i \beta_\alpha + X_i \beta_i + \epsilon_i \quad (5.23)$$

where IO_i is the percentage of institutional ownership on stock i . α_i is estimated by the five factor model with rolling five-year windows¹¹. X_i is the vector of stock characteristics used in Gompers and Metrick [34], including *Size*, *B/M*, *DividendYield*, *Price*, previous two year monthly return *Volatility*, *Momentum1* for the past three month, *Momentum2* for the nine month before the beginning of past three month, share *Turnover*, and *S&P500 dummy*¹². To account for heteroskedastic errors, I use White robust error estimators for the standard error estimations in all regressions [65].

α_i in regression 5.23 represents a measure of stock misvaluation over the past five years. When the dependent variable in regression 5.23 is institutional ownership IO_i , a cumulative measure of institutional ownership on misvalued stocks, regression 5.23 investigates the long-term relationship between institutional holdings and stock misvaluation. When the dependent variable in regression 5.23 is BHM_i or SHM_i , regression 5.23 investigates institutional investors' quarterly response to the level of stock misvaluation over the past five years.

¹¹My results are robust for α_i estimated by five factor model with rolling three-year windows and four factor model with five-year rolling windows. In the rest of this paper, I will only report the results based on α_i estimated by five factor model with rolling five-year windows.

¹²See detailed definition in Appendix D.

5.4.1 Cross-sectional Regressions on Individual Quarters

At first, I estimate separate cross-sectional regressions for each quarter over my whole sample period. Because the regression coefficients are not independent across quarters, I do not report any other time-series statistics other than the average coefficients.

Panel A of Table F.6 reports average regression coefficients, the number of positive and negative coefficients, and the number of significant (5%) positive or negative coefficients for all the separate quarterly OLS regressions of 5.23. The dependent variable is institutional ownership IO and the independent variable α_i is significant $alpha$ dummy, which is equal to 1 (-1) if the actual $alpha$ is positive (negative) and significant at 10%. The results show that there is a consistently negative relationship between institutional ownership and stock $alpha$. For 96 out of 105 quarters, the relationship between institutional ownership and stock $alpha$ is negative. And 67 out of 96 negative coefficients are significant at 5% level.

In Panel B and Panel C of F.6, I change the dependent variable into institutional buy herding measure BHM and institutional sell herding measure SHM . The results show that institutional investors are more likely to herd into (out of) stocks with significantly negative (positive) $alphas$.¹³

5.4.2 Pooled regressions with double-clustered standard errors on firms and quarters

The residual terms in regression 5.23 usually have time-series autocorrelation over the long horizons. Therefore, I corrected the standard errors for cross-sectional and time-series correlation in the residual terms by a pooled regression with double clustering by firm and quarter [56].

Panel A of Table F.7 reports the results of pooled regressions in which the dependent variable is institutional ownership IO . In the first column, the independent variable α_i is significant $alpha$ dummy, which is equal to 1 (-1) if the actual $alpha$ is positive (negative)

¹³In the unreported analysis, I use different α_i measurements such as actual value of significant $alpha$, significant actual $alpha$ lag by 1 quarter, dummy $alpha$ for all stock observations including statistically insignificant $alpha$, and actual stock $alpha$ for all stock observations. Qualitatively similar results have been found.

and significant at 10%. The coefficient of significant *alpha* dummy is -0.042 and significant at 1%, suggesting that the institutional ownership is 8.4% higher in overvalued stocks than undervalued stocks controlling for other stock characteristics. In the second column of Panel A, the independent variable α_i is actual value of significant *alpha* estimated by the five factor model with 5-year rolling windows. The coefficient of actual *alpha* is -1.13 and significant at 1%, suggesting that the institutional ownership on misvalued stocks increase 1.13% when actual *alpha* decreases 1%. From column3 to column5, the independent variable α_i are significant actual *alpha* lag by 1 quarter, dummy *alpha* for all observations including statistically insignificant *alpha*, and actual *alpha* for all observations. All the coefficients of *alpha* variables are negative and statistically significant at 1%. These results show that institutional holdings are higher in overvalued stocks than undervalued stocks cross-sectionally, controlling for other stock characteristics¹⁴.

One interesting finding in Panel A is that the coefficient of *S&P500* dummy is significantly negative, which is opposite to Gompers and Metrick [34]. In untabulated regressions, I divide my sample into two sub-samples: 1980-1996 and 1997-2010. The first sub-sample matches with Gompers and Metrick [34], and I find significantly positive coefficient of *S&P500* dummy. However, the coefficient of *S&P500* dummy in the second sub-sample is significantly negative. And most of the quarterly regression coefficients of *S&P500* are negative and significant. These findings suggest that there exists a structural break for institutional investors' preference on *S&P500* stocks. And the structural break is somewhere between 1996-1998.

Consistent with Gompers and Metrick [34], Panel A also shows that institutional investors are not momentum investors. The coefficients on both past *Momentum1* and *Momentum2* are significantly negative¹⁵. And my finding that institutional ownership is higher in overvalued stocks is robust after controlling for firm size and stock momentum. Momentum trading cannot explain why institutional investors hold more overpriced stocks

¹⁴In unreported tests, I get similar results when I use the five factor three-year rolling *alphas* and four factor five-year rolling *alphas*.

¹⁵Gompers and Metrick [34] argue that although the pairwise relationship between institutional ownership and stock momentum is positive, this simple relation is mainly driven by firm size. The negative relationship between institutional ownership and stock momentum is robust as long as size is controlled

cross-sectionally.

In Panel B of Table F.7, the dependent variables are institutional buy herding measure *BHM*. All five coefficients of *alpha* variables in Panel B are negative and significant above 10% level. These suggest that for all the stocks which institutions buy, the herding intensity on overvalued stocks is higher than undervalued stocks, controlling for other stock characteristics. In Panel C of Table F.6, the dependent variables are institutional sell herding measure *SHM*. All five coefficients of *alpha* variables are positive and three are significant above 10% level. The coefficients for actual significant *alpha* in column2 and *alpha* lag in column3. These results indicate that for all the stocks institutions sell, the herding intensity on undervalued stocks is higher than overvalued stocks, controlling for other stock characteristics.

In Table F.8, I show that the cross-sectional relationship between institutional holdings and stock *alphas* are different across institution types. Following Kamara et al. [46], I separate all institutional investors into three groups: banks and insurance companies, investment companies and independent investment advisors, and all others (pension funds, university endowments, foundations) over the sample period between 1980 and 1997. Among these three groups, investment companies and independent advisors trade the most frequently and are the least risk averse. Therefore, it is expected that investment companies and independent advisors are most likely to ride stock misvaluation. Pension funds, university endowments and foundations are most risk averse among these three groups due to regulation and laws. Therefore, they tend to be the long-term investors and are least likely ride stock overvaluation. The results in Table F.8 show that all the coefficients on *alphas* are significantly negative, suggesting that all three institution groups ride stock overvaluation. Consistent with my expectations, the negative coefficients of *alphas* for investment firms and independent investment companies are less than the other two institution groups. And the coefficients of *alphas* for all other group are the smallest in absolute value, which indicates that institutions in all other group have the least tendency to ride stock overvaluation. During the Dot-com bubble period, almost all institutions increased their exposure to overvalued internet stocks. But due to the restrictions on the investment class and riskiness, pension funds, university endowments and foundations invest relatively less on the over-

valued internet stocks than institutions in the other two groups do. Ofek and Richardson [54] find evidence that pension funds underweigh internet stocks in their portfolios than the other investors. The same story holds true during the recent housing bubble period when every institution increased its investment on the mortgage backed securities.

At last, I investigate the relationship between institutional holdings and stock misvaluation measure SDM . SDM is estimated as the standardized difference between a stock's market value and fair value estimated by the earnings discounted model. Table F.9 reports the results of Fama and Macbeth [28] regressions. Consistent with what I find in Table F.8, institutional investors invest more on stocks with high SDM than stocks with low SDM . Among three types of institutional investors, investment companies and independent investment advisors have a higher tendency to invest on the high SDM stocks than the other two institution types.

The last test is to investigate the time series relationship between institutional holdings and degree of overvaluation. I start with S&P500 Index. Section 5.2.4 presents the dividend discount model in which a bubble term b_t is defined as the unobserved state variable and estimated by Kalman filter. Because the bubble term b_t estimated for S&P500 index is in the annual frequency, I calculate the average of IO_t for all the S&P 500 constituents at every year end. Because institutional holdings increase over time. I use the following regression to test whether the time series of IO_t and b_t are stationary and whether they have a time trend.

$$Y_t - Y_{t-1} = C + (\lambda - 1)Y_{t-1} + \beta T + \epsilon_i \quad (5.24)$$

Panel A of Table F.10 shows that the coefficients of lag IO_t and b_t are both significantly different from zero, indicating that both IO_t and b_t are stationary. The coefficient of time T for IO_t is significant which is consistent with the hypothesis that institutional ownership increases over time. Therefore I use time trend coefficient 0.0091 to calculate the detrended IO series. The third column of Panel A presents that time series relationship between detrended IO_t and b_t is significantly positive, suggesting that institutional investors chase stock overvaluation instead of trading against it.

In Section 5.2.2, the top decile and quintile valuation ratio portfolios have been shown to be overvalued. I use the value weighted, P/S quintile portfolio in the following tests. I record two time series degree of overvaluation on the portfolio: the bubble term b_t estimated by the dividend discount model and the $alpha_t$ estimated by the five factor model with rolling five-year windows. The average institutional ownership measure IO on the portfolio is also recorded. I use the regression 5.24 to test whether the time series of IO , b and $alpha$ are stationary and whether they have a time trend. Panel B of Table F.10 shows that there is no unit root on all three variable time series. But there is a significantly positive time trend for IO . Therefore I use time trend coefficient 0.001 to detrend IO series. Panel C of Table F.10 shows that detrended IO is positively correlated with b_t and negatively correlated with $alpha_t$. When the size of stock bubble term b_t increases (decreases), the average institutional holdings of the overvalued portfolio stocks increase (decrease). When the abnormal return $alpha_t$ decreases (increases), stocks become more overvalued (undervalued) and the average institutional holdings also increase. These findings confirm that on average institutions ride stock overvaluation. Panel D of Table F.10 shows that my findings remain the same if I use top P/E quintile stock portfolio.

In Panel E of Table F.10, I use significantly negative $alpha$ stock portfolio as the overvalued portfolio and the significantly positive $alpha$ stock portfolio as the undervalued portfolio. The first column shows that when the overvalued portfolio $alpha$ decreases, the detrended institutional investor holdings of the overvalued portfolio will increase. The second column shows that when the undervalued portfolio $alpha$ increases, institutional investors do not significantly increase their weights on the undervalued portfolio. Panel D suggests that institutional investors ride stock overvaluation and do not change their holdings respond to stock undervaluation.

Chapter 6

Robustness Tests

6.1 Adjust for Overlapping *Alpha* by Hansen-Hordrick Standard Errors

The main misvaluation measurement variable *Alpha* is estimated by the five-factor model with rolling five year windows. Because the rolling regressions are based on monthly stock return data, the *Alpha* estimators suffer a serious overlapping problem (59 of 60 monthly observations). The overlapping of *Alpha* estimations creates a moving average error term. Therefore ordinary least squares parameter estimates would be inefficient and hypothesis tests would be biased [40]. Past literature has used several heteroskedasticity and autocovariance consistent (HAC) estimators which may provide asymptotically valid hypothesis tests for overlapping data. For example: Hansen and Hodrick [40]; Newey and West [53]; Andrews and Monahan [7]; and West [64].

Following Hansen and Hodrick [40], I estimate regression 5.23 by calculating the Hansen-Hodrick standard errors, and re-calculate the t-ratios for all the regression coefficients. Because institutional ownership variable is at quarterly frequency and the *Alpha* variable is estimated by a rolling five year window, the alpha estimators are in fact overlapped by 19 quarters. Table F.11 shows that the relationship between institutional ownership and stock *Alpha* are significantly negative for all five regressions after adjusting the standard errors for overlapping *Alpha* estimation.

6.2 Average Institutional Ownership and Stock Rolling Five-Year *Alpha*

In regression 5.23, the dependent variable IO is institutional ownership at time t . The independent variable $Alpha$ is estimated by the five-factor model over a rolling five year window between $t - 5$ year to t . $Alpha$ should measure stock misvaluation over the five year period before time t . Therefore, I replace the dependent variable IO by $IO_{Average}$ which is the average of 20 quarterly institutional ownership IO between time $t - 5$ year and t . $IO_{Average}$ may be better to measure institutional ownership on stock i over the five year period than IO . Table F.12 shows that there is still a significantly negative relationship between $IO_{Average}$ and $Alpha$ for all $Alpha$ measures. The coefficient of significant $Alpha$ dummy is -0.062 and significant at 1% level, suggesting that the five-year average institutional ownership is 12.4% higher in overvalued stocks than undervalued stocks controlling for other stock characteristics. The coefficient of actual $Alpha$ is -1.93 and significant at 1% level, suggesting that the five-year average institutional ownership on misvalued stocks increase 1.93% as actual $Alpha$ decreases 1%.

$$IO_{Average}_{i,t} = \frac{\sum_{t-19}^t IO_{i,j}}{20} \quad (6.1)$$

6.3 Institution Fund Inflow

One possible explanation of my results is that individual investors invest more on institutions that chase stock misvaluation than institutions that do not. For example, during the Dot-com bubble period individual investors invest more on institutions that put more weights on tech stocks than institutions that put less weight on tech stocks. Therefore, individual investors are still the driving force of stock misvaluation. To test this hypothesis, I divide my sample into “high-inflow” and “low-inflow” quarters. Following Gompers and Metrick [34], I define the institution fund inflows as the quarterly change in the total value

of aggregate institutional holdings without any price appreciation or depreciation effects:

$$Inflows_t = \frac{\sum_i^N (MV_{i,t-1} * \Delta IO_{i,t})}{\sum_i^N MV_{i,t-1}} \quad (6.2)$$

where N is total number of stocks at time $t - 1$, $MV_{i,t-1}$ is stock i 's market value at time $t - 1$, and $\Delta IO_{i,t}$ is the change of institutional ownership on stock i from time $t - 1$ to t . Using the $Inflow_t$ measure, I sort all quarters in my sample and define the top half as “high inflow” and the bottom half as “low inflow”. The regression 5.23 is estimated for both sub-samples by using the Fama and Macbeth [28] method and the pooled regression. In high-inflow quarters, the absolute value of coefficients on stock misvaluation measures are less than its absolute value on low-inflow quarters. These results suggest that institutional investors chasing stock misvaluation is not driven by individual investors.

6.4 Subperiod Analysis

Brunnermeier and Nagel [17] find that hedge funds ride overvalued stocks during the Dot-com bubble. In order to preclude the possibility that my results are only driven by institution speculating on internet stocks during the Dot-com bubble period, I exclude the observations between 1997 and 2001 from my sample. Untabulated results show that both cross-sectional and time-series test results for the remaining sample are similar to what I find before. Another concern of my finding is that institutions' tendency to ride stock misvaluation may change over time. For example, the number of hedge funds and mutual funds increase significantly after the late 1990s. To address this concern, I separate my sample into two subperiods, 1980-1994 and 1995-2010, and repeat my cross-sectional analysis for each subperiod. Table F.14 presents the results and indicate that institutional investor have a higher tendency to ride stock misvaluation for the 1995-2010 subperiod, when mutual funds and hedge funds are more popular in the U.S. stock market. But my key results remain qualitatively similar for the 1980-1994 subperiod, which suggests that both the Dot-com bubble and the composition change of institutions do not drive the findings of this study.

6.5 Industry-specific or Firm-specific?

During my sample period, certain industries have gone through overvaluation for a sustained period. For example, the technology industry in the late 1990s and the real estate industry in the late 2000s. Following Fama and French 49 industry definition, I assign each stock in my sample to a corresponding industry based on its four-digit SIC code every quarter. Then I check the cross-sectional regression 5.23 of institutional ownership on stock *alphas* within each industry. To include more observations in each industry, I choose *alpha_dummy* as my independent variable which is equal to 1 if the actual *alpha* is positive and 0 otherwise. Table F.15 shows that my findings that institutional investor hold more overvalued stocks than undervalued stocks cross-sectionally are not driven by a few industries. Among the 49 Fama-French industries, the estimated coefficient for *alpha_dummy* is significantly negative for 35 industries, insignificantly negative for 12 industries and insignificantly positive for the other 2 (Beer & Liquor industry and Precious Metals industry). The first reason for the insignificance is the lack of observations. And the second reason is that most the industries with insignificantly negative *alpha_dummy* coefficients or insignificantly positive coefficients are traditional industries such as agricultural, defense, textiles, mining etc. Stocks in these industries are relatively easy to be priced and have less uncertainty.

6.6 Institutional Ownership and Short Interest

Stock short interest and the standard deviation of financial analysts' earnings per share expectations have been used to double sort all stocks. Following Miller [51] and Boehmer et al. [15], stocks with the high short sale interest ratios and high dispersion of opinions are likely to be overvalued. In some empirical literature, stock short-sale constraints alone can be taken as an important obstacle to arbitrage. In this subsection, I investigate the relationship between institutional ownership and short interest ratios.

Table F.16 shows that there is a significantly positive relationship between institutional ownership and short interest ratios, controlling for other stock characteristics. The pooled regressions with double clustered standard errors by both firm and quarter have been applied

in Table F.16. In the first column, the independent variable Vincile RSI Dummy is a number between 1 and 20. I sort all stocks with available short interest data into 20 vincile groups and assign a group number to stocks in each group. For example, Vincile RSI Dummy is 1 if a stock is in the lowest 5% vincile group. In the second column, the independent variable RSI represents the actual short interest ratios. Both coefficients of RSI variables are positive and significant at 1% level.

However Asquith et al. [8] argue that short interest ratios can be taken as a proxy for short sale demand and institutional ownership can be taken as a proxy for lendable supply. Therefore, there is an endogeneity problem for regressions in Table F.16. Actually Asquith et al. [8] find that stocks with high short interest and low institutional ownership underperform during the period 1988-2002. Short-sale interest alone may not be taken as a good proxy for stock overvaluation.

6.7 Are Institutional Investors Better off by Investing on Negative *Alpha* Stocks?

The main results of this paper show that institutional investors invest more on negative *Alpha* stocks than positive *Alpha* stocks. And investment companies and independent investment advisors have a higher tendency to do so than the other types of institutional investors. The implication of these results is that institutional investors are riding stock misvaluation instead of arbitraging immediately. The next interesting question is whether the trend chasing strategies of institutional investors are rational or not. That is, will the subsequent performance of the institutional investors be better off when institutional investors overweight negative *Alpha* stocks in their portfolios?

The ideal method is to track individual institutional investor's time-series performance. However, this method is not feasible in my data sample. In this paper, the stock holdings by financial institutions are collected from CDA/Spectrum S34 dataset that covers entire investment companies in the U.S stock market. Banks, insurance companies, parents of mutual funds, pension funds, university endowments, and professional investment advisors (hedge funds) are all included in the CDA/Spectrum S34 dataset. The advantage of

this dataset is its comprehensiveness. The findings in this paper can represent the trading strategies of the average institutional investors in the U.S stock market, not just a portion of institutional investors. However both fund number (FUNDNO) and manager number (MGRNO) identifiers in CDA/Spectrum S34 dataset are reused. According to the User's Guide to Thomson Reuters Mutual Fund and Investment Company Common Stock Holdings Databases on WRDS, FUNDNO or MGRNO do not provide a unique and permanent identifiers for every fund or manager. The same FUNDNO or MGRNO usually reflects a different and unrelated fund or manager if there is more than 1 year gap in the report date of stock holdings. Because the lack of identifier for the same institutional investor over time, CDA/Spectrum S34 dataset has been rarely used in the institutional investor performance literature.

One possible alternative method is to investigate the relationship between institutional ownership and stock forward looking *Alpha*. I calculate individual stock 5-factor model *Alpha* from time t to time $t+5$ years and individual stock 5-factor model *Alpha* from time t to time $t+3$ years. Then I check the relationship between institutional ownership at time t and the 5 year (3 year) forward looking stock *Alpha*. Table F.17 shows that institutional ownership and stock forward *Alpha* is positively correlated. This positive relationship is significant when the forward 3-year *Alpha* is used, but insignificant when the forward 5-year *Alpha* is used. And if I divide institutional investors into three types following Kamara et al. [46], then the coefficients of forward *Alpha* is larger for investment companies and independent investment companies than for the other two types. All these results show weak evidence that institutional investors riding stock misvaluation may generate future positive *Alpha*. And institutional investors are rational trend chasers on average.

The other alternative method is based on sorting stocks into portfolio by their last quarter institutional ownership and stock *Alpha*, then the portfolio returns may indicate whether institutional investors can make profit by investing on negative *Alpha* stocks. However, this would likely bias the high institutional holdings portfolio towards larger companies as Gompers and Metrick [34] show that institutional investors prefer to invest on firms with bigger size. In addition, institutional ownership has increased over my sample period as this paper shows in the beginning. Therefore, I have to control for both time and firm size in

forming portfolios. I follow Field and Lowry [31] and employ fractional logit methodology. Each quarter, I model the conditional mean of percent institutional ownership as a logistic function:

$$\mathbb{E}(IO_{i,t} | x) = \frac{\exp\{\beta_1 + \beta_2 * Size_{i,t}\}}{1 + \exp\{\beta_1 + \beta_2 * Size_{i,t}\}} \quad (6.3)$$

where $IO_{i,t}$ is the institutional holdings for firm i at quarter t ; $Size_{i,t}$ is firm i 's log total assets at quarter t . The parameters are estimated on a quarter-by-quarter. This method accounts for the fact that institutional ownership has values between zero and one by definition. And it also accommodate cases in which institutional ownership equals zero. Then the difference between actual institutional ownership and expected institutional ownership for each firm is calculated as the unexpected institutional ownership.

Next, I assign stocks in a portfolio at each quarter if stocks' unexpected institutional ownership is among top 20% in the last quarter and stocks' five-year-five-factor *Alpha* is negative (or significantly negative). Panel A of Table F.18 shows the descriptive statistics for the portfolio quarterly returns and the number of stocks in the portfolio. The average quarterly raw portfolio returns is 4.1% if the *Alpha* dummy is used when forming the portfolio and 4.8% if the significant *Alpha* dummy is used when forming the portfolio. Panel B of Table F.18 shows regressions of quarterly portfolio returns on the three Fama-French factors. To account for the effects of changing number of stocks in the portfolio, regressions are estimated using weighted least squares, where each quarterly return is weighted by the number of stocks in the portfolio. The intercept in the regression measures abnormal performance of the portfolio. The results show that both portfolios have significantly positive abnormal returns, which support the hypothesis that institutional investors can make profit by riding on stock misvaluation.

Chapter 7

Conclusion

The goal of this paper is to investigate whether institutional investors ride mispriced stocks or trade against stock misvaluation. Using all the CRSP sample stocks over 1980 to 2010, I identify mispriced stocks with general asset pricing methods. The institutional holdings of these mispriced stocks show that institutional investors are extensively involved in the stock misvaluation process. Cross-sectionally, the aggregate institutional investor overweighs (underweighs) the overvalued (undervalued) stocks in its portfolio. And time-series relationship between institutional holdings and the degree of stock misvaluation is also significantly positive.

Institutions dominate the U.S stock market in terms of both market share and trading volume. When stock misvaluation is still observed in such an institutionalized market, the role of institutions as arbitrageurs is compromised. One explanation of these findings is that although institutional investors are sophisticated, their clients are not. Institutional investors choose stocks in their portfolios based on rational expectation of stock future returns, but their clients (individual investors) only delegate wealth to professionals who have better past performance. And the portfolio managers only have incentive to maximize risk-adjusted returns within their tenure, therefore ignoring the fundamental in the long run. The other possibility is that institutions tend to use asset allocation and diversify their investment in every sector. They may pay little attention to an individual stock fundamental value in their efficient frontier mean-variance analysis.

Several extensions of this study could be pursued. At first, the effect of portfolio manager pay-performance contract on their holdings of mispriced stocks may be studied. In addition, whether the fund governance and fund long-term performance are positively correlated is also interesting. Thirdly, the synchronization among the largest institutions and its effect on stock misvaluation may help to answer the question of whether synchronization risk really delays arbitrage or institutional investors' trading jointly leads to stock misvaluation. At last, a more fined data set about institutional investor stock holdings may help to test the hypothesis that institutional investor is rational to ride stock misvaluation.

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Appendix A

Data Source

Thomson CDA/Spectrum S34 Institutional Investor Ownership Data. The backbone of my data set is institutional investor stock holdings from Thomson Financial (also known as CDA/Spectrum S34). According to a 1978 amendment to the Securities and Exchange Act 1934, all institutional investors with greater than \$100 million of securities under discretionary management must report their holdings to SEC in their 13F report. Thomson Reuters collects institutional investor holding information from their filings to SEC at each quarterly end. There are some potential exclusions for 13F filings: (1) Small holdings under 10,000 shares or \$200,000; (2) Holdings that are confidential due to some particular reasons; (3) Holdings that could not be matched with a master security file. I focus on the institutional investor report dates found in the Thomson Reuters 13F dataset, and adjust the holding information if an institutional investor's file date is later than its report date¹. The 13F data sample period is from 1980 to 2010.

All institutions in CDA/Spectrum S34 database are classified into five types: (1) Bank, (2) Insurance company, (3) Investment Company (Mutual Fund), (4) Independent Investment Advisor and (5) Others (e.g. Pension Fund, University Endowment and Foundation). The institution type information are not accurate after 1998. Therefore my studies related to institutional investor types are restricted to the time period from 1980 to 1997.

¹The only reason to care about file date is that file date is later than report date and stock splits occur between an institutional investor's report date and file date. I recover the correct number of holding shares as of the report date by using the CRSP share adjustment factors.

CRSP Stock Price and Return Data. Stock prices, returns and trading volume at monthly end and daily end are obtained from the CRSP/COMPUSTAT Merged Database, which includes all U.S. ordinary common stocks (i.e., CRSP share code 10 or 11) listed on NYSE, AMEX, and NASDAQ. ADRs, REITS, closed end funds and foreign incorporated companies are excluded from my sample. I also collect stock dividend returns, shares outstanding, trading volume, and firm capitalizations from the CRSP/COMPUSTAT Merged Database. To avoid any potential confounding effect of recent IPOs, only firms that are recorded on the CRSP for at least 12 months are included in my sample. To alleviate the effect of bid-ask bounces on the empirical studies, I exclude stocks with prices below \$3 at the end of each month. To account for market maker activity in calculating NASDAQ trading volume, I divide NASDAQ firms' trading volume by two in the main analysis [9]². My CRSP sample period is from 1980 to 2011.

Corporate Accounting Data and Short Interest Data from COMPUSTAT. Corporate accounting data, such as book equity, earnings, cash flows, come from COMPUSTAT. Short interest data for stocks listed on NYSE and NASDAQ, and S&P500 index constituents are also collected from COMPUSTAT monthly file. The sample period for COMPUSTAT data is from 1980 to 2011.

Analysts' Earnings Forecasts from I/B/E/S. Financial analysts' earnings forecasts are retrieved from I/B/E/S Unadjusted Summary File.³ The Unadjusted Summary File contains summary statistics on analyst earnings per share (EPS) forecasts. Mean, median

²NASDAQ overstating trading volume may no longer exist after 1997, because SEC had changed order-handling rules and trade-reporting rules since then. And in 2010, the SEC reported that by the mid-2000s, more than 40 percent of NASDAQ transactions were being handled by Electronic Communication Networks (ECNs). Since ECNs rarely double count their trades, reported volumes may not go up if some of ECNs trading do not come from dealers. Anderson and Dyl [6] find that NASDAQ volume are still biased (37%) in comparison to NYSE reported volumes for their sample period from 1997 to 2002, but not by as much as they had been (50%). As a robustness check, I take NASDAQ firm's trading volume as it is and redo the analysis. This alternative specification does not significantly change my original findings.

³I/B/E/S also provides Adjusted Summary File, which adjusts EPS for stock splits and stock dividends since the date of forecasts to today. Although this adjustment makes today's EPS comparable with its historical values, it causes two issues. At first, the rounding issue after the adjustment makes some of the standard deviation and the mean of analysts' EPS forecasts equal to zero. The adjustment distorts the rank of historical EPS. For example: firm A and B's historical EPS are \$1 and \$1.49 respectively. If both firms carry out a one-to-ten stock split after the historical EPS report date, then I/B/E/S adjusts both firms' EPS to be ten cents.

and standard deviation of analyst earnings forecasts are included. I/B/E/S data manual indicates that these data are all calculated on the third Thursday of each month based on the individual records from the Unadjusted Detail History File. The sample period is from 1980 to 2011.

Five Factor Time Series Data from WRDS. From WRDS, I collect monthly time series data for excess return on the market portfolio $R_{m,t} - R_{f,t}$, the difference between the average return on the three small firm portfolios and average return on the three big firm portfolios SMB_t , the difference between average return on two high book-to-market (value) stock portfolios and the average return on the two low book-to-market (growth) stock portfolios HML_t , and the difference between the average return on two high prior return portfolios and the average return on two low prior return portfolios UMD_t . These three factors are proposed by Fama and French [29]. The fourth factor momentum is proposed by Carhart [22]. And the fifth factor which I collect from WRDS is Pastor-Stambaugh value weighted liquidity factor [55] with monthly frequency. The sample period is from 1980 to 2010.

S&P500 and CPI. Annual S&P500 index price and dividends data, along with quarterly consumer price index (CPI) data, are collected from Robert Shiller's website. The sample period is from 1871 to 2012.

Fama and French 49 Industry Portfolio Returns. Based on stocks' SIC codes, Fama and French assign each NYSE, AMEX, and NASDAQ stock to an industry portfolio at the end of June. I use their 49 industry portfolio returns in my study. The data is downloaded from Kenneth R. French's website. The sample period is from 01/1980 to 12/2010.

Appendix B

Definition of Valuation Ratios

This appendix describes how valuation ratios are constructed in this paper. The #s in parentheses refer to data items from COMPUSTAT quarterly file.

P: Share price from CRSP, at the end of each month.

S: Per share sales = sum of four consecutive quarterly sales (#12 saleq) deflated by shares outstanding (#25 cshoq).

E: 12 month moving earnings per share (#58 epsx12) excluding extraordinary items.

BV: Per share book value of equity = book equity (# seqq) – preferred stock value (#55 pstkq, 0 is missing) + deferred taxes (#52, txditcq, 0 if missing) deflated by shares outstanding (#25 cshoq). Following the previous literature, I use redemption value, liquidation value or carrying value to measure preferred stock value in descending priority.

EBITDA: Per share earnings before interest, taxes, depreciation and amortization = EBITDA (#13, oibdpq), deflated by shares outstanding (#25 cshoq).

CF: Per share cash from operations = EBITDA (#13, oibdpq) – total interest and related expense (#15, xintq, 0 if missing) – total tax expense (#16, txtq, 0 if missing) –

net change in working capital, deflated by shares outstanding (#25, cshoq), where net change in working capital is change in current assets (#4, actq, 0 if missing) – change in cash and cash equivalents (#1, cheq, 0 if missing) – change in current liability (#5, lctq) + change in debt included in current liabilities (#34, dlcq, 0 if missing).

Appendix C

Definition of Dispersion of Investor Opinion and Short Sale Constraint

This appendix describes how proxy variables for dispersion of investor opinion and short sale constraints are constructed:

$$SD(\text{EPS}) = \frac{\text{SD of EPS Estimation}}{\text{ABS}(\text{Mean of EPS Estimation})} \quad (\text{C.1})$$

SD(EPS): normalized standard deviation of analyst's EPS estimation. Data are collected from I/B/E/S unadjusted summary file. Diether et al. [26] and Boehmer et al. [15] use this measure to capture dispersion of investor opinion.

EPSILON: the unsystematic risk term of stock returns. Following Brown and Warner [16] market model, I run CAPM regression over a rolling 3 month window by using daily stock excess returns and market excess returns. The standard deviations of regression error terms are recorded at the end of each month. For robustness check, I also use a rolling 6 month window and get similar results. Harrison and Raviv [41] and [58] find that return volatility is positively related to dispersion of I/B/E/S analysts' EPS forecasts, and Boehmer et al. [15] use EPSILON as one of their dispersion of investor opinion proxies.

$$\text{Volume} = \frac{\text{Trading Volume}}{\text{Total Share Outstandings}} \quad (\text{C.2})$$

VOLUME: past one month, three month, six month, and 12 month trading volume. Due to space availability, I only report results by using past three month trading volume. But my results are qualitatively similar by using other trading volume periods. Diether et al. [26], Boehmer et al. [15] and Cao and Ou-Yang [21] use this measure to capture dispersion of investor opinion. Following previous literature, NASDAQ trading volume is divided by two to account for market-maker activity in calculating NASDAQ trading volume¹.

$$\text{SI} = \frac{\text{Number of Shares Shorted}}{\text{Total Shares Outstanding}} \quad (\text{C.3})$$

SI: short interest. Figlewski [32] finds that the unobserved demand to short a stock rises with the observed short interest level and firms with high observed short interests are more difficult to be shorted. Ofek and Richardson [54] also find that short interest was considerably higher for Internet stocks than for “old economy” firms during the period of 01/1998 to 12/2000.

¹See Atkins and Dyl [9] for a detailed discussion of this practice.

Appendix D

Definition of Control Variables for Stock Characteristics

This appendix describes how control variables for stock characteristics are constructed by following Gompers and Metrick [34] with minor modifications.

Size: market capitalization at the end of quarter t .

B/M: most recent book value before quarter t , divided by Size at the end of quarter t .

Yield: dividend yield for the past 12 months before the end of quarter t .

Price: stock price per share at the end of quarter t

Volatility: the variance of monthly stock returns over the past 24 months before the end of quarter t .

Momentum1: past 3-month gross return before the end of quarter t .

Momentum2: past nine-month gross return preceding the beginning of Momentum1 measurement period.

Turnover: trading volume at the end of quarter $t-1$ divided by shares outstanding.

S&P500: dummy variable which is equal to 1 if a stock is in S&P500 index, and 0 otherwise.

Appendix E

Details of Stock Bubble Model

This appendix describes the model specification of my bubble test. In the standard consumer utility optimization setting, a representative agent maximizes the present value of his life time utility:

$$\text{Max}_S \mathbb{E}_t \left\{ \sum_{i=0}^{\infty} \beta^i u(c_{t+i}) \right\}$$

subject to

$$c_{t+i} = w_{t+i} + (P_{t+i} + D_{t+i-1})S_{t+i} - P_{t+i}S_{t+i+1}$$

Take the first order derivative of the representative agent's utility function with respect to S_{t+i} and set it equal to zero:

$$\mathbb{E}_t \{ \beta u'(c_{t+i}) [P_{t+i} + D_{t+i-1}] \} = \mathbb{E}_t \{ u'(c_{t+i-1}) P_{t+i-1} \} \quad (\text{E.1})$$

Assuming the representative agent is risk neutral and has constant marginal utility function, the first order condition is simplified:

$$\beta \mathbb{E}_t (P_{t+i} + D_{t+i-1}) = \mathbb{E}_t (P_{t+i-1}) \quad (\text{E.2})$$

Further assuming that the risk free bond pays net interest rate R for one period and the riskless bond is in zero net supply, then no arbitrage implies

$$\mathbb{E}_t(P_{t+i-1}) = \frac{1}{1+R} \mathbb{E}_t(P_{t+i} + D_{t+i-1}) \quad (\text{E.3})$$

At time t , the above equation can be rewritten as

$$P_t = \frac{1}{1+R} [\mathbb{E}_t(P_{t+1}) + D_t] \quad (\text{E.4})$$

I transform all the variables into natural logarithm terms so that stock prices are not negative even with a negative bubble. From the beginning of time t to the beginning of time $t+1$, I define the log gross return as

$$r_t \equiv \ln(\mathbb{E}_t(P_{t+1}) + D_t) - \ln(P_t) \quad (\text{E.5})$$

Following Campbell and Shiller [20], I express r_t as a linear combination of the natural logarithms of stock price and dividend.

$$r_t \cong \xi_t = \kappa + \rho \mathbb{E}_t[\ln(P_{t+1})] - (1 - \rho) \ln(D_t) - \ln(P_t) \quad (\text{E.6})$$

$$= \kappa + \rho \mathbb{E}_t[p_{t+1}] - (1 - \rho) d_t - p_t \quad (\text{E.7})$$

where lowercase letters denote natural logarithms of the corresponding uppercase variables. The parameter ρ is close to but a little smaller than 1, and κ is a constant term which will be defined later. To prove this approximation, the ratio of stock price to the sum of stock price and dividend are assumed to be approximately constant ρ through time. Then P_t and D_{t-1} can be written as

$$P_t = \rho(P_t + D_{t-1}) \quad (\text{E.8})$$

$$D_{t-1} = (1 - \rho)(P_t + D_{t-1}) \quad (\text{E.9})$$

This is the exact case in the static Gordon model, where the log stock return and the dividend growth rate are both constants. In calculus $d\ln(x) = \frac{1}{x}dx$, so the change in $\ln(P_{t+1} + D_t)$ is approximately equal to the proportional change in the level. That is:

$$\Delta \ln(P_{t+1} + D_t) = \ln(P_{t+1} + D_t) - \ln(P_t + D_{t-1}) \quad (\text{E.10})$$

$$\cong \frac{P_{t+1} + D_t - P_t - D_{t-1}}{P_{t+1} + D_t} \quad (\text{E.11})$$

$$= \frac{P_{t+1} - P_t}{P_{t+1} + D_t} + \frac{D_t - D_{t-1}}{P_{t+1} + D_t} \quad (\text{E.12})$$

$$\cong \frac{\rho(P_{t+1} - P_t)}{P_t} + \frac{(1 - \rho)(D_t - D_{t-1})}{D_{t-1}} \quad (\text{E.13})$$

$$\cong \rho \Delta \ln(P_{t+1}) + (1 - \rho) \Delta \ln(D_t) \quad (\text{E.14})$$

In a static world, the log dividend-price ratio is constant c

$$c_t = c = \ln\left(\frac{D_{t-1}}{P_t}\right) = \ln\left(\frac{P_t + D_{t-1} - P_t}{P_t}\right) \quad (\text{E.15})$$

$$= \frac{P_{t+1} + D_t - P_t - D_{t-1}}{P_{t+1} + D_t} \quad (\text{E.16})$$

$$= \ln\left(\frac{\frac{P_t + D_{t-1}}{P_t + D_{t-1}} - \frac{P_t}{P_t + D_{t-1}}}{\frac{P_t}{P_t + D_{t-1}}}\right) \quad (\text{E.17})$$

$$= \ln\left(\frac{1 - \rho}{\rho}\right) \quad (\text{E.18})$$

$$= d_{t-1} - p_t \quad (\text{E.19})$$

Give what I have above, the constant term κ can be derived as:

$$\kappa = \ln(P_{t+1} + D_t) - \rho \ln(P_{t+1}) - (1 - \rho) \ln(D_t) \quad (\text{E.20})$$

$$= \ln(P_{t+1} + D_t) - \ln(P_{t+1}) + \ln(P_{t+1}) - \rho \ln(P_{t+1}) - (1 - \rho) \ln(D_t) \quad (\text{E.21})$$

$$= \ln\left(\frac{P_{t+1} + D_t}{P_{t+1}}\right) + (1 - \rho) \ln(P_{t+1}) - (1 - \rho) \ln(D_t) \quad (\text{E.22})$$

$$= \ln\left(\frac{1}{\rho}\right) + (1 - \rho) \ln\left(\frac{P_{t+1}}{D_t}\right) \quad (\text{E.23})$$

$$= -\ln(\rho) - (1 - \rho)c \quad (\text{E.24})$$

Therefore,

$$r_t = \ln(P_{t+1} + D_t) - \ln(P_t) \quad (\text{E.25})$$

$$= \ln(P_{t+1} + D_t) - \rho \ln(P_{t+1}) - (1 - \rho) \ln(D_t) \quad (\text{E.26})$$

$$+ \rho \ln(P_{t+1}) + (1 - \rho) \ln(D_t) - \ln(P_t) \quad (\text{E.27})$$

$$= \kappa + \rho \ln(P_{t+1}) + (1 - \rho) \ln(D_t) - \ln(P_t) \quad (\text{E.28})$$

$$= \kappa + \rho p_{t+1} + (1 - \rho)d_t - p_t \quad (\text{E.29})$$

$$\text{Adding expectation at time } t \Rightarrow p_t = \kappa + \rho \mathbb{E}_t p_{t+1} + (1 - \rho)d_t - r_t \quad (\text{E.30})$$

By induction and assuming the required rate of return r is constant over time, one solution for p_t at time t is:

$$p_t = (\kappa - r) + (1 - \rho)(\kappa - r) + (1 - \rho)^2(\kappa - r) + \cdots + (1 - \rho)^i(\kappa - r) \quad (\text{E.31})$$

$$+ (1 - \rho)d_t + (1 - \rho)\rho \mathbb{E}_t d_{t+1} + (1 - \rho)\rho^2 \mathbb{E}_t d_{t+2} + \cdots + (1 - \rho)\rho^i \mathbb{E}_t d_{t+i} \quad (\text{E.32})$$

$$\rho^{i+1} \mathbb{E}_t d_{t+i+1} \quad (\text{E.33})$$

If the transversality condition is satisfied,

$$\lim_{i \rightarrow \infty} \rho^i \mathbb{E}_t d_{t+i} = 0 \quad (\text{E.34})$$

$$\Rightarrow p_t^f = \frac{\kappa - r}{1 - \rho} + (1 - \rho) \sum_{i=0}^{\infty} \mathbb{E}_t(d_{t+i}) \quad (\text{E.35})$$

If the transversality condition is violated and there is a bubble term in stock prices, then the general solution for stock price p_t is:

$$p_t = p_t^f + b_t \quad (\text{E.36})$$

$$\text{and } \mathbb{E}_t(b_{t+i}) = \frac{1}{\rho^i} b_t \quad \text{for } i = 1, 2, \dots \quad (\text{E.37})$$

Appendix F

Details of State Space Model and Kalman Filter

Rewrite equation (5.13) (5.16), and (5.19) into the state-space model:

Measurement Equation:

$$Y_t = C + H\beta_t + DZ_t + e_t, \quad t = 1, 2, 3, \dots, T \quad (\text{F.1})$$

Transition Equation:

$$\beta_t = F\beta_{t-1} + \nu_t \quad (\text{F.2})$$

where

$$\mathbb{E}_t(e_t\nu_t') = 0 \quad (\text{F.3})$$

$$e_t \sim i.i.d.N(0, R) \text{ and } \nu_t \sim i.i.d.N(0, Q) \quad (\text{F.4})$$

$$R = \begin{pmatrix} \sigma_\delta^2 & 0 \\ 0 & 0 \end{pmatrix} \text{ and } Q = \begin{pmatrix} \sigma_\eta^2 & 0 \\ 0 & 0 \end{pmatrix} \quad (\text{F.5})$$

And

$$\begin{aligned}
Y'_{t,2 \times 1} &= (\Delta d_t \quad \Delta p_t) \\
\beta'_{t,2 \times 1} &= (bt \quad b_{t-1}) \\
Z'_{t,h \times 1} &= (\Delta d_t \quad \Delta d_{t-1} \quad \Delta d_{t-2} \quad \cdots \quad \Delta d_{t-h}) \\
e'_{t,2 \times 1} &= (\eta_t \quad 0) \\
\nu'_{t,2 \times 1} &= (\delta_t \quad 0) \\
C'_{2 \times 1} &= (\mu \quad 0)
\end{aligned}$$

$$\begin{aligned}
H_{2 \times 2} &= \begin{pmatrix} 0 & 0 \\ 1 & -1 \end{pmatrix} \\
D_{2 \times h} &= \begin{pmatrix} 0 & \phi_1 & \phi_2 & \cdots & \phi_{h-1} & \phi_h \\ 1 + m_1 & m_2 - m_1 & m_3 - m_2 & \cdots & m_h - m_{h-1} & -m_h \end{pmatrix} \\
F_{2 \times 2} &= \begin{pmatrix} \frac{1}{\rho} & 0 \\ 1 & 0 \end{pmatrix}
\end{aligned}$$

Kalman Filter

Prediction

$$\beta_{t|t-1} = F\beta_{t-1|t-1} \tag{F.6}$$

$$P_{t|t-1} = \mathbb{E}_t[(\beta_t - \beta_{t|t-1})(\beta_t - \beta_{t|t-1})'] = FP_{t-1|t-1}F' + Q \tag{F.7}$$

$$\eta_{t|t-1} = Y_t - Y_{t-1} = Y_t - C - H\beta_{t|t-1} - DZ_t \tag{F.8}$$

$$f_{t|t-1} = \mathbb{E}_t[\eta_{t|t-1}^2] = HP_{t|t-1}H' + R \tag{F.9}$$

Updating

$$K_t = P_{t|t-1}H'f_{t|t-1}^{-1} \quad (\text{Kalman Gain}) \quad (\text{F.10})$$

$$\beta_{t|t} = \beta_{t|t-1} + K_t\eta_{t|t-1} \quad (\text{F.11})$$

$$P_{t|t} = P_{t|t-1} - K_tHP_{t|t-1} \quad (\text{F.12})$$

The sample log-likelihood function is represented by

$$\ln(L) = -\frac{1}{2} \sum_{t=1}^T [\ln(2\pi f_{t|t-1})] - \frac{1}{2} \sum_{t=1}^T [\eta'_{t|t-1} f_{t|t-1}^{-1} \eta_{t|t-1}] \quad (\text{F.13})$$

Smoothing

$$\beta_{t|T} = \beta_{t|t} + P_{t|t}F'P_{t+1|t}^{-1}(\beta_{t+1|T} - F\beta_{t+1|t}) \quad (\text{F.14})$$

$$P_{t|T} = P_{t|t} + P_{t|t}F'P_{t+1|t}^{-1}(P_{t+1|T} - P_{t+1|t})(P_{t+1|t}^{-1})'FP'_{t|t} \quad (\text{F.15})$$

where $\beta_{T|T}$ and $P_{T|T}$ are the initial values for smoothing and obtained from the last iteration of the forward induction.

Figure F.1: The Rise of Institutions in the U.S. Stock Market

Figure 1.1 presents the cumulative institutional holdings as a percentage of total stock market value for all institutions, top 100, top 10 and the largest institution ranked by market value of institutional holdings. Figure 1.2 plots institutional holdings as a percentage of total stock market value by five institution types. Figure 1.3 plots the number of total institutions and the number of institutions by five types. All numbers are calculated at the end of each year. The sample period is from 1980 to 2010. Plots related to institution types only span from 1980 to 1997.

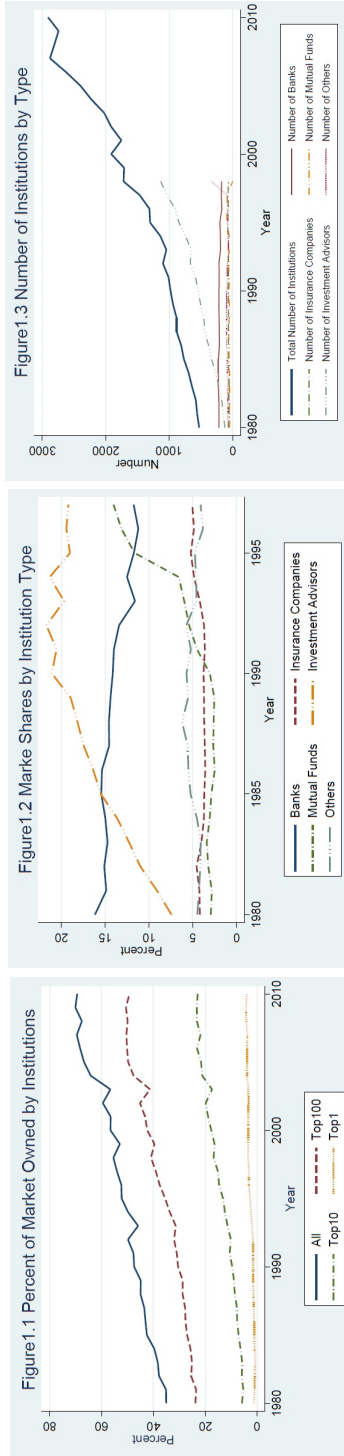


Figure F.2: Bubble/Price Ratio of S&P500 Index.

This Figure shows the replicated results of Wu [66] bubble test. The sample period is from 1871 to 2011. I use the first 20 year data to achieve the stationarity. The actual estimated bubble term b_t starts from 1890.

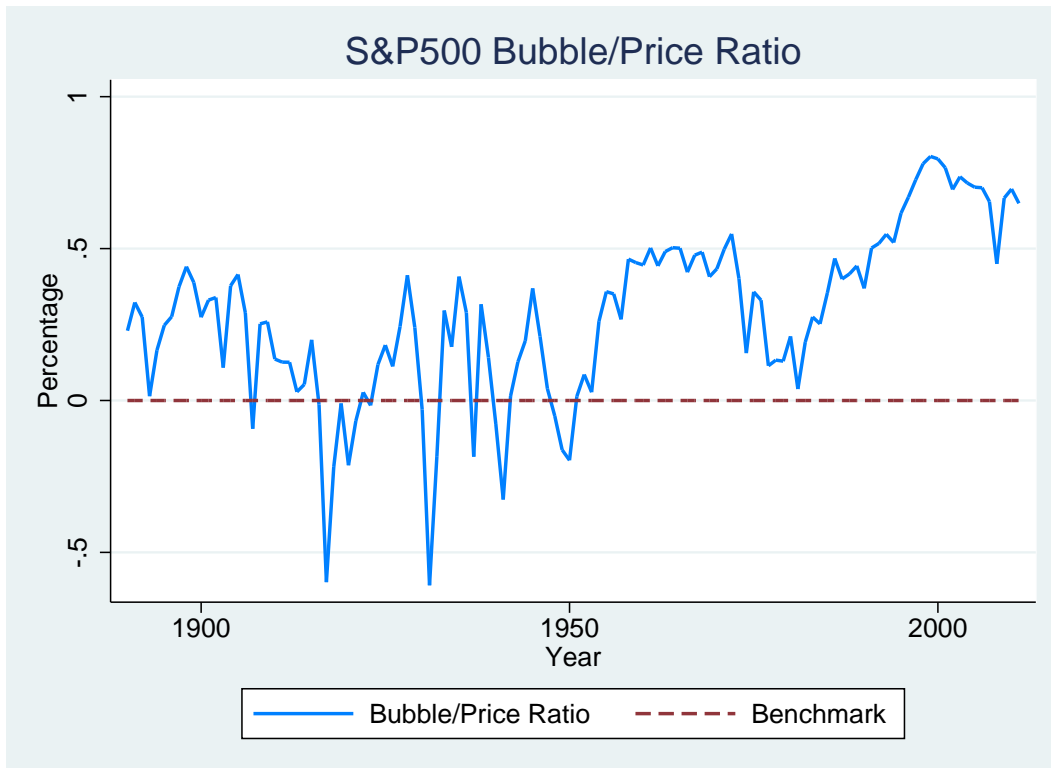


Figure F.3: Weights of Significantly Negative *Alpha* and Significantly Positive *Alpha* stock Portfolios in Aggregate Institutional Investor Portfolio versus Weights in the Market Portfolio.

At the end of each quarter, I include all significantly (10%) negative *alpha* stocks in an overvalued portfolio. And I include all significantly (10%) positive *alpha* stocks in an undervalued portfolio. The weights of overvalued (undervalued) portfolio stocks in the aggregate institutional investor portfolio and the weights of overvalued (undervalued) portfolio in the market portfolio is shown on the top (bottom) panel.

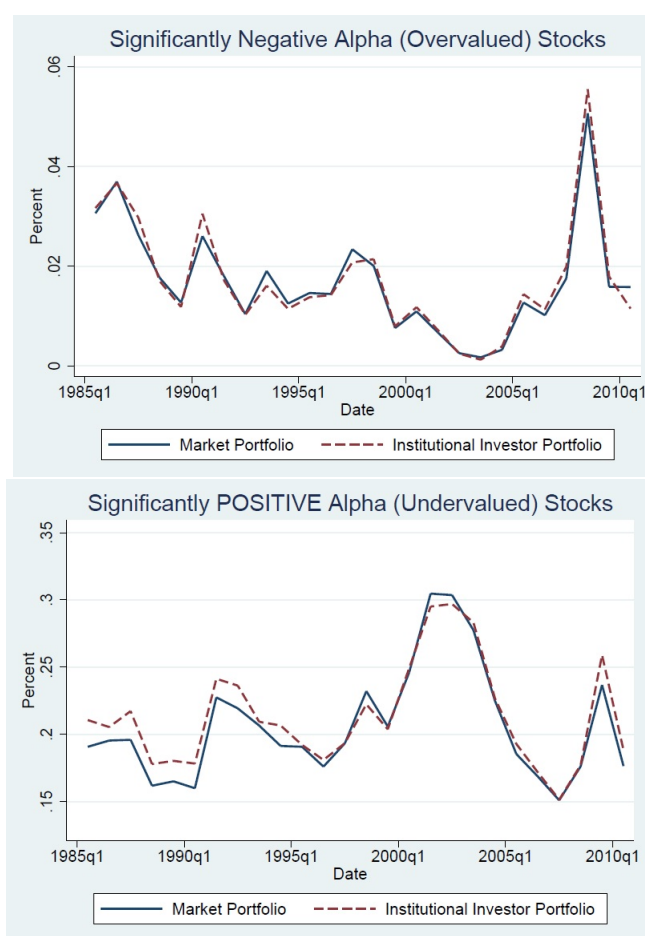
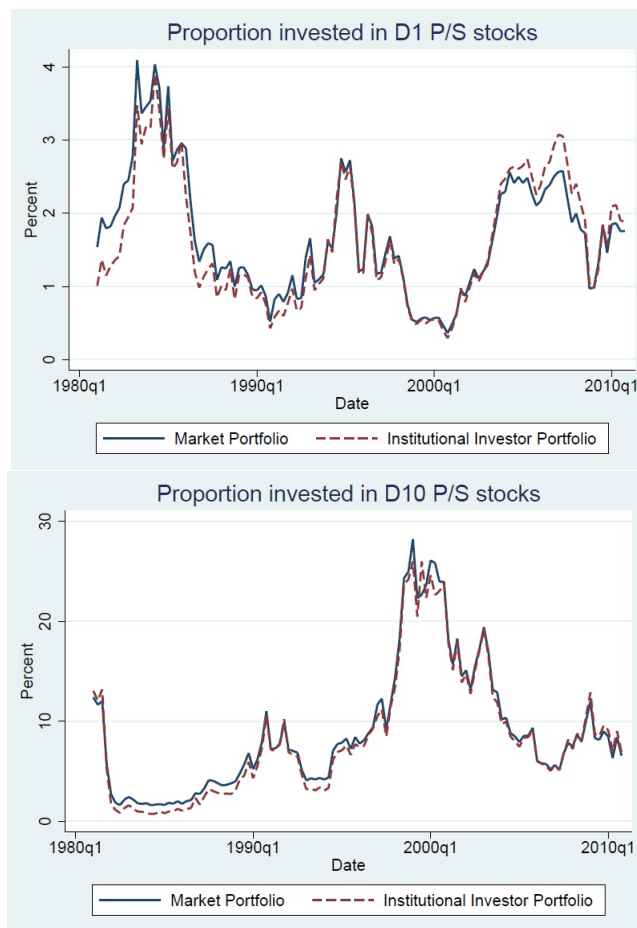


Figure F.4: Weights of Top and Bottom Valuation Ratio Decile Portfolios in Aggregate Institutional Investor Portfolio versus Weights in the Market Portfolio. Excluding Negative Valuation Ratios.

At the end of each quarter, I sort stocks into ten decile portfolio by their P/S, P/E, P/CF, P/EBITDA and P/B ratios. The ratios of the market value of top and bottom decile portfolios to the market portfolio value are calculated at quarterly end as benchmarks (TMV, blue color). The ratios of the market value of top and bottom decile portfolios held by institutions to the market value of aggregate institutional investors' portfolio are also calculated at quarterly end (IH, red color). All the negative valuation ratios are excluded before forming decile portfolios. D1 represents bottom decile portfolio which includes the lowest valuation ratio stocks. D10 represents top decile portfolio which includes the highest valuation ratio stocks. The sample period is from March 1980 to December 2010.



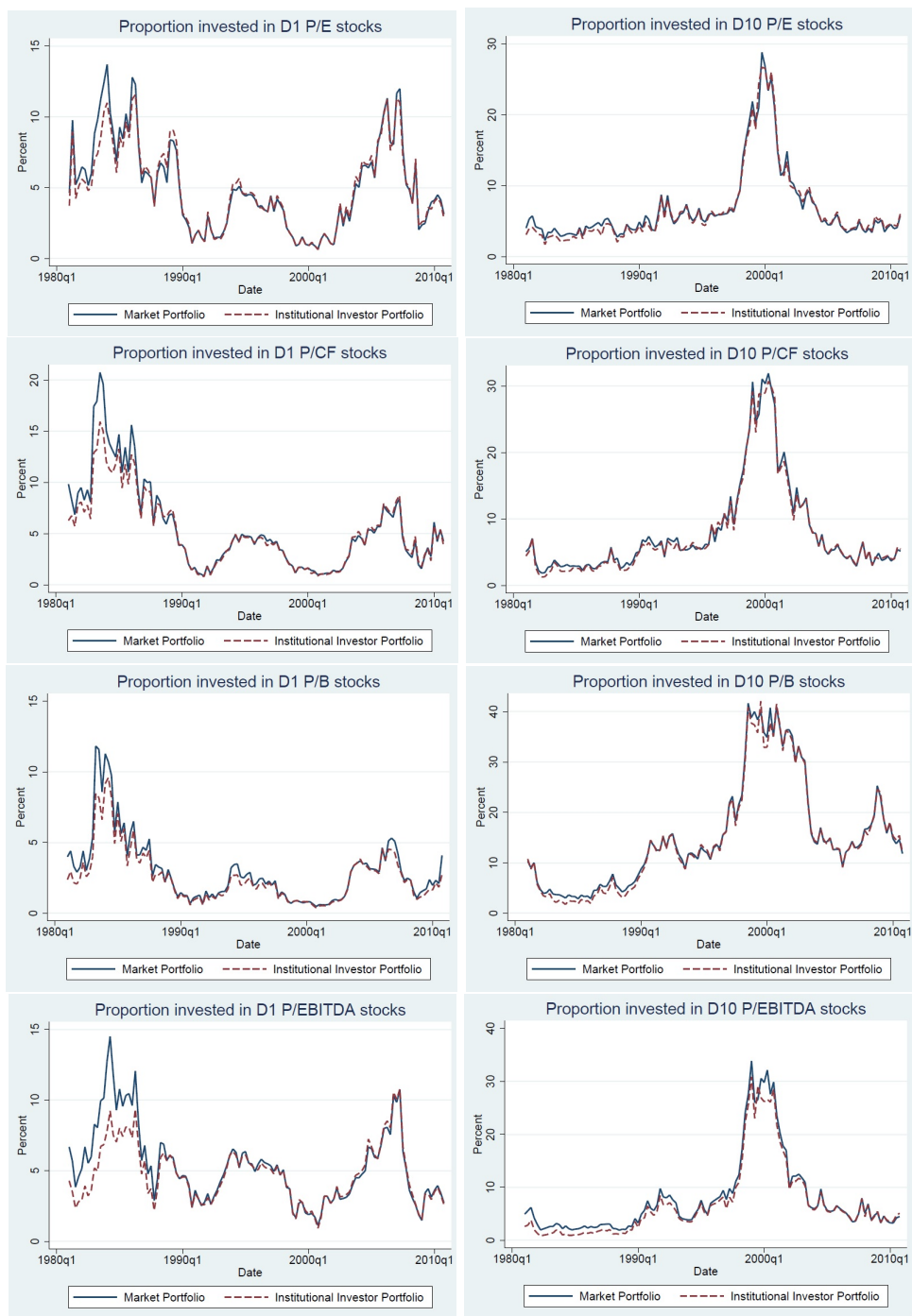


Figure F.5: Weights of Top and Bottom Valuation Ratio Decile Portfolios in Aggregate Institutional Investor Portfolio versus Weights in the Market Portfolio. Transferring Negative Valuation Ratios.

The only difference between this Figure and the above one is that all the negative valuation ratios are transferred to be positive and have higher ranking than the highest positive valuation ratio stock when sorting them into decile portfolios.

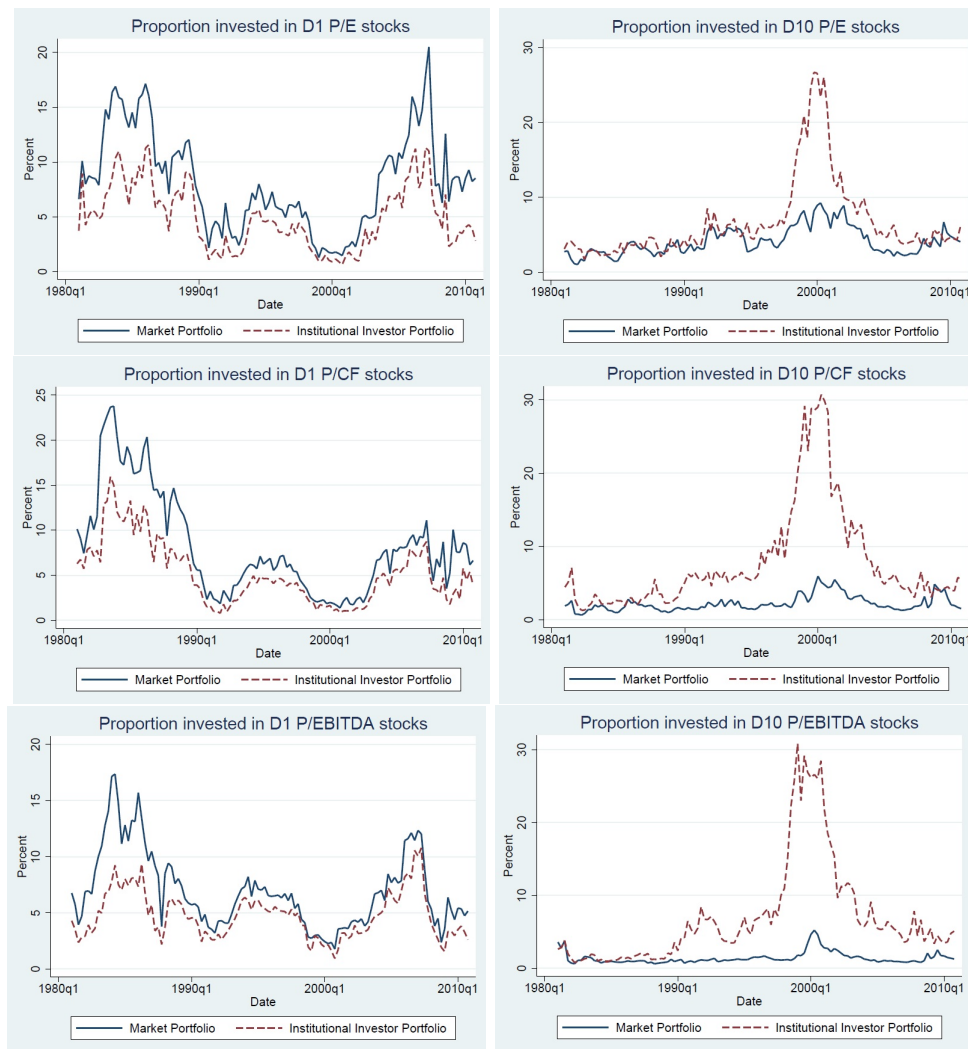


Table F.1: Summary Statistics of Institutional Holdings and Stock Market Data

Panel A. Time Series of Institutional Holdings and Stock Market Data. This table shows the selected market value of institutional holdings, their percentage of the total stock market value, the total number of institutions reporting their holdings, and the number of stocks available on the market. The market value of institutional holdings and total stock market value are in billions of nominal dollars. The sample range is from December 1980 to December 2010.

Year	Number of Reported Institutional Positions	Number of Stocks	Number of Institutions	Total Market Value of Institutional Holdings	Total Stock Market Value	Percentage
Dec-80	90,783	4,698	528	460.91	1,314.65	35.06%
Dec-85	158,129	5,724	769	886.83	2,086.00	42.51%
Dec-90	206,216	5,705	979	1,303.72	2,749.60	47.41%
Dec-95	324,175	6,952	1,302	3,299.82	6,317.43	52.23%
Dec-00	445,079	6,340	1,907	8,094.32	14,316.06	56.54%
Dec-05	510,220	4,758	2,399	9,874.37	14,795.22	66.74%
Dec-10	521,529	3,952	2,908	10,057.83	14,497.44	69.38%

Panel B. Descriptive Statistics. In the first two rows of Panel B, the number of institutional investors and the number of stocks in the stock market are calculated at the end of each quarter, and then the descriptive statistics of these two time-series data are reported. In the last two rows of Panel B, I average the number of stocks in institutional portfolios and the total value of their portfolio across institutions at the end of each quarter, and then the descriptive statistics of time-series of cross-sectional averages are reported. The value of institutional holdings is in billions of nominal dollars. The sample period is 1980-2010.

	Average	Minimum	25 th	75 th	Maximum	Median	S.D.
Number of Institutions	1,436	466	839	1,922	2,907	1,203	740
Number of stocks	4,604	2,878	6,477	4,106	5,020	4,389	820
Number of Stocks in Institution's portfolio	219	161	194	240	269	221	27
Value of institutional holdings	2.54	0.66	0.75	2.27	5.23	0.32	1.34

Panel C. The Number of Institutions Per Stock. This table shows the summary statistics for the number of institutions holding one stock at the year end. All stocks in this summary statistics have at least one institutional owner. The sample period is from 1980 to 2010.

Date	mean(OBS)	med(OBS)	sd(OBS)	max(OBS)
1980/12	26.74	6	52.67	472
1981/12	26.5	6	52.39	497
1982/12	27.29	7	52.65	513
1983/12	27.36	8	52.85	551
1984/12	28.23	8	55.49	592
1985/12	32.23	10	60.91	634
1986/12	32.55	10	61.15	632
1987/12	34.28	11	66.02	687
1988/12	36.62	12	68.74	694
1989/12	39.17	13	73.27	689
1990/12	40.08	14	74.94	736
1991/12	42.29	15	76.2	716
1992/12	46.52	17	81.94	766
1993/12	41.61	16	72.04	728
1994/12	43.98	17	76.62	777
1995/12	49.2	19	85.27	881
1996/12	47.29	18	83.71	902
1997/12	52.86	20	92.1	985
1998/12	59.75	21	106.24	1100
1999/12	72.62	32	117.76	1133
2000/12	82.12	35	130.33	1231
2001/12	86.22	45	126.12	1156
2002/12	96.33	53	134.6	1256
2003/12	113.41	74	144.32	1347
2004/12	124.42	83	151.51	1366
2005/12	125.27	80	157.9	1409
2006/12	134.7	88	165.62	1519
2007/12	138.67	87	176.1	1608
2008/12	133.24	84	170.03	1557
2009/12	147.55	97	182.86	1618
2010/12	156.38	99	194.61	1689

Table F.2: Individual Stock Alpha with Rolling Windows

Panel A. Individual stock monthly returns are fitted to the five factor model with a five-year rolling window at the end of each month: $R_{p,t} - R_{f,t} = \alpha_p + \beta_p(R_{m,t} - R_{f,t}) + s_pSMB_t + h_pHML_t + u_pUMD_t + l_pL_t + \epsilon_{p,t}$; where $R_{m,t} - R_{f,t}$, SMB_t , and HML_t are the Fama and French [29] three factors; UMD_t is the Carhart [22] momentum factor; and L_t is the Pastor and Stambaugh [55] liquidity factor. The *alphas* are estimated from December 1984 to December 2010. **Panel B.** Individual stock monthly returns are fitted to the Carhart [22] four factor model over a five-year rolling window at the end of each month. The *alphas* are estimated from December 1984 to December 2010. **Panel C.** Individual stock monthly returns are fitted to the five factor model with a three-year rolling window at the end of each month. The *alphas* are estimated from December 1982 to December 2010. The summary statistics for the number of negative *alphas*, positive *alphas*, significantly negative *alphas* (20%, two tailed), insignificant *alphas*, and significantly positive *alpha* (20%, two tailed) are reported.

Panel A. Five Factor Model Alphas with Five-Year Rolling Windows					
	Negative	Positive	Significantly Negative at 10%	Insignificant	Significantly Positive at 10%
Maximum	2,812	1,892	262	3,824	381
Minimum	1,698	988	20	2,745	109
Average	2,190	1,491	106	3,356	220
25 Percentile	1,821	1,370	70	2,990	191
75 Percentile	2,494	1,678	145	3,641	244
S.D.	334	200	49	309	47
Panel B. Four Factor Model Alphas with Five-Year Rolling Windows					
	Negative	Positive	Significantly Negative at 10%	Insignificant	Significantly Positive at 10%
Maximum	2,878	1,905	259	3,830	390
Minimum	1,683	943	19	2,756	102
Average	2,191	1,491	104	3,361	217
25 Percentile	1,818	1,371	66	3,002	187
75 Percentile	2,487	1,675	144	3,650	235
S.D.	347	212	49	309	50
Panel A. Five Factor Model Alphas with Three-Year Rolling Windows					
	Negative	Positive	Significantly Negative at 10%	Insignificant	Significantly Positive at 10%
Maximum	3,151	2,396	390	4,553	893
Minimum	1,785	1,282	46	2,971	167
Average	2,519	1,857	169	3,732	474
25 Percentile	2,124	1,648	116	3,466	291
75 Percentile	2,876	2,048	207	3,972	626
S.D.	401	254	68	380	199

Table F.3: Misvaluation and Valuation Ratios

Panel A. Top and Bottom Quintile Portfolios. Each month, all stocks are sorted into five quintile portfolios based on their valuation ratios at the end of the previous month. Stocks in the Quintile 5 portfolios have the highest valuation ratios. Five valuation ratios are used: P/S , P/E , P/CF , $P/EBITDA$, and P/B . Portfolios are rebalanced monthly. Equally-weighted (EW) and value-weighted (VW) monthly portfolio returns are calculated. Portfolios' abnormal returns α_p are estimated by the five factor model: $R_{p,t} - R_{f,t} = \alpha_p + \beta_p(R_{m,t} - R_{f,t}) + s_p SMB_t + h_p HML_t + u_p UMD_t + l_p L_t + \epsilon_{p,t}$ where $R_{m,t} - R_{f,t}$, SMB_t , and HML_t are the Fama and French [29] three factors; UMD_t is the Carhart [22] momentum factor; and L_t is the Pastor and Stambaugh [55] liquidity factor. Portfolio abnormal returns α_p are presented as percentages per month. The sample period is from January 1980 to December 2010. The t-statistics are in parentheses. *, **, *** denote significance levels of 10%, 5%, and 1%, respectively, two-tailed.

	P/S		P/E		P/CF		P/EBITDA		P/B	
	EW	VW	EW	VW	EW	VW	EW	VW	EW	VW
Quintile 5	-0.6 (4.17)***	-0.1 (2.05)**	-0.4 (5.43)***	-0.3 (4.21)***	-0.5 (6.77)***	-0.2 (3.06)***	-0.4 (5.40)***	-0.2 (2.74)***	-0.6 (5.60)***	0 (-0.19)
Quintile 1	1.1 (6.38)***	0.3 (2.26)**	-0.7 (4.95)***	-0.6 (4.20)***	-0.6 (3.00)***	-0.9 (5.43)***	-0.2 (-0.75)	-0.9 (4.56)***	1.5 (8.81)***	0.4 (3.56)***
Quintile 5			-0.5 (6.41)***	-0.3 (3.84)***	-0.5 (6.41)***	-0.2 (-1.91)*	-0.5 (5.39)***	-0.1 (-1.74)*		
Quintile 1			1.7 (15.22)***	0.7 (6.26)***	1.4 (12.82)***	0.4 (4.66)**	1.2 (9.56)***	0.3 (3.09)***		
Quintile 5			-0.8 (5.60)***	-0.7 (4.65)***	-0.7 (3.58)***	-1 (6.08)***	-0.6 (2.35)**	-1.1 (6.19)***		
Adjusting Negative Ratios to Positive Ratios			1.4 (14.09)***	0.5 (5.21)***	1.2 (12.42)***	0.4 (4.60)***	1.1 (9.96)***	0.3 (3.48)***		

Panel B. Decile Portfolios Sorted by Positive Valuation Ratios

Each month, all stocks are sorted into ten decile portfolios based on their valuation ratios at the previous month end. Negative valuation ratio observations have been excluded from the sample. Stocks in the Decile 10 portfolios have the highest valuation ratios. Five valuation ratios are used: P/S , P/E , P/CF , $P/EBITDA$, and P/B . Portfolios are rebalanced monthly. Equally-weighted (EW) and value-weighted (VW) monthly portfolio returns are calculated. Portfolio abnormal returns α_p are estimated by the five factor model: $R_{p,t} - R_{f,t} = \alpha_p + \beta_p(R_{m,t} - R_{f,t}) + s_pSMB_t + h_pHML_t + u_pUMD_t + l_pL_t + \epsilon_{p,t}$ where $R_{m,t} - R_{f,t}$, SMB_t , and HML_t are the Fama and French [29] three factors; UMD_t is the Carhart [22] momentum factor; and L_t is the Pastor and Stambaugh [55] liquidity factor. Portfolio abnormal returns α_p are presented as percentages per month. The sample period is from January 1980 to December 2010. The t-statistics are in parentheses. *, **, *** denote significance levels of 10%, 5%, and 1%, respectively, two-tailed.

	P/S		P/E		P/CF		P/EBITDA		P/B	
	EW	VW	EW	VW	EW	VW	EW	VW	EW	VW
Decile 1	1.5 (6.52)***	0.5 (2.75)***	2 (15.40)***	0.8 (5.60)***	1.7 (12.18)***	0.6 (4.34)***	1.5 (8.32)***	0.4 (2.51)**	2.2 (9.64)***	0.5 (3.06)***
Decile 2	0.8 (5.52)***	0.2 (1.69)*	1.3 (12.94)***	0.6 (5.53)***	1 (11.55)***	0.3 (3.18)***	1 (10.05)***	0.3 (2.50)**	0.8 (6.47)***	0.3 (2.70)***
Decile 3	0.5 (4.92)***	0.1 (0.67)	0.9 (9.28)***	0.4 (3.24)***	0.8 (8.24)***	0.3 (2.70)***	0.8 (9.34)***	0.3 (3.12)***	0.6 (5.63)***	0.1 (0.82)
Decile 4	0.4 (4.11)***	0.1 (1.21)	0.6 (6.09)***	0.2 (2.13)**	0.6 (6.64)***	0.2 (1.62)	0.5 (5.24)***	0 (0.03)	0.3 (3.24)***	0 (0.29)
Decile 5	0.3 (3.35)***	0.1 (0.9)	0.3 (2.85)***	0.2 (2.25)**	0.4 (4.32)***	0 (0.3)	0.3 (3.65)***	0.2 (1.68)*	0.2 (2.10)**	-0.1 (-0.94)
Decile 6	0.2 (2.23)**	0 (0.54)	0.1 (1.28)	0 (0.27)	0.2 (2.73)***	0.1 (0.85)	0.1 (1.36)	0 (-0.31)	0 (0.01)	0 (0.09)
Decile 7	0 (0.43)	0.1 (0.94)	0 (-0.05)	-0.1 (-0.78)	0 (0.42)	0 (0.13)	0 (0.24)	-0.1 (-0.71)	-0.1 (-1.55)	-0.1 (-0.85)
Decile 8	-0.1 (-1.51)	0 (0.19)	-0.2 (-1.72)*	-0.2 (-1.5)	-0.2 (-2.59)**	-0.1 (-0.78)	-0.1 (-1.32)	-0.2 (-1.44)	-0.3 (-2.97)***	0 (0.41)
Decile 9	-0.3 (-3.28)***	-0.1 (-0.64)	-0.4 (-4.25)***	-0.3 (-2.97)***	-0.3 (-3.85)***	0 (-0.43)	-0.3 (-3.56)***	0 (-0.26)	-0.3 (-2.82)***	0 (-0.07)
Decile 10	-0.8 (-3.99)***	-0.2 (-1.73)*	-0.6 (-6.94)***	-0.3 (-2.12)**	-0.7 (-6.55)***	-0.3 (-2.92)***	-0.6 (-5.55)***	-0.3 (-2.66)***	-0.9 (-6.38)***	-0.1 (-0.79)

Panel C. Decile Portfolios Sorted by Transferred Valuation Ratios

I use the following transformation to mitigate the negative valuation ratio issue for P/E , P/CF and $P/EBITDA$. For example, if an observation has a negative $P/E_{i,t}$ ratio, I replace $P/E_{i,t}$ with $Max_i\{P/E_{i,t}\}$ minus $P/E_{i,t}$. Then, all stocks are sorted into ten decile portfolios based on their transformed valuation ratios at the end of the previous month. Stocks in the Decile 10 portfolios have the highest valuation ratios. Portfolios are rebalanced monthly. Equally-weighted (EW) and value-weighted (VW) monthly portfolio returns are calculated. Portfolio abnormal returns α_p are estimated by the five factor model: $R_{p,t} - R_{f,t} = \alpha_p + \beta_p(R_{m,t} - R_{f,t}) + s_p SMB_t + h_p HML_t + v_p UMD_t + l_p L_t + \epsilon_{p,t}$ where $R_{m,t} - R_{f,t}$, SMB_t , and HML_t are the Fama and French [29] three factors; UMD_t is the Carhart [22] momentum factor; and L_t is the Pastor and Stambaugh [55] liquidity factor. Portfolio abnormal returns α_p are presented as percentages per month. The sample period is from January 1980 to December 2010. The t-statistics are in parentheses. *, **, *** denote significance levels of 10%, 5%, and 1%, respectively, two-tailed.

	P/E		P/CFI		P/EBITDA	
	$\frac{EW}{VW}$	$\frac{VW}{EW}$	$\frac{EW}{VW}$	$\frac{VW}{EW}$	$\frac{EW}{VW}$	$\frac{VW}{EW}$
Decile 1	1.8 (15.15)***	0.7 (5.97)***	1.6 (12.70)***	0.5 (4.32)***	1.4 (8.79)***	0.3 (2.40)**
Decile 2	1 (10.76)***	0.5 (4.67)***	0.9 (9.94)***	0.3 (3.15)***	0.9 (10.01)***	0.3 (3.20)***
Decile 3	0.5 (5.32)***	0.3 (2.94)***	0.6 (6.98)***	0.1 (1.28)	0.6 (6.92)***	0.1 (1.41)
Decile 4	0.2 (1.75)*	0.1 (1.13)	0.4 (4.12)***	0.1 (0.98)	0.3 (4.05)***	0.1 (1.16)
Decile 5	0 (0.4)	-0.1 (-0.95)	0.1 (1.53)	0.1 (0.62)	0.1 (1.44)	0 (-0.3)
Decile 6	0.1 (0.7)	-0.3 (2.49)**	-0.1 (-1.3)	-0.1 (-1.14)	0 (0.07)	-0.1 (-0.62)
Decile 7	0.7 (2.56)**	-0.2 (-1.1)	0.1 (0.42)	0 (0.23)	-0.3 (-3.19)**	-0.1 (-1.28)
Decile 8	-0.2 (-0.91)	-1 (-5.10)***	0.5 (1.89)*	-0.3 (-1.4)	-0.4 (-1.8)*	-0.3 (-1.91)*
Decile 9	-0.7 (-4.18)***	-1.1 (-6.23)***	-0.5 (-2.13)**	-1.3 (5.73)***	-0.1 (-0.26)	-1.0 (-3.64)***
Decile 10	-0.9 (-6.84)***	-0.5 (-3.76)***	-0.9 (-5.38)***	-0.9 (4.99)***	-1.1 (5.39)***	-1.3 (6.63)***

Table F.4: Misvaluation by Dispersion of Opinions and Short Sale Constraints

Each month, stocks are sorted into five quintile portfolios based on the dispersion of opinions proxy at the end of the previous month. Then each quintile portfolio is further divided into five groups based on the proxy variable for short sale constraints at the end of the previous month. The dispersion proxy is estimated by vicile-based model in Panel A, and is estimated by continuous-value model in Panel B. The equally weighted (EW) and valued weighted (VW) monthly returns of portfolios with the highest dispersion of opinions and short sale constraints (Q5&Q5) and of portfolios with the lowest dispersion of opinions and short sale constraints (Q1&Q1) are calculated. The five factor model is fitted to portfolio monthly returns and the intercept terms are reported. Both Ordinary Least Squares (OLS) and Weighted Least Squares (WLS) regressions are used. The weights in WLS are the number of stocks in portfolios each month. The t-statistics are in parentheses. *,**,*** denote significance levels of 10%, 5%, and 1%, respectively, two-tailed.

Panel A. Five Factor Model Alpha with Constraint and Dispersion Estimated from Vicile-Based Model

	EW		VW	
	<u>OLS</u>	<u>WLS</u>	<u>OLS</u>	<u>WLS</u>
Q5 & Q5	-1.2 (-2.69)***	-0.9 (-4.06)***	-1.5 (-3.15)***	-1.0 (-3.16)***
Q1 & Q1	0.3 (2.97)***	0.3 (2.92)***	0.1 (0.48)	0.1 (0.61)

Panel B. Five Factor Model Alpha with Constraint and Dispersion Estimated from Continuous-Value Model

	EW		VW	
	<u>OLS</u>	<u>WLS</u>	<u>OLS</u>	<u>WLS</u>
Q5 & Q5	-1.1 (-2.39)**	-0.7 (-3.39)***	-1.8 (-3.36)***	-1.0 (-2.51)**
Q1 & Q1	0.3 (3.10)***	0.3 (3.10)***	0.1 (0.55)	0.1 (0.44)

Table F.5: Institutional Holdings of Misvalued Stocks: Preliminary Summary Statistics

Panel A. Average Institutional Holdings of Significantly Positive *Alpha* Stocks and Significantly Negative *Alpha* Stocks. At each quarter, all stocks are sorted into five quintile groups by their total market value. Then the cross-sectional average of institutional holdings (*IO*) of significantly positive *alpha* stocks and significantly negative *alpha* stocks are both calculated. Panel A reports the time-series mean of cross-sectional average *IO*. *Alphas* are estimated by using the five factor model with five-year rolling windows, four factor model with five-year rolling windows, and five factor model with three-year rolling windows. The significance level for alpha is 10%. Sample period is from January 1980 to December 2010.

		Size Quintile 1	Size Quintile 2	Size Quintile 3	Size Quintile 4	Size Quintile 5
5Y5F	Alpha (+)	5.70%	14.37%	30.42%	48.10%	59.77%
	Alpha (-)	13.07%	29.24%	42.57%	51.04%	56.50%
4F5Y	Alpha (+)	5.36%	14.35%	30.38%	0.48028	59.69%
	Alpha (-)	12.87%	29.51%	42.56%	0.51052	56.27%
5F3Y	Alpha (+)	5.81%	14.91%	28.23%	0.45667	57.73%
	Alpha (-)	10.40%	25.29%	38.15%	0.48296	54.80%

Panel B. Mean Institutional Holding Measures by Quintile Positive Valuation Ratios. Each quarter, stocks are sorted into five quintile portfolios based on each of these five quarterly end valuation ratios: P/S, P/E, P/CF, P/B and P/EBITDA. The cross-sectional averages of stocks' institutional holding measurements are calculated for every portfolio at each quarterly end from March 1981 to December 2010. Panel B reports the time-series averages of cross-sectional average for institutional holding measures. All negative valuation ratio observations are excluded when forming portfolios.

		Q5	Q4	Q3	Q2	Q1
IO	P/S	29.48%	34.20%	35.31%	36.27%	28.14%
	P/E	37.55%	40.60%	39.37%	35.62%	32.28%
	P/CF	36.98%	39.15%	37.47%	37.63%	33.09%
	P/B	30.74%	36.21%	34.28%	31.64%	27.00%
	P/EBITDA	34.95%	39.51%	37.53%	35.96%	32.28%
BHM	P/S	0.61%	0.58%	0.49%	0.38%	0.06%
	P/E	0.84%	0.85%	0.71%	0.55%	0.35%
	P/CF	0.73%	0.70%	0.58%	0.51%	0.29%
	M/B	0.80%	0.76%	0.58%	0.32%	0.02%
	P/EBITDA	0.70%	0.69%	0.58%	0.50%	0.25%
SHM	P/S	0.63%	0.73%	0.59%	0.47%	0.40%
	P/E	0.58%	0.86%	0.79%	0.57%	0.43%
	P/CF	0.68%	0.77%	0.63%	0.62%	0.50%
	P/B	0.76%	0.74%	0.46%	0.32%	0.33%
	P/EBITDA	0.65%	0.76%	0.66%	0.60%	0.47%

Panel C. Mean Institutional Holding Measures by Quintile Transferred Valuation Ratios. Before I assign stocks into quintile portfolios, I transfer all the negative valuation ratios by using the following method: if an observation has negative $P/E_{i,t}$, I replace $P/E_{i,t}$ as $Max_i\{P/E_{i,t}\}$ minus $P/E_{i,t}$. The same transformation is applied for P/CF and P/EBITDA ratios. Each quarter, stocks are sorted into five quintile portfolios based on each of these three quarterly end transferred valuation ratios: P/E, P/CF, and P/EBITDA. The cross-sectional averages of each stock's institutional holding measurements are calculated for each portfolio at the end of each quarter from March 1981 to December 2010. Panel C reports the time-series averages of cross-sectional average for institutional holding measures.

		Q5	Q4	Q3	Q2	Q1
IO	P/E	37.55%	40.60%	39.37%	35.62%	32.28%
	P/CF	36.98%	39.15%	37.47%	37.63%	33.09%
	P/EBITDA	34.95%	39.51%	37.53%	35.96%	32.28%
BHM	P/E	0.84%	0.85%	0.71%	0.55%	0.35%
	P/CF	0.73%	0.70%	0.58%	0.51%	0.29%
	P/EBITDA	0.70%	0.69%	0.58%	0.50%	0.25%
SHM	P/E	0.22%	0.46%	0.80%	0.73%	0.46%
	P/CF1	0.21%	0.69%	0.75%	0.60%	0.54%
	P/EBITDA	0.25%	0.69%	0.72%	0.60%	0.50%

Panel D. Mean Institutional Holding Measures by Decile Positive Valuation Ratios. Each quarter, stocks are sorted into ten decile portfolios based on each of these five quarterly end valuation ratios: P/S, P/E, P/CF, P/B and P/EBITDA. The cross-sectional averages of stocks' institutional holding measurements are calculated for every portfolio at each quarterly end from March 1981 to December 2010. Panel D reports the time-series averages of cross-sectional average for institutional holdings of Decile 10 and Decile 1 portfolios. All negative valuation ratio observations are excluded when forming portfolios.

		D10	D1			D10	D1			D10	D1
	P/S	24.42%	24.83%	P/S	0.47%	-0.08%	P/S	0.45%	0.44%		
	P/E	36.62%	30.27%	P/E	0.77%	0.28%	P/E	0.48%	0.41%		
IO	P/CF	35.01%	30.30%	BHM	P/CF	0.62%	0.17%	SHM	P/CF	0.55%	0.44%
	P/B	27.16%	25.62%	P/B	0.69%	-0.06%	P/B	0.71%	0.40%		
	P/EBITDA	31.44%	30.03%	P/EBITDA	0.58%	0.12%	P/EBITDA	0.52%	0.43%		

Panel E. Average Institutional Ownership of Overvalued (Undervalued) Stocks with Highest (Lowest) Dispersion of Opinions and Highest (Lowest) Short Sale Constraints. At each quarter, the cross-sectional average of institutional ownership of stocks with top (bottom) decile dispersion of opinions and top (bottom) decile short sale constraints is calculated. The time-series means of the cross-sectional average are reported. The sample period is 1980-2010

	Dispersion of Opinions Decile10 & Short Sale Constraints Decile 10	Dispersion of Opinions Decile1 & Short Sale Constraints Decile 1
IO	26.91%	24.38%

Panel F. Average Institutional Ownership and Stock Misvaluation Estimated by an Earnings Discounted Model. The fair value of stocks at each quarter are estimated by discounting future five year quarterly earnings and a terminal value. Average of a stock's book value and market value is used as a proxy for the fifth-year end terminal value. Quarterly discounted rate is estimated by the CAPM model based on individual stock's daily return over that quarter. Stock industries are defined by using Fama-French 49 industries. The first two columns report the time-series mean of cross-sectional average of institutional ownerships of stocks whose market value is greater than the fair value and whose market value is lower than the fundamental value. Then for each stock at each quarter, I define a stock's degree of misvaluation as $(\text{Market Value} - \text{Fair Value}) / \text{Fair Value}$. I sort all stocks into 20 portfolios based on their degree of misvaluation at each quarter. The third and fourth column of Panel F report the time-series mean of cross-sectional average of institutional ownership of stocks whose degree of misvaluation is among the top 5% and the bottom 5%

	MV>FV	MV<FV	Top 5% SDM	Bottom 5% SDM
IO	30.78%	27.43%	28.93%	21.54%

Table F.6: Cross Sectional Studies of Institutional Holdings and Stock *Alphas*

Panel A. Institutional Ownership *IO* and Individual Stock 5-Factor-5-Year-Rolling *Alphas*. This Panel presents the results of cross-sectional regression of quarterly institutional holdings of individual stocks on stock rolling *Alphas* and other stock characteristics. The dependent variable is the institutional ownership as a percentage of the firm's market capitalization (*IO*). Independent variable $Alpha_i$ is a dummy variable which is equal to 1 (-1) if $Alpha_i$ estimated by the 5 factor model with 5-year rolling windows is positive (negative) at 10%. Other independent variables are following Gompers and Metrick [34]: *Size*, *B/M*, *DividendYield*, *Price*, *Momentum1*, *Momentum2*, *Turnover* and *S&P500 Dummy*. The sample size ranges from December 1984 to December 2010. White [65] standard errors are used in the quarterly cross-sectional regressions. The table reports the average regression coefficients on 105 separate quarterly OLS regressions. And the table also reports the number of positive coefficients, the number of significantly positive coefficients at 5% level, number of negative coefficients, and the number of significantly negative coefficients at 5% level.

Variable	Average Coefficient	Pos	Pos/Sig*	Neg	Neg/Sig*
Significant_Alpha_Dummy	-0.041	9	0	96	67
Size	0.049	105	105	0	0
Q	-0.002	27	12	78	43
Yield	-0.016	3	0	102	70
Price	0.054	105	85	0	0
Volatility	-0.015	17	0	88	28
Momentum1	-0.040	16	0	89	32
Momentum2	-0.038	8	0	97	58
Turnover	0.072	105	105	0	0
S&P500 Dummy	-0.063	30	11	75	53
Constant	-0.478	8	0	97	84

* Significant at 5%

Panel B. Institutional Buy Herding Measure and Individual Stock 5-Factor-5-Year-Rolling Alphas. This Panel presents the results of cross-sectional regression of quarterly institutional buy herding measure *BHM* on stock rolling *Alphas* and other stock characteristics. The dependent variable is the institutional ownership as a percentage of the firm's market capitalization (*IO*). Independent variable $Alpha_i$ is a dummy variable which is equal to 1 (-1) if $Alpha_i$ estimated by the 5 factor model with 5-year rolling windows is positive (negative) at 10%. Other independent variables are following Gompers and Metrick [34]: *Size*, *B/M*, *DividendYield*, *Price*, *Momentum1*, *Momentum2*, *Turnover* and *S&P500 Dummy*. The sample size ranges from December 1984 to December 2010. White [65] standard errors are used in the quarterly cross-sectional regressions. The table reports the average regression coefficients on 105 separate quarterly OLS regressions. And the table also reports the number of positive coefficients, the number of significantly positive coefficients at 5% level, number of negative coefficients, and the number of significantly negative coefficients at 5% level.

Variable	Average Coefficient	Pos	Pos/Sig*	Neg	Neg/Sig*
Significant_Alpha_Dummy	-0.001	45	5	60	8
Size	0.021	105	104	0	0
Q	0.000	41	6	64	17
Yield	0.000	51	3	54	5
Price	-0.005	27	2	78	21
Volatility	-0.001	45	1	60	3
Momentum1	-0.005	44	1	61	8
Momentum2	-0.004	32	4	73	20
Turnover	0.007	94	45	11	0
S&P500 Dummy	0.011	69	26	32	6
Constant	-0.347	0	0	105	100

* Significant at 5%

Panel C. Institutional Sell Herding Measure and Individual Stock 5-Factor-5-Year-Rolling Alphas. This Panel presents the results of cross-sectional regression of quarterly institutional sell herding measure SHM on stock rolling $Alphas$ and other stock characteristics. The dependent variable is the institutional ownership as a percentage of the firm's market capitalization (IO). Independent variable $Alpha_i$ is a dummy variable which is equal to 1 (-1) if $Alpha_i$ estimated by the 5 factor model with 5-year rolling windows is positive (negative) at 10%. Other independent variables are following Gompers and Metrick [34]: $Size$, B/M , $DividendYield$, $Price$, $Momentum1$, $Momentum2$, $Turnover$ and $S\&P500$ Dummy. The sample size ranges from December 1984 to December 2010. White [65] standard errors are used in the quarterly cross-sectional regressions. The table reports the average regression coefficients on 105 separate quarterly OLS regressions. And the table also reports the number of positive coefficients, the number of significantly positive coefficients at 5% level, number of negative coefficients, and the number of significantly negative coefficients at 5% level.

Variable	Average Coefficient	Pos	Pos/Sig*	Neg	Neg/Sig*
Significant_Alpha_Dummy	0.003	66	8	39	3
Size	0.006	92	38	13	1
Q	0.000	54	14	51	9
Yield	-0.001	39	0	66	13
Price	-0.009	26	1	79	17
Volatility	-0.001	52	0	53	4
Momentum1	0.003	49	3	56	2
Momentum2	0.006	63	7	42	1
Turnover	0.004	77	22	28	0
S&P500 Dummy	0.005	60	14	45	6
Constant	-0.078	24	2	81	30

* Significant at 5%

Table F.7: Pooled Regression with Two Dimensional Clustered Standard Errors

Panel A. Institutional Ownership IO and Individual Stock 5-Factor-5-Year-Rolling $Alphas$. This table presents the pooled regression results of $IOMeasure_i = C_{i,t} + \alpha_i + X_i\beta_i + \epsilon_i$. And I cluster the standard errors by both firm and quarter. The dependent variable is IO_i , the percentage of institutional ownership of stock i . Independent $Alpha$ is estimated by the 5 factor model with 5-year rolling windows on stock monthly returns. Other independent variables are following Gompers and Metrick [34]: $Size$, B/M , $DividendYield$, $Price$, $Momentum1$, $Momentum2$, $Turnover$ and $S\&P500$ Dummy. The absolute value of t-statistics are in parentheses. The sample period is from December 1984 to December 2010.

	(1)	(2)	(3)	(4)	(5)
Significant_Alpha_Dummy	-0.042 (9.03)***				
Significant_Alpha		-1.133 (9.35)***			
Significant_Alpha_Lag			-1.122 (8.99)***		
Alpha				-1.405 (12.36)***	
Alpha_Dummy					-0.023 (12.44)***
Size	0.065 (21.75)***	0.065 (21.69)***	0.066 (21.61)***	0.066 (28.45)***	0.066 (28.30)***
Q	-0.0000 (1.31)	-0.0000 (0.35)	-0.0000 (0.37)	-0.0000 (1.79)	-0.0000 (1.85)
Yield	-0.012 (6.07)***	-0.011 (6.20)***	-0.011 (5.50)***	-0.012 (10.85)***	-0.012 (10.98)***
Price	0.03 (4.70)***	0.027 (4.63)***	0.026 (4.47)***	0.037 (8.50)***	0.035 (8.12)***
Volatility	-0.016 (3.76)***	-0.008 (1.83)*	-0.011 (2.48)**	0 (0.04)	-0.005 (1.52)
Momentum1	-0.048 (4.96)***	-0.044 (4.59)***	0.016 (2.33)**	-0.039 (4.66)***	-0.043 (5.16)***
Momentum2	-0.034 (6.23)***	-0.032 (5.94)***	-0.032 (5.66)***	-0.033 (6.85)***	-0.036 (7.26)***
Turnover	0.079 (18.65)***	0.08 (18.74)***	0.08 (18.95)***	0.069 (18.42)***	0.068 (18.38)***
S&P500 Dummy	-0.106 (8.90)***	-0.105 (8.84)***	-0.108 (8.99)***	-0.083 (7.14)***	-0.081 (7.00)***
Constant	-0.689 (13.02)***	-0.642 (12.04)***	-0.667 (12.41)***	-0.697 (17.84)***	-0.717 (18.40)***
Observations	64,348	64,348	63,024	357,109	357,109
R-squared	0.59	0.59	0.59	0.59	0.59

Absolute value of t statistics in parentheses

* significant at 10%; ** significant at 5%; *** significant at 1%

Panel B. Institutional Buy Herding Measure and Individual Stock 5-Factor-5-Year-Rolling Alphas. This table presents the pooled regression results of $IOMeasure_i = C_{i,t} + \alpha_i + X_i\beta_i + \epsilon_i$. And I cluster the standard errors by both firm and quarter. The dependent variable is the institutional buy herding measure BHM [37, 63]. Independent $Alpha$ is estimated by the 5 factor model with 5-year rolling windows on stock monthly returns. Other independent variables are following Gompers and Metrick [34]: $Size$, B/M , $DividendYield$, $Price$, $Momentum1$, $Momentum2$, $Turnover$ and $S\&P500$ Dummy. The absolute value of t-statistics are in parentheses. The sample period is from December 1984 to December 2010.

	(1)	(2)	(3)	(4)	(5)
Significant_Alpha_Dummy	-0.0019 (1.93)*				
Significant_Alpha		-0.1349 (5.96)***			
Significant_Alpha_Lag			-0.1039 (3.61)***		
Alpha				-0.0794 (4.26)***	
Alpha_Dummy					-0.0009 (2.52)**
Size	0.0134 (19.08)***	0.0135 (19.38)***	0.0129 (15.02)***	0.0119 (18.47)***	0.0119 (18.43)***
Q	0.0000 (1.9)*	0.0000 (1.9)*	0.0000 (1.78)*	0.0000 (1.93)*	0.0000 (1.99)**
Yield	-0.0001 (0.43)	-0.0001 (0.48)	-0.0002 (0.83)	0.0005 (2.37)**	0.0005 (2.39)**
Price	0.0000 (0.01)	0.0009 (1.04)	0.0011 (1.17)	0.0011 (1.49)	0.0008 (1.12)
Volatility	-0.0004 (0.31)	0.0012 (1.01)	0.0006 (0.54)	-0.0009 (1.00)	-0.0013 (1.51)
Momentum1	-0.0028 (1.15)	-0.0019 (0.79)	-0.0027 (1.15)	-0.0023 (1.45)	-0.0026 (1.58)
Momentum2	-0.0012 (1.52)	-0.0006 (0.84)	-0.0007 (0.85)	-0.0011 (1.59)	-0.0013 (1.88)*
Turnover	0.0033 (5.13)***	0.0033 (5.15)***	0.0034 (5.44)***	0.0034 (7.41)***	0.0034 (7.38)***
S&P500 Dummy	0.0182 (3.75)***	0.0170 (3.54)***	0.0171 (3.66)***	0.0269 (5.95)***	0.0272 (5.98)***
Constant	-0.2281 (17.67)***	-0.2241 (17.66)***	-0.2173 (15.27)***	-0.2064 (18.16)***	-0.2077 (18.22)***
Observations	23,695	23,695	23,951	128,444	128,444
R-squared	0.1974	0.2003	0.1947	0.1834	0.1830

Absolute value of t statistics in parentheses

* significant at 10%; ** significant at 5%; *** significant at 1%

Panel C. Institutional Sell Herding Measure and Individual Stock 5-Factor-5-Year-Rolling Alphas. This table presents the pooled regression results of $IOMeasure_i = C_{i,t} + \alpha_i + X_i\beta_i + \epsilon_i$. And I cluster the standard errors by both firm and quarter. The dependent variable is the institutional sell herding measure SHM [37, 63]. Independent $Alpha$ is estimated by the 5 factor model with 5-year rolling windows on stock monthly returns. Other independent variables are following Gompers and Metrick [34]: $Size$, B/M , $DividendYield$, $Price$, $Momentum1$, $Momentum2$, $Turnover$ and $S\&P500$ Dummy. The absolute value of t-statistics are in parentheses. The sample period is from December 1984 to December 2010.

	(1)	(2)	(3)	(4)	(5)
Significant_Alpha_Dummy	0.0022 (2.16)**				
Significant_Alpha		0.0045 (0.13)			
Significant_Alpha_Lag			0.0357 (0.94)		
Alpha				0.0532 (1.83)*	
Alpha_Dummy					0.0011 (3.15)***
Size	0.0046 (6.50)***	0.0047 (6.87)***	0.0046 (6.36)***	0.0043 (7.55)***	0.0043 (7.53)***
Q	0.0000 (1.12)	0.0000 (1.17)	0.0000 (1.37)	0.0000 (1.30)	0.0000 (1.29)
Yield	-0.0009 (3.36)***	-0.0009 (3.74)***	-0.0010 (4.21)***	0.0000 (0.12)	0.0000 (0.19)
Price	-0.0063 (4.99)***	-0.0054 (4.33)***	-0.0056 (4.74)***	-0.0052 (4.84)***	-0.0052 (4.89)***
Volatility	0.0008 (0.69)	0.0011 (0.91)	0.0008 (0.69)	0.0006 (0.72)	0.0007 (0.92)
Momentum1	0.0067 (1.61)	0.0073 (1.73)*	0.0060 (1.46)	0.0055 (1.80)*	0.0056 (1.83)*
Momentum2	0.0035 (1.78)*	0.0039 (2.02)**	0.0037 (1.90)*	0.0022 (1.18)	0.0023 (1.22)
Turnover	0.0011 (1.21)	0.0009 (1.04)	0.0008 (0.96)	0.0009 (1.35)	0.0009 (1.39)
S&P500 Dummy	0.0114 (4.69)***	0.0107 (4.47)***	0.0113 (4.66)***	0.0138 (5.96)***	0.0138 (5.94)***
Constant	-0.0553 (4.15)***	-0.0588 (4.54)***	-0.0577 (4.45)***	-0.0586 (5.85)***	-0.0579 (5.75)***
Observations	35,278	35,278	35,969	190,631	190,631
R-squared	0.0225	0.0222	0.0225	0.0200	0.0201

Absolute value of t statistics in parentheses
 * significant at 10%; ** significant at 5%; *** significant at 1%

Table F.8: Cross-Sectional Analysis on Institutional holdings and Stock *Alphas* by Institution Type

This table presents the results of pooled regressions of quarterly institutional ownership on individual stock rolling *alphas*, controlling for other stock characteristics. The standard errors are clustered by both firm and quarter. Following Kamara et al. [46], I divide these five institutional investors into three groups: banks and insurance companies, investment companies and independent investment advisors, and others. Only the coefficients for *alpha* are reported. *Alphas* are estimated by the 5 factor model with 5 year rolling windows on stock monthly returns. The sample period is from December 1984 to December 1997. The t-statistics are in parentheses. *,**,*** denote significance levels of 10%, 5%, and 1%, respectively, two-tailed.

	Bank & Insurance	Investment Company & Independent Investment Advisor	All Others (Pension, University Endowment, Foundation)
Significant_Alpha_Dummy	-0.0029 (1.78)*	-0.0218 (4.72)***	-0.0030 (3.2)***
Significant_Alpha	0.3182 (6.83)***	-0.8622 (6.07)***	-0.0822 (4.03)***
Significant_Alpha_Lag	-0.3356 (6.79)***	-0.9029 (6.07)***	-0.0855 (4.01)***
Alpha	-0.3133 (10.32)***	-0.9288 (10.29)***	-0.0970 (6.24)***
Alpha_Dummy	-0.0026 (4.73)***	-0.0129 (9.15)***	-0.0015 (4.85)***

Table F.9: Cross-Sectional Analysis on Institutional holdings and Stock Misvaluation Estimated by an Earnings Discounted Model

This table presents the results of pooled regressions of quarterly institutional ownership on individual stock SDM , controlling for other stock characteristics. The standard errors are clustered by both firm and quarter. Only the coefficients for SDM are reported. The dependent variables are IO for all institutional investors, Banks&Insurance, Investment Company & Investment Advisors, and All Others respectively for each column. On the first row, the independent variable SDM is the winsorized actual value of SDM with 2.5% tail percentage. On the second row, the independent variable SDM is the dummy variable which is 1 if actual SDM is positive and 0 otherwise. The table presents the time-series average of cross-sectional regression coefficients. The t-statistics are in parentheses. *,**,*** denote significance levels of 10%, 5%, and 1%, respectively, two-tailed.

	All Institutions	Banks & Insurance	Investment Company & Independent Investment Advisor	All Others (Pension, Endowment, Foundation)
SDM	0.00069 (4.52)***	0.00002 (1.62)	0.00045 (6.21)***	0.00005 (3.37)***
SDM_Dummy	0.00274 (5.53)***	0.00035 (1.73)*	0.00276 (2.88)***	0.00046 (5.14)***

Table F.10: Time Series of Institutional Holdings and the Degree of Stock Overvaluation

Panel A. Time Series Relationship between Institutional Ownership and S&P500 Index Bubbles The first two columns show the unit root and the time trend tests for IO_t , b_t : $Y_t - Y_{t-1} = C + (\lambda - 1)Y_{t-1} + \beta T + \epsilon_i$. The third column show that time-series relationship between institutional ownership IO_t and the bubble term b_t of S&P 500 index. The bubble term b_t is estimated as the unobserved terms in the dividend discount model by using Kalman filter. All the time-series data are annual. The sample period is from 1980 to 2010. The t-statistics are in parentheses. *,**,*** denote significance levels of 10%, 5%, and 1%, respectively, two-tailed.

	Delta IO	Delta Bubble	Detrend IO
IO_Lag	-0.695 (-3.81)***		
T	0.009 (3.65)***		
Bubble_Lag		-0.274 (-1.98) *	
T		0.004 (1.19)	
Bubble			0.141 (5.29)***
Constant	0.266 (4.05)***	0.092 (2.25)**	0.367 (24.57)***
Observations	30	30	31
R-squared	0.36	0.15	0.49

Panel B. Dickey-Fuller Test for Unit Root This Panel shows the unit root and the time trend tests for IO_t , b_t and $alpha_t$: $Y_t - Y_{t-1} = C + (\lambda - 1)Y_{t-1} + \beta T + \epsilon_i$. The t-statistics are in parentheses. *,**,*** denote significance levels of 10%, 5%, and 1%, respectively, two-tailed.

	Delta IO	Delta B	Delta Alpha
IO_Lag	-0.336 (-4.61)***		
Bubble_Lag		-0.059 (-1.8) *	
Alpha_Lag			-0.059 (-1.76) *
T	0.001 (4.38)***	0 (-0.82)	0 (1.61)
Constant	0.112 (4.53)***	0.026 (1.87) *	0 (-0.57)
Observations	108	108	100
R-squared	0.16	0.03	0.11

Panel C. Detrended IO and the Degree of Overvaluation: Top Quintile P/S Portfolio The quarterly institutional percentage holdings of the overvalued portfolio IO_t are regressed on the time-series of bubble term b_t and the five factor model $alpha_t$. The sample period for the first two regressions is from December 1983 to December 2010. The overvalued portfolio is composed of the top quintile P/S ratio stocks. The sample period for the third regression is from December 1984 to December 2010. The t-statistics are in parentheses. *,**,*** denote significance levels of 10%, 5%, and 1%, respectively, two-tailed.

	Detrended IO	Detrended IO
Bubble	0.358 (9.00)***	
Alpha		-8.307 (-2.22)**
Constant	0.209 (6.74)***	0.486 (69.27)***
Observations	109	101
R-squared	0.43	0.05

Panel D. Detrended IO and the Degree of Overvaluation: Top Quintile P/E Portfolio The quarterly institutional percentage holdings of the overvalued portfolio IO_t are regressed on the time-series of bubble term b_t and the five factor model $alpha_t$. The overvalued portfolio is composed of the top quintile P/E ratio stocks. The sample period is from December 1984 to December 2010. The t-statistics are in parentheses. *,**,*** denote significance levels of 10%, 5%, and 1%, respectively, two-tailed.

	Detrend IO	Detrend IO
Bubble	0.262 (8.58)***	
Alpha		-14.058 (-2.93)***
Constant	0.329 (18.34)***	0.452 (34.47)***
Observations	109	101
R-squared	0.41	0.08

Panel E. Detrended IO and the Degree of Overvaluation: Significant Alpha Portfolio The quarterly institutional percentage holdings of the overvalued portfolio and undervalued portfolio IO_t are regressed on the five factor model $alpha_t$. The overvalued portfolio is composed of the significantly negative $alpha$ stocks and the undervalued portfolio is composed of the significantly positive $alpha$ stocks. The sample period is from December 1984 to December 2010. The t-statistics are in parentheses. *,**,*** denote significance levels of 10%, 5%, and 1%, respectively, two-tailed.

	Detrend IO Overvalued	Detrend IO Undervalued
Alpha_Overvalued	-9.8 (-3.53)***	
Alpha_Undervalued		1.299 (0.76)
Constant	0.321 (6.63)***	0.501 (14.11)***
Observations	105	105
R-squared	0.11	0.01

Table F.11: Hansen-Hordrick Standard Errors for Overlapping *Alpha* Estimators

This table presents the regression results of $IOMeasure_i = C_{i,t} + \alpha_i + X_i\beta_i + \epsilon_i$. And I use Hansen-Hordrick standard error estimators to fix the overlapping *Alpha* estimation problem. The dependent variable is IO_i , the percentage of institutional ownership of stock i . The absolute value of t-statistics are in parentheses. The sample period is from December 1984 to December 2010.

	(1)	(2)	(3)	(4)	(5)
Significant_Alpha_Dummy	-0.0421 (21.15)***				
Significant_Alpha		-1.1574 (20.35)***			
Significant_Alpha_Lag			-1.2381 (21.42)***		
Alpha				-1.4049 (26.86)***	
Alpha_Dummy					-0.0227 (25.5)***
Size	0.0651 (47.54)***	0.0643 (46.97)***	0.0650 (48.81)***	0.0658 (60.77)***	0.0658 (60.61)***
Q	0.0000 (0.94)	0.0000 (0.82)	0.0000 (0.66)	0.0000 (4.75)***	0.0000 (5.08)***
Yield	-0.0122 (20.08)***	-0.0117 (19.32)***	-0.0117 (19.87)***	-0.0121 (29.28)***	-0.0121 (29.40)***
Price	0.0296 (13.34)***	0.0274 (12.50)***	0.0293 (13.74)***	0.0373 (22.24)***	0.0351 (21.12)***
Volatility	-0.0164 (9.20)***	-0.0088 (4.75)***	-0.0084 (4.70)***	0.0001 (0.10)***	-0.0052 (4.39)***
Momentum1	-0.0482 (18.47)***	-0.0441 (16.82)***	-0.0590 (22.23)***	-0.0391 (33.65)***	-0.0428 (36.46)***
Momentum2	-0.0344 (25.10)***	-0.0320 (23.33)***	-0.0335 (24.02)***	-0.0332 (44.89)***	-0.0363 (48.01)***
Turnover	0.0795 (62.94)***	0.0811 (64.29)***	0.0820 (65.89)***	0.0686 (74.34)***	0.0683 (73.86)***
S&P500 Dummy	-0.1055 (19.06)***	-0.1049 (18.96)***	-0.1119 (20.81)***	-0.0827 (17.87)***	-0.0808 (17.43)***
Constant	-0.6892 (27.80)***	-0.6309 (25.49)***	-0.6395 (26.42)***	-0.6966 (36.05)***	-0.7172 (37.02)***
Observations	64,348	64,348	65,381	64,348	357,109
Centered R2	0.5896	0.5895	0.5891	0.5906	0.5884

Absolute value of t statistics in parentheses

* significant at 10%; ** significant at 5%; *** significant at 1%

Table F.12: Five-Year Average of Institutional Ownership IO and Individual Stock 5-Factor-5-Year-Rolling $Alphas$.

This table presents the pooled regression results of $IO_{Measure_i} = C_{i,t} + \alpha_i + X_i\beta_i + \epsilon_i$. And I cluster the standard errors by both firm and quarter. The dependent variable is $IO_{Average}$, the average of five year quarterly institutional ownership of stock i . Independent $Alpha$ is estimated by the 5 factor model with 5-year rolling windows on stock monthly returns. Other independent variables are following Gompers and Metrick [34]: $Size$, B/M , $DividendYield$, $Price$, $Momentum1$, $Momentum2$, $Turnover$ and $S\&P500$ Dummy. The absolute value of t-statistics are in parentheses. The sample period is from December 1984 to December 2010.

	(1)	(2)	(3)	(4)	(5)
Significant_Alpha_Dummy	-0.0616 (13.08)***				
Significant_Alpha		-1.9309 (13.18)***			
Significant_Alpha_Lag			-2.0926 (10.65)***		
Alpha				-2.2095 (14.62)***	
Alpha_Dummy					-0.0315 (15.8)***
Size	0.0702 (24.66)***	0.0692 (24.36)***	0.0708 (22.83)***	0.0662 (26.54)***	0.0661 (25.99)***
Q	0.0000 (1.10)	0.0000 (0.92)	0.0000 (0.66)	0.0000 (2.15)**	0.0000 (2.20)**
Yield	-0.0089 (5.16)***	-0.0082 (4.99)***	-0.0083 (5.07)***	-0.0093 (9.19)***	-0.0094 (9.36)***
Price	0.0042 (0.78)	0.0041 (0.84)	0.0065 (1.1)	0.0204 (5.12)***	0.0159 (4.01)***
Volatility	-0.0178 (4.84)***	-0.0035 (0.92)	-0.0016 (0.36)	0.0071 (1.98)*	-0.0020 (0.58)
Momentum1	-0.0456 (4.09)***	-0.0370 (3.36)***	-0.0621 (5.54)***	-0.0294 (3.12)***	-0.0359 (3.83)***
Momentum2	-0.0415 (5.57)***	-0.0365 (5.22)***	-0.0384 (5.20)***	-0.0370 (5.82)***	-0.0426 (6.32)***
Turnover	0.0633 (15.88)***	0.0654 (16.74)***	0.0669 (17.60)***	0.0586 (16.95)***	0.0583 (16.78)***
S&P500 Dummy	-0.0535 (5.07)***	-0.0553 (5.12)***	-0.0665 (4.77)***	-0.0456 (4.32)***	-0.0415 (3.97)***
Constant	-0.8324 (16.78)***	-0.7427 (14.73)***	-0.7556 (14.42)***	-0.7063 (17.49)***	-0.7379 (18.37)***
Observations	64,348	64,348	65,381	357,109	357,109
R-squared	0.5757	0.5832	0.5831	0.5772	0.5673

Absolute value of t statistics in parentheses

* significant at 10%; ** significant at 5%; *** significant at 1%

Table F.13: High Inflow vs. Low Inflow Quarters

This table summarizes the results of the Fama and Macbeth [28] regressions and the pooled regressions of institutional ownership IO on stock misvaluation measures. I separate all quarters into two groups by the normalized institution fund inflows. The t-statistics are in parentheses. The sample period is from 1980 to 2010. *,**,*** denote significance levels of 10%, 5%, and 1%, respectively, two-tailed.

	Fama-Macbeth Regression		Pooled Regression	
	High Inflow	Low Inflow	High Inflow	Low Inflow
Significant_Alpha_Dummy	-0.039 (-8.96)***	-0.042 (-9.96)***	-0.041 (-7.1)***	-0.043 (-7.36)***
Significant_Alpha	-1.113 (-11.8)***	-1.167 (-13.9)***	-1.114 (-7.34)***	-1.152 (-8.13)***
Significant_Alpha_Lag	-1.157 (-11.8)***	-1.147 (-14.48)***	-1.140 (-7.23)***	-1.107 (-7.69)***
Alpha	-1.381 (-13.41)***	-1.447 (-17.46)***	-1.392 (-9.24)***	-1.414 (-9.92)***
Alpha_Dummy	-0.021 (-11.55)***	-0.023 (-12.81)***	-0.022 (-9.64)***	-0.023 (-9.47)***
SDM_Dummy	0.0030 (4.43)***	0.0027 (3.28)***	0.0031 (1.97)**	0.0028 (2.21)**
Number of Quarters	67	66	67	66

Table F.14: Subperiod Analysis

This table summarizes the results of the Fama and Macbeth [28] regressions and the pooled regressions of institutional ownership IO on stock misvaluation measures. I separate my sample into two subperiod: 1980-1994 and 1995-2010. The t-statistics are in parentheses. The sample period is from 1980 to 2010. *,**,*** denote significance levels of 10%, 5%, and 1%, respectively, two-tailed.

	Fama-Macbeth Regression		Pooled Regression	
	1980-1994	1995-2010	1980-1994	1995-2010
SignificantDummy	-0.0142 (-5.22)***	-0.0574 (-18.02)***	-0.0144 (-3.21)***	-0.0532 (-9.4)***
alpha_5Y5FM	-0.8025 (-7.99)***	-1.3566 (-19.81)***	-0.7528 (-4.87)***	-1.3347 (-9.57)***
alpha_5Y5FM_Lag	-0.8367 (-8.13)***	-1.3491 (-19.72)***	-0.7871 (-4.86)***	-1.3170 (-9.19)***
alpha_5Y5FM	-0.8693 (-15.71)***	-1.7631 (-23.77)***	-0.8158 (-7.96)***	-1.6187 (-11.49)***
alphadummy_5Y5FM	-0.0107 (-13.77)***	-0.0292 (-20.5)***	-0.0138 (-4.62)***	-0.0466 (-10.42)***
SDM	0.0002 (2.28)**	0.0006 (4.73)***	0.0000 (-1.27)	0.0007 (3.61)**
SDM_Dummy	0.0023 (3.24)***	0.0036 (4.37)***	0.0019 (1.43)	0.0035 (2.12)**

Table F.15: Industry Analysis

This table presents the results of pooled regressions of quarterly institutional ownership on individual stock rolling *alphas* for the Fama-French 49 industries separately, controlling for other stock characteristics: $IOMeasure_i = C_{i,t} + \alpha_i + X_i\beta_i + \epsilon_i$. Only the coefficients for *alpha* are reported. *alpha_i* is the dummy variable equal to 1 if the 5 factor model 5-year rolling *alpha* is positive, and 0 otherwise. The standard errors are clustered by firm and quarter for each industry regression. The sample period is from 1980 to 2010. *, **, *** denote significance levels of 10%, 5%, and 1%, respectively, two-tailed.

Industry	Alpha	# of Obs	Industry	Alpha	# of Obs	Industry	Alpha	# of Obs
Agriculture	-0.0100	926	Construction	-0.0349***	4,255	Computer Hardware	-0.0181***	10,228
Food Products	-0.0195***	6,039	Steel Works Etc	-0.0146**	5,043	Computer Software	-0.0252***	14,562
Candy & Soda	-0.0011	1,188	Fabricated Products	-0.0004	1,380	Electronic Equipment	-0.0231***	19,347
Beer & Liquor	0.0054	1,265	Machinery	-0.0260***	13,137	Measuring and Control Equipment	-0.0365***	7,871
Tobacco Products	-0.0098	487	Electrical Equipment	-0.0248***	9,182	Business Supplies	-0.0317***	4,207
Recreation	-0.0367***	3,301	Automobiles and Trucks	-0.0290***	4,990	Shipping Containers	-0.0327***	1,600
Entertainment	-0.0091	3,784	Aircraft	-0.0313***	1,843	Transportation	-0.0044	7,289
Printing and Publishing	-0.0216***	4,273	Shipbuilding, Railroad Equipment	-0.0268*	594	Wholesale	-0.0236***	14,973
Consumer Goods	-0.0334***	7,298	Defense	-0.0199	740	Retail	-0.0187***	17,420
Apparel	-0.0142**	4,852	Precious Metals	0.0079	1,641	Restaurants, Hotels, Motels	-0.0126**	7,597
Healthcare	-0.0323***	5,946	Non-Metallic and Industrial Metal Mining	-0.0123	1,759	Banking	-0.0146***	27,815
Medical Equipment	-0.0200***	9,955	Coal	-0.0077	634	Insurance	-0.0102*	10,626
Pharmaceutical Products	-0.0165***	13,628	Petroleum and Natural Gas	-0.0040	14,858	Real Estate	-0.0245***	3,052
Chemicals	-0.0298***	6,707	Utilities	-0.0057*	15,009	Trading	-0.0164***	20,401
Rubber and Plastic Products	-0.0290***	2,893	Communication	-0.0152*	6,110	Almost Nothing	-0.0124	3,271
Textiles	-0.0055	2,192	Personal Services	-0.0328***	3,371			
Construction Materials	-0.0111***	8,924	Business Services	-0.0276***	18,646			

Number of Negative and Significant Coefficients of Alpha	35
Number of Negative and Insignificant Coefficients of Alpha	12
Number of Positive and Insignificant Coefficients of Alpha	2

Table F.16: Institutional Ownership and Short Sale Interest

This table presents the pooled regression results of $IOMeasure_i = C_{i,t} + RSI_i\beta_{RSI} + X_i\beta_i + \epsilon_i$. The standard errors are clustered by firm and quarter. The dependent variable is IO_i , the percentage of institutional ownership of stock i . In the first column, the independent variable RSI_i is the vincile dummy variable which is equal to a number between 1 to 20. In the second column, the independent variable RSI_i is the actual short interest. The absolute value of t-statistics are in parentheses. The sample period is from December 1980 to December 2010.

	(1)	(2)
Vincile_RSI Dummy	0.0073 (8.3)***	
RSI		0.2411 (3.75)***
Size	0.0574 (16.01)***	0.0599 (16.98)***
Q	0.0000 (1.74)*	0.0000 (1.75)*
Yield	-0.0130 (10.45)***	-0.0127 (10.30)***
Price	0.0334 (6.23)***	0.0421 (7.66)***
Volatility	-0.0128 (2.73)***	-0.0086 (1.89)*
Momentum1	-0.0550 (3.45)***	-0.0586 (3.64)***
Momentum2	-0.0349 (4.04)***	-0.0382 (4.41)***
Turnover	0.0743 (14.96)***	0.0847 (17.97)***
S&P500 Dummy	-0.0900 (8.32)***	-0.0901 (7.96)***
Constant	-0.6399 (10.21)***	-0.5931 (9.54)***
Observations	267,345	267,345
R-squared	0.5232	0.5159

Absolute value of t statistics in parentheses

* significant at 10%; ** significant at 5%; *** significant at 1%

Table F.17: Institutional Ownership and Stock Forward Alpha

This table presents the pooled regression results of $IOMeasure_i = C_{i,t} + ForwardAlpha_i \beta_{ForwardAlpha} + X_i \beta_i + \epsilon_i$. The standard errors are clustered by firm and quarter. The dependent variable is IO_i , the percentage of institutional ownership of stock i at time t . In the first four columns, the independent variable $ForwardAlpha_i$ is the actual forward 5-year rolling 5 factor $Alpha$. In the last four columns, the independent variable $ForwardAlpha_i$ is the actual forward 3-year rolling 5 factor $Alpha$. The absolute value of t-statistics are in parentheses. *, **, *** denote significance levels of 10%, 5%, and 1%, respectively, two-tailed.

	All	Banks & Insurance	Investment & Independent	All Others	All	Banks & Insurance	Investment & Independent	All Others	All Others
Alpha_5 Year Rolling	0.0245 (0.24)	0.0402 (1.19)	0.3122 (3.54)***	0.0405 (3.09)***	0.1476 (2.32)**	0.0695 (3.9)***	0.2790 (5.35)***	0.0298 (4.33)***	0.0298 (4.33)***
Alpha_3 Year Rolling									
Size	0.0611 (23.92)***	0.0183 (19.13)***	0.0504 (21.75)***	0.0059 (12.67)***	0.0656 (27.29)***	0.0182 (20.72)***	0.0515 (23.33)***	0.0058 (13.46)***	0.0058 (13.46)***
Q	0.0000 (1.81)*	-0.0001 (3.24)***	-0.0002 (3.11)***	0.0000 (2.63)**	0.0000 (1.74)*	-0.0001 (3.28)***	-0.0002 (3.45)***	0.0000 (2.36)**	0.0000 (2.36)**
Yield	-0.0133 (10.24)***	0.0013 (3.59)***	-0.0116 (9.64)***	-0.0007 (3.03)***	-0.0144 (12.11)***	0.0014 (4.09)***	-0.0119 (10.44)***	-0.0007 (3.29)***	-0.0007 (3.29)***
Price	0.0355 (8.03)***	0.0099 (6.53)***	0.0372 (9.38)***	0.0009 (1.42)	0.0317 (7.54)***	0.0092 (6.88)***	0.0344 (9.19)***	0.0007 (1.18)	0.0007 (1.18)
Volatility	-0.0101 (3.01)***	-0.0038 (3.59)***	-0.0138 (4.59)***	0.0006 (1.31)	-0.0157 (4.69)***	-0.0039 (4.02)***	-0.0154 (5.52)***	0.0003 (0.75)	0.0003 (0.75)
Momentum1	-0.0410 (5.95)***	-0.0157 (6.47)***	-0.0337 (4.82)***	-0.0057 (6.35)***	-0.0424 (6.39)***	-0.0148 (6.48)***	-0.0329 (5.02)***	-0.0053 (6.52)***	-0.0053 (6.52)***
Momentum2	-0.0345 (9.83)***	-0.0095 (9.81)***	-0.0262 (6.89)***	-0.0046 (10.97)***	-0.0354 (10.52)***	-0.0086 (9.80)***	-0.0242 (7.01)***	-0.0042 (10.63)***	-0.0042 (10.63)***
Turnover	0.0579 (16.12)***	0.0018 (1.92)*	0.0391 (15.38)***	0.0009 (1.10)	0.0631 (16.53)***	0.0018 (2.05)*	0.0382 (16.07)***	0.0009 (1.2)	0.0009 (1.2)
S&P500 Dummy	-0.0391 (3.81)***	0.0394 (9.8)***	0.0197 (2.46)**	0.0223 (10.99)***	-0.0573 (5.17)***	0.0404 (10.53)***	0.0230 (2.95)***	0.0228 (11.26)***	0.0228 (11.26)***
Constant	-0.7235 (16.43)***	-0.2900 (17.05)***	-0.6420 (14.39)***	-0.0859 (8.83)***	-0.7950 (19.39)***	-0.2890 (18.66)***	-0.6653 (15.70)***	-0.0863 (9.65)***	-0.0863 (9.65)***
Observations	273,794	177,393	177,393	177,393	329,806	197,161	197,161	197,161	197,161
R-squared	0.561	0.413	0.5431	0.2227	0.5737	0.4102	0.5456	0.2199	0.2199

Table F.18: Are Institutional Investors Rational Trend Chasers?

Panel A. Raw Returns of Portfolios Sorted by Unexpected Institutional Ownership and Stock Alpha Panel A shows the raw returns of portfolios sorted by unexpected institutional ownership and stock alpha. Following Field and Lowry [31], I estimate the quarterly conditional mean of percent institutional ownership as a logistic function:

$$\mathbb{E}(IO_{i,t} | x) = \frac{\exp\{\beta_1 + \beta_2 * Size_{i,t}\}}{1 + \exp\{\beta_1 + \beta_2 * Size_{i,t}\}}$$

I calculate unexpected institutional ownership by $IO_{i,t} - \mathbb{E}(IO_{i,t} | x)$. At the beginning of each quarter, I assign a stock in the portfolio if its last quarter unexpected institutional ownership is within the top quintile and its last quarter stock *Alpha* dummy is -1. I report the summary statistics for the portfolio quarterly return and the number of stocks in the portfolio.

Alpha Dummy & Q5 Unexpected Institutional Ownership					
	Obs.	Mean	S.D.	Min	Max
Portfolio Raw Returns	105	0.041	0.114	-0.308	0.404
Number of Firms in the Portfolio	105	265.857	59.320	132	416
Significant Alpha Dummy & Q5 Unexpected Institutional Ownership					
	Obs.	Mean	S.D.	Min	Max
Portfolio Raw Returns	105	0.048	0.144	-0.374	0.538
Number of Firms in the Portfolio	105	31.410	17.159	4	94

Panel B. Fama-French Factor Regressions for the Returns of Portfolio Sorted by Unexpected Institutional Ownership and Stock Alpha Panel B shows weighted least squares of quarterly returns on the three Fama-French factors. Weights equal the number of stocks in the portfolio. The stocks in the portfolio have top quintile unexpected institutional ownership and negative *Alpha* dummy in the previous quarter. The t-statistics are in parentheses.

	Alpha Dummy & Q5 Unexpected Institutional Ownership	Significant Alpha Dummy & Q5 Unexpected Institutional Ownership
Intercept	0.0145 (5.04)***	0.0174 (2.66)***
RmRf	0.9989 (27.7)***	1.1184 (13.63)***
SMB	0.6379 (10.73)***	0.8068 (5.96)***
HML	0.5929 (15.13)***	0.7604 (8.53)***
Obs	105	105
Adj. R2	0.9372	0.7967

Absolute value of t statistics in parentheses

* significant at 10%; ** significant at 5%; *** significant at 1%