Arbitrage Trading: The Long and the Short of It

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Abstract

We propose a measure of net arbitrage trading by the difference between abnormal hedge fund holdings and abnormal short interest on a stock. In the cross section, net arbitrage trading strongly predicts future stock returns. More importantly, this predictability is not due to temporary price pressure, cannot be produced using total institutional holdings, but is consistent with information advantage of arbitrageurs and copycat trading of other institutional investors. Across a broad set of return anomalies, we find that anomaly returns come exclusively from the anomaly stocks traded by arbitrageurs, and such stocks are on average harder to arbitrage. Overall, our findings confirm that arbitrage trading is informative about mispricing.

Keywords: Arbitrage trading, hedge fund holdings, short interest, stock return anomalies, limits to arbitrage

JEL Classification: G11, G23

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1. Introduction

Arbitrageurs play a crucial role in financial markets. By simultaneously taking long and short positions in different assets, they help to eliminate relative mispricing and therefore enforce market efficiency. As a result, their trading pins down the expected return on these assets, according to the seminal Arbitrage Pricing Theory of Ross (APT, 1976). On the other hand, investors' behavioral biases may lead to persistent mispricing when arbitrageurs face limits to arbitrage (e.g., Shleifer and Vishny, 1997).

Empirically, however, tracking arbitrage trading has been a challenging task due to the lack of data on arbitrageurs.[1] In recent years, as hedge funds emerge as a group of likely arbitrageurs and their stock holdings data become available, a series of papers have inferred the long side of arbitrage trading by investigating their stock holdings (e.g., Brunnermeier and Nagel, 2004; Griffin and Xu, 2009; Cao, Chen, Goetzmann, and Liang, 2014). Meanwhile, since short positions are involved in an arbitrage trade, several studies track the short side of arbitrage trading by examining short interest on stocks (e.g., Hanson and Sunderam, 2014; Hwang and Liu, 2014; Wu and Zhang, 2014).

One innovation of our paper is to combine hedge fund holdings on the long side with short interest on the short side to infer *net* arbitrage trading on a stock. The advantage of our approach is straightforward. A correctly priced stock can be traded by arbitrageurs for hedging purposes, and thus some may purchase it while others sell it short.[2] Alternatively, arbitrageurs may disagree on the valuation of a stock, and it will be purchased in some arbitrage transactions and sold short in others. At the end of 2012, there are more than 2,300 stocks with both hedge fund holdings and short interest and they cover more than 90% of the U.S. equity universe in terms of market capitalization. For these stocks, focusing on either the long- or the short-side alone will give imprecise inference about arbitrageurs' view on the stocks in aggregate. However, the net position should represent a better proxy for arbitrage trading and a more powerful predictor of future stock returns. Indeed, we confirm this conjecture in our empirical

[1] The type of arbitrage trading we are interested in is similar to that in the APT where arbitrageurs take long and short positions in well-diversified portfolios with similar risk exposures but different expected returns. It is different from pure arbitrage in which assets in the long and short positions have identical cash flows.

[2] For example, a correctly priced value stock with large negative recent returns may be bought by a value trader and simultaneously sold short by a momentum trader to hedge the other leg of their long-short strategies.

analysis. In particular, we find that stocks with large abnormal hedge fund ownership and simultaneously little abnormal short interest realize high future abnormal returns, while stocks with large abnormal hedge fund ownership but heavy abnormal short interest do not earn any abnormal return in the future.

We combine a comprehensive dataset on hedge fund stock holdings with data on short interest during the period 1990–2012. Over time, aggregate hedge fund holdings track aggregate short interest well, and both experienced exponential growth since the early 1990s. The average percentages of shares outstanding held by hedge funds or sold short are both less than 1% in 1990 but peak around 5% in 2008 before leveling off afterwards. The common trend shared by both the long- and the short-sides of arbitrage trading confirms the increasing arbitrage activities documented by Hanson and Sunderam (2014) who examine short interest only. In the cross section, we find similar distributions in hedge fund holdings and short interest. For example, these two variables exhibit similar means, medians and standard deviations across stocks. The similarity in their distributions supports the notion that on average, hedge fund holdings and short interest reveal the two legs of arbitrage trades.

Since stocks may be held or sold short for reasons other than arbitrage,[3] to better measure arbitrage trading, we define abnormal hedge fund holding (AHF) and abnormal short interest (ASR) as their values in the current quarter minus their moving averages in the prior four quarters. At the aggregate level, AHF and ASR track each other well. This is particularly true during crisis periods when mispricing is prevalent. Finally, AHFSR, defined as the difference between AHF and ASR, is our measure of *net* arbitrage trading that captures trade imbalance of arbitrageurs. For example, an AHFSR of 1% (–1%) on a stock means that arbitrageurs, as a group, have purchased (sold) an additional 1% of the stock during the most recent quarter relative to their past averages.

[3] Hedge fund may hold certain stocks to neutralize portfolio risk. Also, stocks may be sold short to hedge against a convertible bond purchase. For example, when the company AMD issued a convertible bond with a conversion value amounting to 13% of its market capitalization in 2007/Q3, its short interest (as a percentage of the total number of shares outstanding) increased from 6.3% to 13.7%. The increase is consistent with a hedging ratio of 0.57. Overall, there are only 37 large convertible bond issuances in our sample with an average conversion size equal to or greater than 5% of total shares outstanding. Adjusting the short interest for related hedging demand does not change our results.

Consistent with the existing literature, we find both abnormal hedge fund holdings (AHF) and abnormal short interest (ASR) to predict stock returns. On the long side, stocks in the highest AHF quintile outperform those in the lowest quintile by 0.44% per month in the next quarter. On the short side, stocks in the highest ASR quintile underperform those in the lowest quintile by 0.41% per month in the next quarter. Most importantly, by focusing on net arbitrage trading, AHFSR generates the highest return spread in the same sample. Stocks in the highest AHFSR quintile outperform those in the lowest quintile by 0.68% per month (t-value = 7.93) in the next quarter. The return spread is highly significant but declines quickly over time. It drops to 0.42% per month in the second quarter and further down to 0.18% per month in the third quarter. When we extend the return horizon up to two years, we do not observe any significant spread beyond the third quarter. In addition, the lack of return reversal in the long-run suggests that the abnormal return spread associated with AHFSR during the first three quarters is more likely to capture corrections to mispricing rather than temporary price pressure caused by arbitrage trading.

The strong return predictability of our net arbitrage trading measure AHFSR holds in a battery of robustness checks. The return predictability is not explained by the common risk factors. Further, we obtain similar results when we restrict both hedge fund holdings and short interest to be strictly positive (i.e., excluding zero values) and when we include small stocks in the sample.[4] It is strong in both the first and the second halves of the sample period. It is also robust to Fama-MacBeth cross-sectional regressions that control for other well-known stock return predictors. The return predictability cannot be generated by combining total institutional holdings and short interest. In other words, our results are not driven by the interaction between short interest and institutional ownership previously documented by Asquith, Pathak, and Ritter (2005) and Nagel (2005) among others. The results also confirm that abnormal hedge fund holdings reveal the long leg of arbitrage trading much better than abnormal institutional ownership change.

[4] In our base sample, we exclude small stocks and penny stocks from our main analysis to minimize measurement errors and market microstructure-related noise. We verify that our return results are similar when we add back small stocks.

The advantage of our net arbitrage trading measure can also be illustrated by a double sort on AHF and ASR. Holding one variable constant, sorting on the second variable still generates a large and significant return spread, suggesting that arbitrage activities are informative on both legs. Interestingly, we find stocks with high-AHF-high-ASR to have about the same future returns as stocks with low-AHF-low-ASR, confirming that future returns are driven by the net arbitrage trading. Finally and not surprisingly, stocks with high-AHF-low-ASR earn much higher future returns than stocks with low-AHF-high-ASR (1.18% vs. 0.40% per month).

The predictive power of AHFSR for stock returns suggests that arbitrage trading is informative about stock mispricing. Though the result is interesting on its own, we examine how mispricing is corrected in depth. We find evidence that the correction comes from two channels. First, a significant fraction of price correction in the first two quarters takes place during earnings announcements when fundamental information is released to the public, which suggests an information-related channel. Second, other types of institutional investors trade in the same direction as arbitrageurs subsequently, further facilitating price convergence. Interestingly, other institutional investors trade in the opposite direction to hedge funds in the contemporaneous quarter and only follow hedge fund trades with a lag of at least one quarter, suggesting that abnormal hedge fund holdings (AHF) reveal arbitrage trading better. Our result is also consistent with Edelen, Ince, and Kadlec (2014) who show that institutional investors, mostly non-hedge funds, tend to trade on the wrong side in that they increase (decrease) their holdings of overvalued (undervalued) stocks.

After showing that AHFSR captures net arbitrage trading well, we examine the relation between arbitrage trading and anomalous stock returns in the cross section. We examine a total of 10 well-known stock return anomalies: book-to-market ratio of Fama and French (2008); gross profitability of Novy-Marx (2013); operating profit of Fama and French (2015); momentum of Jegadeesh and Titman (1993); market capitalization of Fama and French (2008); asset growth of Cooper, Gulen, and Schill (2008), Hou, Xue, and Zhang (2014), and Fama and French (2015); investment growth of Xing (2008); net stock issues of Fama and French (2008); accrual of Fama and French (2008); and net operating assets of Hirshleifer, Hou, Teoh, and Zhang (2004). We verify that the long-minus-short future return spreads averaged across these anomalies are positive and significant in our sample. The return spreads are 0.28%, 0.25%, 0.20%, and 0.15% per month during the first, second, third, and fourth quarters, respectively.[5]

More importantly, anomalous returns are completely driven by those anomaly stocks traded by arbitrageurs. We define an anomaly stock to be traded by arbitrageurs if it is in the long portfolio and recently bought by arbitrageurs (its AHFSR belongs to the top 30%), or in the short portfolio and recently sold short by arbitrageurs (its AHFSR belongs to the bottom 30%). This subset of anomaly stocks earns return spreads of 0.88%, 0.61%, 0.34%, and 0.27% per month during the first, second, third, and fourth quarters, respectively, after portfolio formation. In sharp contrast, the rest of anomaly stocks that are not traded by arbitrageurs do not earn any significant return spread in the next four quarters. The fact that future abnormal returns only appear among anomaly stocks traded by arbitrageurs and these abnormal returns decline quickly during the first year suggests that arbitrageurs are effective in identifying mispriced stocks.

Finally, we examine stock characteristics that are related to limits to arbitrage. We find that anomaly stocks traded by arbitrageurs are on average harder to arbitrage, with high arbitrage risk and transaction costs proxied by idiosyncratic volatility, low stock price, and high illiquidity (e.g., Pontiff, 2006). Since they are harder to arbitrage, such stocks are more likely to be mispriced and have larger future abnormal returns. In addition, the future abnormal return on anomaly stocks traded by arbitrageurs, as before, is realized through two channels. First, it comes from price correction following the release of fundamental information in earnings announcements. Second, it benefits from subsequent trades of other institutions in the same direction as arbitrageurs. Among anomaly stocks that are not traded by arbitrageurs, however, the ones with high arbitrage costs still earn smaller but more persistent return of 0.36% per month on average in the first year. Take collectively, our findings suggest that arbitrage trading is informative about mispricing and mispricing arises from limits to arbitrage.

Our paper contributes to a growing literature that studies hedge fund holdings and short interest as return predictors and proxies for arbitrage activities.[6] Brunnermeier and Nagel (2004)

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[5] The magnitude is smaller compared to other studies, since we use quintile sorts instead of the more common decile sorts and we exclude small stocks from our main analysis.

[6] There are other proxies for arbitrage trading in the literature. For example, Lou and Polk (2013) infer arbitrage activities from the comovement of stock returns.

find that hedge funds ride with the bubble during the tech bubble period. Griffin and Xu (2009) find only weak predictive power of changes in hedge fund ownership for future stock returns. Griffin, Harris, Shu and Topaloglu (2011) show that hedge funds destabilized the market during the tech bubble period. On the other hand, Agarwal, Jiang, Tang, and Yang (2013) find that hedge fund "confidential holdings" are informative about future stock returns. Cao, Chen, Goetzmann, and Liang (2014) find that, compared with other institutional investors, hedge funds tend to hold and purchase undervalued stocks, and undervalued stocks with higher hedge fund ownership realize higher future returns and are more likely to get mispricing corrected. Reca, Sias, and Turtle (2015) also find that hedge fund demand shocks predict future stock returns.

Prior research has also studied, both theoretically and empirically, the impact of short sales on security returns. Miller (1977) argues that in the presence of heterogeneous beliefs, binding short sale constraints prevent stock prices from fully reflecting negative opinions of pessimistic traders, leading to overpricing and low subsequent returns. Diamond and Verrecchia (1987) show that given the high costs (e.g., no access to proceeds) of short selling, short sales are more likely to be informative trades. Consistent with these theories, several empirical papers document a negative association between short interest and abnormal stock returns (e.g., Asquith and Meulbroek, 1995; Desai et al., 2002; Boehmer, Jones, and Zhang, 2008). Using institutional ownership of stocks as a proxy for stock loan supply, Asquith, Pathak, and Ritter (2005) and Nagel (2005) examine the impact of short sale constraints on stock returns. Asquith, Pathak, and Ritter (2005) find that for small stocks with high short interest, low institutional ownership is associated with more negative future returns, which confirms the effect of binding short constraints on stock prices. However, they show that only 5% of the stocks trading on the NYSE, AMEX, and NASDAQ have institutional ownership smaller than short interest, suggesting that short sale constraints are not pervasive. Nagel (2005) finds that short sale constraints help explain cross-sectional stock return anomalies related to book-to-market ratio, analyst forecast dispersion, turnover, and return volatility. More recently, Drechsler and Drechsler (2014) find that short-rebate fee is an informative signal about overpricing and arbitrage trades on the short leg. Our net arbitrage trading measure that uses hedge fund holdings provides incremental value over both examining short interest alone and combining institutional ownership and short interest.

To the best of our knowledge, our paper is the first to combine information about arbitrage trading on both the long- and the short-sides.[7] Different from prior research that focuses on either the long- or the short-side, our study provides a more complete view about the effect of arbitrage activities. We propose a simple measure of net arbitrage trading that better predicts future stock returns. When using the measure to study well-known return anomalies, we find strong evidence supporting the notion that mispricing arises from limits to arbitrage and arbitrage trading is informative about mispricing.

The rest of the paper is organized as follows. Section 2 describes our data and sample. Section 3 examines our net arbitrage trading measure (AHFSR) as a stock return predictor. Section 4 uses AHFSR to study stock return anomalies. Finally, Section 5 concludes.

2. Data and Sample Construction

We start our sample in 1990 as hedge fund holdings and short interest are relatively sparse before that.[8] At the end of each quarter, we exclude from our main sample stocks with share price less than $5 and market capitalization below the 20th percentile size breakpoint of NYSE firms. We exclude such stocks from our main analysis for two reasons. First, hedge funds only need to report stock positions greater than 10,000 shares or $200,000 in market value. As a result, hedge fund holdings of small stocks and penny stocks are often underestimated. Second, excluding these stocks helps to alleviate the associated market microstructure noise. Our final sample still represents over 85% of the CRSP universe on average.

[7] In a contemporaneous study, Jiao, Massa, and Zhang (2015) also find that an increase (decrease) in hedge fund holdings accompanied with a decrease (increase) in short interest is informative about future stock return and firm fundamental. However, they do not define AHFSR and relate it to arbitrage trading and asset pricing anomalies as we focus on in our paper. In addition, they identify hedge funds by matching 13F institutional filings with SEC Form ADV. Since From ADV became mandatory filings for hedge funds only in recent years, hedge funds that became defunct before Form ADV was required cannot be identified through such matching and survivorship bias is likely to occur.

[8] For example, the aggregate hedge fund holdings and short interest, as a percentage of total market capitalization of the CRSP universe, was less than 1% on average prior to 1990.

2.1. Hedge Fund Holdings

For the long side, we employ the same data on hedge fund equity holdings as studied by Cao, Chen, Goetzmann, and Liang (2014). The data are constructed by manually matching the Thomson Reuters 13F institutional ownership database with a comprehensive list of hedge fund company names. The hedge fund company names are collected from six hedge fund databases, including TASS, HFR, CISDM, Bloomberg, Barclay Hedge, and Morningstar, augmented with additional sources. Hedge funds were historically exempt from registering with the SEC as an investment company. However, similar to other institutional investors, hedge fund management companies with more than $100 million in assets under management are required to file quarterly reports disclosing their holdings of registered equity securities. Common stock positions greater than 10,000 shares or $200,000 in market value are subject to disclosure. 13F filings contain long positions in stocks, while short positions are not required to be reported.

In our study, a hedge fund is identified as a management company included in a hedge fund database, a firm that self-identifies as a hedge fund, or a firm that imposes a threshold of high-net-worth investors and a performance-based compensation. To address the concern that a hedge fund manager may not appear in any hedge fund database because of the voluntary nature of reporting to a database, a manual search is used based on a variety of online resources. Further, following Brunnermeier and Nagel (2004) and Griffin and Xu (2009), each identified company is manually checked to ensure that hedge fund management is its primary business using two criteria: first, over 50% of its clients are either high-net-worth individuals or invested in “other pooled investment vehicle (e.g., hedge funds)”, and second, the adviser is compensated by a performance-based fee. Our final sample includes 1,517 hedge fund management firms that collectively manage over 5,000 individual hedge funds.

The way we identify hedge fund companies has an advantage over the alternative approach of matching 13F filings with SEC Form ADV (e.g., Jiao, Massa, and Zhang, 2015). Since From ADV became mandatory filings for hedge funds only in recent years, hedge funds that became defunct before Form ADV was required cannot be identified through such matching. As a result, stock ownership of many defunct hedge funds is missing by such an approach, and the data is likely to be contaminated with survivorship bias.

For each stock in our sample, we compute its quarterly hedge fund holding (HF) as the number of shares held by all hedge funds at the end of the quarter divided by the total number of shares outstanding. If the stock is not held by any hedge fund in that quarter, its HF is set to zero. Since stocks can be held by hedge funds for reasons other than arbitrage, to better measure hedge fund trading, we define abnormal hedge fund holding (AHF) as the current quarter HF minus the average HF in the past four quarters. Though AHF is correlated with the change in hedge fund holdings from the one to the next quarter, it can help to alleviate the effect of sporadic variations in hedge fund ownership that is less likely to reveal the fund manager's trading decisions. For instance, when the market value of the holdings in a stock by a hedge fund fluctuates around the disclosure requirement (i.e., $200,000) possibly due to a price change, such holdings may be disclosed in one quarter but not in the next quarter, which creates a sporadic variations unrelated to the fund trading. Therefore, AHF better captures the trading behavior of hedge funds.

2.2 Short Interest

For the short side, mid-month short interest is obtained from the Compustat Short Interest file from 1990 to 2012. These monthly short interest data are reported by the NYSE, AMEX, and NASDAQ. The Compustat Short Interest file covers NASDAQ stocks only from 2003, and following the literature, we supplement our sample with short interest data on NASDAQ prior to 2003 obtained from the exchange.

For each stock in our sample, we compute its quarterly short interest (SR) as the number of shares sold short at the end of the quarter divided by the total number of shares outstanding. If the stock is not covered by our short interest files, its SR is set to zero. Again, we define abnormal short interest (ASR) as the current quarter SR minus the average SR in the past four quarters.

2.3 Stock Return Anomalies

In our examination of the relation of net arbitrage trading to anomalous stock returns, we consider 10 well-documented return anomalies largely following Fama and French (2008) and Stambaugh, Yu and Yuan (2012).

The first anomaly is book-to-market ratio (BM) of Fama and French (1996, 2008). It is well documented that firms with high book-to-market ratio on average have high future returns and these returns do not disappear after adjusting market risk using the CAPM (Sharpe, 1964). The second anomaly is operating profit (OP) of Fama and French (2015), who show that firms' operating profits are positively related to future stock returns. The third anomaly is gross profitability (GP) of Novy-Marx (2013), who shows that firms with higher gross profit have higher future returns. The fourth anomaly is return momentum (MOM) of Jegadeesh and Titman (1993). In our setting, at the end of each quarter, we compute stock returns in the past 13 months by skipping the immediate month prior to the end of the quarter, divide them into winners and losers, and hold them in the next quarter. The fifth anomaly is market capitalization (MC) of Fama and French (1996, 2008). On average, the larger the firm size, the lower its expected return. This size anomaly, similar to the book-to-market ratio anomaly, has a long history, survives the CAPM risk adjustment, and has been used as a factor in the three-factor model of Fama and French (1996), the five-factor model of Fama and French (2015), and the four-factor model of Hou, Xue, and Zhang (2014). The sixth anomaly is asset growth (AG) of Cooper, Gulen, and Schill (2008), Hou, Xue, and Zhang (2014), and Fama and French (2015), who show that firms with higher growth rates of asset have lower future return. The seventh anomaly is investment growth (IK) of Xing (2008), who shows that firms with higher investment have lower future returns. The eighth anomaly is net stock issues (NS) examined in Ritter (1991), Loughran and Ritter (1995), and Fama and French (2008), who find that the larger the net stock issues, the lower the future returns. The ninth anomaly is accrual (AC) examined in Sloan (1996) and Fama and French (2008), who find a negative relationship between accrual and future stock returns. The tenth anomaly is net operating assets (NOA) of Hirshleifer, Hou, Teoh, and Zhang (2004). They show that firms with larger operating assets have lower future returns.

We follow Fama and French (2008), Novy-Marx (2013), and Hou Xue, and Zhang (2014) to compute book-to-market ratio, market capitalization, net stock issues, and accrual. The calculation of gross profit follows Novy-Marx (2013). The calculation of operating profit follows Fama and French (2015). The calculation of momentum follows Jegadeesh and Titman (1993). The calculation of asset growth follows Cooper et al. (2008). The calculation of investment growth follows Xing (2008). The calculation of net operating assets follows Hirshleifer et al. (2004). For each anomaly, we construct quintile portfolios at the end of each quarter. We then compute the monthly long-minus-short portfolio return spreads for the next quarter. Details of the anomaly constructions are provided in the Appendix.

2.4 Sample Description

Our baseline sample contains about 1,600 stocks per quarter with small stocks and penny stocks excluded. As shown in Figure 1, the number of stocks in the sample started around 1,400 in 1990, reached a peak of 2,000 during the tech bubble, and then leveled off to 1,400 afterwards. Since only small stocks and penny stocks are excluded, our baseline sample still covers more than 86% of the CRSP universe in terms of market capitalization.

Figure 1(a) plots the cross-sectional coverages of the hedge fund holdings (HF) data and the short interest (SR) data over time. While most of the stocks in our sample have positive short interest, the coverage of hedge fund holdings was relatively small at the beginning. For example, in 1990, out of the 1,400 stocks in our sample, less than 1,000 have positive hedge fund holdings. However, the hedge fund holdings coverage has increased rapidly. Since 2000, most of the stocks in our sample have both positive hedge fund holdings and short interest. Figure 1(b) plots the percentage of market cap coverage of hedge fund holdings and short interest. The market cap coverage is large. Stocks with positive hedge fund ownership account for more than 90% of our baseline sample in terms of market capitalization.

Figure 2(a) plots aggregate hedge fund holdings and aggregate short interest over time. As can be seen, aggregate hedge fund holdings and short interest track each other well. They were both less than 1% in the early 1990s but increased to around 5% in 2008. The abnormal hedge fund holdings (AHF) and abnormal short interest (ASR) also track each other well (with a correlation of 0.26) as shown in Figure 2(b). AHF and ASR are particularly highly correlated during crisis periods when mispricing is widespread. For example, their correlations exceed 60% during the two four-year-periods surrounding the tech bubble (1999–2002) and the recent financial crisis (2006–2009). Finally, Figure 2(c) plots the difference between hedge fund holdings and short interest, i.e., HFSR, and the difference between abnormal hedge fund holdings and abnormal short interest, i.e., AHFSR. Here, AHFSR can be viewed as a measure of trade imbalance of arbitrageurs. An aggregate AHFSR of 1% (–1%) means that arbitrageurs, as a group, have purchased (sold) an additional 1% of the market during the most recent quarter relative to the average of the previous four quarters. We find that aggregate AHFSR fluctuates between –0.5% and 0.5% for most of the time. One exceptionally large value (below –1%) of AHFSR occurred in late 2008 when arbitrageurs fled the market due to funding liquidity constraints.

Panel A of Table 1 summarizes the cross-sectional distributions of our main variables. We find a similar distribution in HF and SR that, across stocks, have similar means (3.72% vs. 3.49%), medians (2.37% vs. 2.35%), and standard deviations (3.97% vs. 3.66%). AHF and ASR have similar distributions as well, exhibiting similar means (0.19% vs. 0.18%), medians (0.04% vs. 0.02%), and standard deviations (1.90% vs. 1.83%). The similarity in the distributions supports the idea that HF and SR reflect the two legs of arbitrage trades on average.[9] Compared with HF and SR, AHF and ASR are less persistent. Our net arbitrage trading measure AHFSR has an autocorrelation coefficient of 0.42 at quarterly frequency.

Panel B of Table 1 reports cross-sectional correlations among the variables. There is a positive correlation of 0.23 between HF and SR across stocks. In other words, a stock with high HF is also likely to have high SR. It is therefore important to isolate net arbitrage trading on the long- and short-sides. When we examine the correlations among AHF, ASR and AHFSR, we find AHFSR to be positively correlated with AHF (0.64) and negatively correlated with ASR (–0.68). These correlations are far from being perfect, however, suggesting that net arbitrage trading is quite different from arbitrage trading on either the long- or the short-side.

3. Arbitrage Trading and Future Stock Returns

Since the majority of stocks are both held by hedge funds and simultaneously sold short, we argue that *net* arbitrage trading between the long- and the short-sides should be a more

[9] Though the long- and short-sides in our sample track each other well, they are likely to contain measurement errors. First, long positions of hedge funds that do not meet the 13F filing requirement are omitted in the sample, which understates the long side. Nonetheless, since such funds tend to be small, the underestimation should not be severe. Second, our data on short interest reflects not only that from hedge funds but that from other short sellers including individual investors, which overstates the short sides. Finally, many hedge funds hold securities beyond US stocks (e.g., emerging market stocks) that may be hard to short sell. Therefore, hedge funds on average show a long bias, rather than perfectly balancing out long and short positions.

powerful predictor of future stock returns. In this section, we test the predictive power of our measure of net arbitrage trading (AHFSR).

3.1 Portfolio Sorts

We first examine whether net arbitrage trading forecasts future stock returns using a portfolio formation approach. As our hedge fund holdings data are at a quarterly frequency, we form portfolios at the end of each quarter and track the portfolio returns in the following quarters. Specifically, at the end of each quarter, we rank stocks based on their values of AHF, ASR or AHFSR, and assign them into quintiles. The highest (lowest) quintile includes stocks that have high (low) values of AHF, ASR or AHFSR. After forming the portfolios, we track excess returns of each portfolio in the following quarters. We compute excess return of a portfolio by equally averaging excess returns of all stocks that belong to the portfolio in that quarter. We first present excess returns of these quintile portfolios, and then adjust risk exposures to the three factors of Fama and French (1996), the three factors of Fama and French augmented with the Carhart (1997) momentum factor, and the five factors of Fama and French (2015) that expand their original three factors to include a profitability factor and an asset growth factor.

Table 2 presents results from portfolio formation. Table 2A reports results from the base sample. Panel A shows results of the AHF quintile portfolios. The results indicate that on average, stocks experiencing a large increase in hedge fund holding (AHF-quintile 5) have monthly excess return of 1.05% (t-value = 2.97) in the next quarter, while stocks experiencing a large decrease in hedge fund holdings (AHF-quintile 1) have monthly excess return of 0.61% (t-value = 1.77). The high-minus-low AHF portfolio (AHF-HML) has monthly excess return of 0.44% (t-value = 4.98) in the next quarter. The finding is consistent with the view that changes in hedge fund holdings have return predictability (e.g., Cao, Chen, Goetzmann, and Liang, 2014).

There are several reasons why our result on the predictability of changes in hedge fund holdings is somewhat stronger than Griffin and Xu (2009) who find only weak predictive power. First, our AHF variable may capture the trading behavior of hedge funds better than a simple change in quarterly hedge fund holdings. Second, our hedge fund coverage is more comprehensive than Griffin and Xu (2009). Third, the sample period in Griffin and Xu (2009) ends in 2004, while our sample extends to 2012. Cao, Liu, and Yu (2015) find that changes in hedge fund ownership has stronger stock return predictability in the recent period. In Table 2E, we confirm that AHF predicts stock returns better in the second half of our sample period.

Panel B presents results of the ASR quintile portfolios. Stocks that experience large increase in short interest (ASR-quintile 5) have excess return of 0.49% per month (t-value = 1.32), while stocks that experience large decrease in short interest (ASR-quintile 1) have monthly excess return of 0.90% per month (t-value = 2.70). The high-minus-low ASR portfolio (ASR-HML) has monthly excess return of –0.41% (t-value = –4.21). The finding confirms the return predictive power of short interest as documented in prior research (e.g., Asquith, Pathak, and Ritter, 2005).

Panel C combines AHF and ASR and uses AHFSR to sort the same set of stocks into quintiles. Our results show that stocks recently bought by arbitrageurs as a group (AHFSR-quintile 5) have monthly excess return of 1.11% with a t-value of 3.23, while stocks recently sold by arbitrageurs as a group (AHFSR-quintile 1) have monthly excess return of 0.43% with a t-value of 1.20. The high-minus-low AHFSR portfolio (AHFSR-HML) has monthly excess return of 0.68% (or, about 8.16% per year) with a t-value of 7.93. Therefore, the return spread is both economically and statistically significant.

Next, we examine alphas (i.e., risk-adjusted returns) of these quintile portfolios. The alphas seem to be large in magnitude at extreme quintiles. This is especially true for stocks that have high AHF and stocks that have high ASR. In particular, for the three asset pricing models we consider, high AHF stocks have monthly alphas of 0.28% (t-value = 3.11), 0.34% (t-value = 3.92), and 0.19% (t-value = 2.12), while high ASR stocks have monthly alphas of –0.32% (t-value = –3.09), –0.17% (t-value = –1.91), and –0.35% (t-value = –3.31), respectively. This is not surprising, since both the hedge fund holdings variable (HF) and the short interest variable (SR) are bounded below by zero, and thus an increase in HF or SR tends to be more informative than a decrease.

When AHF and ASR are combined into AHFSR, alphas are large in magnitude for both high and low AHFSR portfolios. High AHFSR stocks have monthly alphas of 0.36%, 0.42%, and 0.27%, and low AHFSR stocks have monthly alphas of –0.34%, –0.22%, –0.38%, respectively. The alphas of high-minus-low portfolios are also larger and statistically significant for the AHFSR portfolio when comparing to those of AHF and ASR portfolios. Across the three factor models, the monthly alphas of AHFSR-HML portfolios are 0.70%, 0.64%, and 0.65% with t-values of 8.17, 7.57, and 7.20, compared with the alphas of AHF-HML portfolios being 0.40%, 0.38%, 0.35% with t-values of 4.50, 4.27, and 3.80, and the alphas of ASR-HML portfolios being –0.50%, –0.42%, and –0.44% with t-values of –5.42, –4.71, and –4.58, respectively.

Panel D tracks excess returns of these quintile portfolios in subsequent quarters in addition to the immediate next quarter, and reports the high-minus-low return spread in the next four quarters.[10] The results show that, for all the three measures of arbitrage capital, excess returns decrease over time. The high-minus-low excess returns from AHFSR quintile portfolio is the largest at 0.68% per month (t-value = 7.93) in the immediate next quarter after portfolio formation. It drops to 0.42% (t-value = 4.90) in the second quarter, further drops to 0.18% (t-value = 1.90) in the third quarter, and finally drops to zero in the fourth quarter after portfolio formation. The alpha decay is consistent with the pattern recently documented by Di Mascio, Lines, and Naik (2015) using transaction-level data of institutional trading. As shown in Figure 3, when we extend the return horizon up to two years, we do not observe any significant spreads beyond the third quarter.

Overall, the results confirm that net arbitrage trading consistently predicts future stock returns better than arbitrage activities on either the long- or the short-side alone. The fact that the abnormal returns decline quickly during the first year suggests that the returns are more likely capturing "correction" to temporary mispricing rather than compensation for the exposure to a missing risk factor. The lack of return reversal in the long run suggests that the abnormal return spread associated with AHFSR is not driven by temporary price pressure caused by arbitrage trading.[11]

[10] From a practical perspective, it is useful to examine the subsequent quarters since hedge fund holdings are often reported with a temporal delay averaged about 45 days. However, in some rare cases, the disclosure delay can be as long as a year, and such "confidential holdings" are usually omitted in the Thomson Reuters 13F holdings data. Agarwal, Jiang, Tang, and Yang (2013) find that the "confidential holdings" contain substantial information that predicts future stock returns. Therefore, our results about the return predictability of arbitrage trading partially inferred from the Thomson Reuters 13F holdings data can be conservative.

[11] Indeed, for both high- and low-AHFSR portfolios, their AHFSR mean reverts to zero after two quarters. If their abnormal return spreads in the first two quarters reflect price pressure associated with abnormal trading, we would see a reversal beyond the second quarter as abnormal trading disappears.

Tables 2B through 2H provide an array of robustness checks. In Table 2B, we lift the restriction on firm size that is applied in our base sample. Specifically, we expand the base sample with stocks whose market capitalizations are below the 20th percentile breakpoint of NYSE firms, at the time of portfolio formation. In Table 2C, we exclude firms whose hedge fund holdings or short interest equal to zero from the base sample. In Table 2D, we repeat our test using the first half of the sample period covering January 1990 to June 2000, while in Table 2E, we use the second half of the sample period covering July 2000 to December 2012. Overall, the results from these robustness checks are similar to those presented in Table 2A. That is, our inference is not overly sensitive to the application of size breakpoints, deletion of firms having no hedge fund holdings or short interest, or the choice of the sample period.

So far we have assumed AHF and ASR to be comparable so that a simple difference between them produces a measure of net arbitrage trading. The assumption seems reasonable given that AHF and ASR have similar distributions in the cross-section (see Panel A of Table 1). Nevertheless, to account for the possibility that true net arbitrage trading could be a nonlinear function in both AHF and ASR, we consider an alternative approach to examine the incremental contribution of AHF or ASR by performing two-way independent sorting based on AHF and ASR.

At the end of each quarter, we form tercile portfolios based on AHF, and independently form tercile portfolios based on ASR. Then, nine AHF-ASR portfolios are taken from the intersections of these two sets of tercile portfolios. Our premise is that, in the high AHF tercile, some stocks may have high ASR, but other stocks may have low ASR. Similarly, in the low AHF tercile, some stocks may have low ASR, but other stocks may have high ASR. However, we posit that it is the net value that should matter. As shown in Table 2F, the average excess return of stocks that have both high AHF and high ASR is 0.81% in the following quarter, while it is 0.71% for stocks that have both low AHF and low ASR. Their corresponding alphas are both very close to zero with small t-values, which is consistent with our expectation. In sharp contrast, the excess returns are 1.18% for stocks that have high AHF and low ASR, and 0.40% for stocks that have high ASR and low AHF. The corresponding risk-adjusted returns (i.e., alphas) are also large, with the magnitude of t-values greater than 2.50 across the three factor models. Therefore, the double-sort results provide strong support that net arbitrage trading is the driving force of the predictability for future stock returns.

In Table 2G, we first normalize HF and SR by the aggregate level of institutional ownership IO, and then compute AHFIO, ASRIO, and AHFSRIO using the scaled HF and SR. The aggregate institutional holdings serve as a proxy for the total supply of borrowable shares on a stock. It turns out that our results are not affected by the scaling of IO. Finally, Table 2H reports the result of double sorting from abnormal institutional holdings (AIO) and abnormal short interest (ASR), with AIO defined similarly to AHF. Interestingly, the result is dramatically different from that based on AHF. The level of AIO does not predict future stock return or alpha. Furthermore, there is no predictive power even when AIO is combined with ASR. This suggests that hedge funds, as a likely group of arbitrageurs, are substantially different from other types of institutional investors, which is consistent with the finding of Cao, Chen, Goetzmann, and Liang (2014).

To summarize, the results suggest that some arbitrage capital buys a stock for one reason sometimes, while other arbitrage capital sells short the same stock for another reason. Therefore, it would be incomplete to rely on only one side of arbitrage capital to infer about arbitrageurs' views on mispricing and future stock returns, and thus it is crucial to consider both hedge fund holdings (the long side) and short interest (the short side).

3.2 Fama-MacBeth Cross-Sectional Regressions

As discussed in Fama and French (2008), it is difficult for the portfolio approach to identify which variable has unique information in predicting future stock returns, because the portfolio approach can be contaminated by choices of percentiles in the breakpoints and the order of sorting variables. Here, we conduct Fama-MacBeth (1973) cross-sectional regressions to further investigate the roles of AHF, ASR and AHFSR in predicting stock returns. Our sample is quarterly at the stock level from 1990 to 2012.

The Fama-MacBeth procedure has two steps. In the first step, for each quarter, we run a cross-sectional regression of average monthly stock excess returns over the next quarter on the end-of-quarter AHF, ASR, or AHFSR, along with control variables. The control variables are other return predictors identified in the existing literature, including book-to-market ratio of Fama and French (2008); gross profitability of Novy-Marx (2013); operating profit of Fama and French (2015); momentum of Jegadeesh and Titman (1993); market capitalization of Fama and French (2008); asset growth of Cooper, Gulen, and Schill (2008), Hou, Xue, and Zhang (2014), and Fama and French (2015); investment growth of Xing (2008); net stock issues of Fama and French (2008); accrual of Fama and French (2008); and net operating assets of Hirshleifer, Hou, Teoh, and Zhang (2004). In constructing the control variables, monthly stock returns are obtained from the CRSP. Annual accounting data used for calculating the control variables are from COMPUSTAT. These characteristics of each firm from the third quarter of year *t* to the second quarter of year *t*+1 are based on its accounting information of the last fiscal year that ends in calendar year *t*-1. All explanatory variables are winsorized at the 1% and 99% levels, and standardized at the end of each quarter. Next, in the second step, we average the regression coefficient estimates over the quarters and compute their t-values based on Newey and West (1987) standard errors with four lags.

Table 3 reports the results from Fama-MacBeth regressions. Panel A presents results from the base sample. The regression coefficients on AHF, ASR, and AHFSR are all significant and have expected signs, even after controlling for other stock return predictors. The coefficient on AHF is 0.15% (t-value = 5.39), while the coefficient on ASR is -0.14% (t-value = –4.10). The coefficient on AHFSR is 0.22% (t-value = 5.82). Thus, if AHFSR increases by one standard deviation in the current quarter, the stock excess return would rise by 0.22% per month in the next quarter. Again, combing information in AHF and ASR leads to greater forecasting power for future stock returns.

Next, we repeat the test by restricting our sample to only stocks that have positive hedge fund holdings and short interest, and breaking the sample period into two equal subperiods. As presented in Panels B–D of Table 3, our main results hold in these sensitivity tests.

A number of control variables are included in the Fama-MacBeth regressions. Overall, regression coefficients on the control variables have correct signs, but many of these control variables are statistically insignificant. Apart from the NYSE size filter and $5 price filter we apply, a possible explanation is that these anomalies compete with each other and render each other insignificant. For example, AG competes with IK, and OP competes with GP, though each of these variables by themselves can be significant. The other possible explanation is the sample period we use. In our sample from 1990 to 2012, the value spread (from Kenneth French's website) is small at 0.25% per month. During the period, momentum trading suffers from a crash in the first half of 2009. In fact, momentum is highly significant in the first half of our sample period (see Panel C) but insignificant in the second half of the sample period (see Panel D). Combined, momentum is insignificant in predicting future excess returns in our sample. Intriguingly, net operating asset is significant in our base sample. Nevertheless, further check reveals that it is only significant in the first half of the sample period.

In sum, by performing Fama-MacBeth regressions, we show that net arbitrage trading as proxied by AHFSR has stronger predictive power for future stock returns than either the long- or the short-side does. The predictability of AHFSR is over and above that of many other firm-level variables that can potentially forecast stock returns as well.

3.3 Sources of the Arbitrage Profits

Our results suggest that net arbitrage trading is informative about stock mispricing and associated with future abnormal returns for at least two quarters. This predictive power for stock returns can arise from at least two channels. First, arbitrageurs possess and trade on private information about fundamental value of a stock. The information is later released to the market through earnings announcement or other information dissemination channels. Under this information channel, we would expect the abnormal returns associated with AHFSR to occur during future information announcement events. Second, arbitrage trading, after its disclosure, attracts the attention of other traders. Then, the initial arbitrage trades and subsequent copycat trading in the same direction together move stock prices closer to fundamental values.[12] Under the copycat trading channel, we would expect AHFSR in quarter *t* to predict trading by other institutional investors in the near future.

Table 4 examines both the channels. Panel A reports the average stock return around earnings announcements (in a three-day window) across the AHFSR-sorted quintiles. The stocks

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[12] Brown and Schwarz (2013) show evidence of copycat trading after the disclosure of hedge fund holdings. In particular, they find abnormal trading volume and positive returns immediately after the disclosure.

purchased by arbitrageurs in quarter *t* (high-AHFSR) outperform those sold by arbitrageurs (low-AHFSR) by 0.11% (t-value = 4.10) during the earnings-announcement window in quarter *t*+1, and another 0.08% (t-value = 3.22) in quarter *t*+2. Thus, the evidence supports the private information channel. Recently, Engelberg, McLean, and Pontiff (2015) find that in general, anomaly returns are much higher on earnings announcement days.

Panel B of Table 4 reports, for each of the AHFSR-sorted quintile portfolios, the average changes in institutional ownership (excluding hedge fund ownership) from quarter *t* to *t*+1, *t*+2, *t*+3, and *t*+4, respectively. Consistent with the rise in equity ownership by institutions during our sample period, the average change in institutional ownership is always positive. Nevertheless, the change is monotonically increasing in AHFSR. The differences in institutional ownership change between the high- and the low-AHFSR quintiles are significant for up to a year.[13] In other words, net arbitrage purchase in quarter *t* strongly predicts the purchase by other institutions in the next year. Hence, the evidence supports the copycat trading channel. To have a complete picture, we also look at changes in non-hedge fund holdings (CNHF) in the current quarter *t*. Interestingly, non-hedge funds appear to trade in the opposite direction to the arbitrage force. In particular, stocks with highest (lowest) AHFSR actually experience selling (buying) from non-hedge funds as a whole in the current quarter. This result confirms the importance to separate hedge funds from other institutional investors. In addition, given the lack of return reversal in the long run associated with AHFSR (as shown in Section 3.1), the opposite trading patterns of hedge funds and non-hedge funds in the current quarter do not support a “fire sale” explanation that hedge funds trade with non-hedge funds that rush to liquidate assets.

To summarize, arbitrage trading is informative about stock mispricing and the mispricing is corrected through two channels. First, stock prices move closer to fundamentals as the private information is released to the public. Second, other institutional investors trade in the same direction as the arbitrageurs subsequently, which further facilitates price convergence.

[13] When we extend the horizon, we find the difference to mean revert to zero in quarter t+7.

4. Arbitrage Trading and Stock Return Anomalies

As AHFSR measures net arbitrage trading, we now use it to shed light on how arbitrageurs trade on well-known return anomalies. As detailed in Section 2.3, we examine a total of 10 anomalies, namely book-to-market ratio, gross profitability, operating profit, momentum, market capitalization, asset growth, investment-to-capital ratio, net stock issues, accrual, and net operating assets.

Panel A of Table 5A verifies that the long-minus-short future return spreads averaged across these 10 anomalies are positive and significant in our sample. The average monthly return spreads are 0.28% (t-value = 3.47), 0.25% (t-value = 3.19), 0.20% (t-value = 2.48), and 0.15% (t-value = 1.97) per month during the first, second, third, and fourth quarters, respectively. The magnitude is somewhat smaller compared with previous studies, since we use quintile sorts instead of the more common decile sorts and we exclude small stocks from our main sample. As discussed above, the sample period is likely to play a role as well, and several anomalies have smaller returns during the recent period. Not surprisingly, when we control for return factors constructed on some of the anomalies, the resulting average five-factor alphas become smaller. They are 0.14% (t-value = 2.27), 0.13% (t-value = 1.99), 0.11% (t-value = 1.46), and 0.08% (t-value = 1.18) per month during the first, second, third, and fourth quarters, respectively. The average alphas are still significant during the first two quarters after portfolio formation, as shown in Panel A of Table 5B. In addition, consistent with the findings of Stambaugh, Yu, and Yuan (2012), most of the anomaly alphas come from the short leg since overpricing is harder to arbitrage due to short-sale constraints.

We then identify stocks in the long- and short-anomaly portfolios that are traded by arbitrageurs in the same direction. We classify an anomaly stock to be traded by arbitrageurs if it is in the long portfolio and recently bought by arbitrageurs (its AHFSR belongs to the top 30%), or it is in the short portfolio and recently sold short (its AHFSR belongs to the bottom 30%).[14] Table 5C shows that these stocks account for about 30% of both the long- and the short-portfolios. Strikingly, the anomaly returns are completely driven by these stocks that are traded

[14] Alternatively, we consider a less restrictive classification. Specifically, we classify an anomaly stock to be traded by arbitrageurs if it is in the long portfolio with a positive AHFSR, or it is in the short portfolio with a negative AHFSR. We find the same result using such a classification.

by arbitrageurs. As shown in Panel B of Table 5A, this subset of anomaly stocks earn return spreads of 0.88% (t-value = 7.10), 0.61% (t-value = 4.88), 0.34% (t-value = 2.68), and 0.27% (t-value = 2.18) per month during the first, second, third, and fourth quarters, respectively. The corresponding five-factor alphas are 0.70% (t-value = 6.31), 0.45% (t-value = 3.90), 0.25% (t-value = 1.98), and 0.22% (t-value = 1.73). Hence, the alpha shows a quick decline over time during the first year.[15] When we examine the alphas on the long- and short-legs separately, we find the alphas to come mostly from the short-leg. While the alpha on the long-leg is small and significant only in the first quarter, the alpha more than doubles on the short-leg and persists for a longer time.

In sharp contrast, the other 70% of anomaly stocks that are not traded by arbitrageurs do not earn significant return spreads or alphas in any of the next four quarters, as reported in Panel C of Table 5A. This is true for both the long- and the short-legs. The fact that future abnormal returns only appear among anomaly stocks traded by arbitrageurs and these abnormal returns decline quickly during the first year provides further support to the idea that arbitrage trading is informative about the mispricing. A close examination of Tables 5A and 5B confirms that our findings are not driven by one or two anomalies. Instead, the pattern appears consistently and uniformly across the 10 return anomalies.

So far, our findings have suggested that anomaly stocks are not created equal. Only the anomaly stocks traded by arbitrageurs seem to be mispriced. A natural question follows: How do anomaly stocks that are traded by arbitrageurs differ from those that are not traded? We compare these two subsets of anomaly stocks by examining their stock price, idiosyncratic volatility, and the Amihud (2002) illiquidity measure at the portfolio level. The Amihud measure is transformed into percentiles among NYSE/AMEX or NASDAQ firms separately.

Table 6 reports results of the comparisons. Across almost all the anomalies and for both the long- and the short-portfolios, anomaly stocks traded by arbitrageurs have significantly lower prices and higher idiosyncratic volatilities and are also significantly less liquid according to the Amihud measure. Pontiff (1996, 2006) and Shleifer and Vishny (1997) show that idiosyncratic volatility is a major arbitrage cost. Low share price and high illiquidity are associated with high

[15] Akbas, Armstrong, Sorescu, and Subrahmanyam (2014) find that aggregate money flow into the hedge fund industry attenuates stock return anomalies.

transactions costs. Indeed, it is well known that hedge funds often hold illiquidity assets (e.g., Getmansky, Lo, and Marakov, 2004). Thus, the evidence here is consistent with a notion that anomaly stocks are harder to arbitrage with high arbitrage risk and transaction costs, explaining why they are mispriced on average to start with.

Table 6 also reports the difference in the average anomaly characteristic variables (standardized by their cross-sectional deviations) between anomaly stocks traded by arbitragers and those not traded. In general, the difference in the anomaly characteristics is too small to explain the future return difference. For example, among all value stocks, the ones bought by arbitrageurs have an average book-to-market ratio only 5% lower (relative to the cross-sectional deviation in BM) than the other value stocks, while among all growth stocks, the ones sold by arbitrageurs have an average book-to-market ratio only 1% higher than the other growth stocks.

Finally, Table 7 examines future stock returns surrounding earnings announcements as well as non-hedge-fund institutional trading of the long- and the short-portfolios. Consistent with the earlier findings in Table 4, the abnormal returns on anomaly stocks traded by arbitrageurs come from two channels. First, as the private information is released to the public, prices move closer to fundamentals. Second, other institutions trade in the same direction as the arbitrageurs subsequently, further facilitating price convergence for the anomaly stocks. Interestingly, among the anomaly stocks not traded by arbitrageurs, other institutions actually purchase more overpriced stocks (short-portfolio) than underpriced stocks (long-portfolio) subsequently despite the fact the underprice stocks indeed experience higher earnings-announcement-window returns during quarters t+3 and t+4 (but not in the first two quarters). Finally, similarly to the result in Table 4, other institutional investors appear to trade in the opposite direction to the arbitrage force in the current quarter.[16]

While anomaly stocks not traded by arbitrageurs have lower arbitrage costs and do not earn abnormal returns on average, there still exists significant heterogeneity among them. Intuitively, arbitrageurs may choose not to trade an anomaly stock for two reasons. First, the stock may be extremely easy to arbitrage and therefore correctly priced. Second, the stock may

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

be extremely difficult to arbitrage, the mispricing may persist long, and price correction will only gradually take place when new information is released to the market in the future. Unreported results confirm such a pattern. When we further partition anomaly stocks that are not traded by arbitrageurs based on a composite arbitrage cost measure, those with very high arbitrage costs earn smaller but more persistent returns of 0.36% per month on average, significant up to four quarters.[17] In contrast, those with low arbitrage costs earn insignificant future returns.

Taken together, we find that our net arbitrage trading measure contains useful prospective information about stock returns. Furthermore, the anomalous returns on anomaly stocks are significantly associated with net arbitrage trading. These findings confirm that arbitrage trading is informative about mispricing and mispricing is related to limits to arbitrage.

5. Conclusion

Arbitrageurs play a crucial role in financial markets, but measuring their activities has been a challenge task empirically. By merging hedge fund stock holdings with short interest on stocks, we track arbitrage trading on both the long- and the short-sides. Over time, aggregate hedge fund holdings track aggregate short interest well, and both experienced fast growth since the early 1990s. In the cross section, net arbitrage trading, defined as the difference between abnormal hedge fund holdings and abnormal short interest on a stock, strongly predicts future stock returns. When examining a broad set of stock return anomalies, we find anomaly returns to come exclusively from the anomaly stocks that are traded by arbitrageurs. Overall, our results confirm that arbitrage trading is informative about mispricing and mispricing is related to limits to arbitrage.

Our simple measure of arbitrage trading can be used in many other applications. For example, one could relate arbitrage trading on an anomaly to its future performance. It would also be interesting to use the return spread between stocks with high- and low-AHFSR as a pricing factor in the spirit of the APT. We leave these topics for future research.

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[17] The composite score is computed using a combination of idiosyncratic volatility, institutional ownership and th Amihud (2002) illiquidity measure (IVOL, IO and Amihud). Each quarter, each stock is assigned a score from 1 to 10, for each of the three variables, with 10 capturing the highest value. The composite score equals the score on IVOL, plus 10 minus the score on IO, plus the score on Amihud rank.

Appendix: Details of the Constructions of Stock Return Anomalies.

This appendix provides details of constructing the 10 stock return anomalies examined in the paper. Following the convention in Fama and French (2008), Novy-Marx (2013), and Hou, Xue, and Zhang (2014), the financial and accounting ratios for each stock from July of year *t* to June of year *t*+1 (i.e., third quarter of year *t* to second quarter of year *t*+1) are computed based on information from the previous fiscal year ending in year *t*-1. At the end of each quarter, we sort stocks into quintile portfolios based on their financial ratios. Monthly excess returns in the next three months are calculated as equal-weighted averages of excess returns of individual firms in each portfolio. The portfolios are rebalanced each quarter at the end of March, June, September, and December.

1. Book-to-market ratio (BM). Book equity is stockholders' book equity, plus balance sheet deferred taxes (Compustat item ITCB) and investment tax credit (TXDB) if available, minus the book value of preferred stock. We employ tiered definitions largely consistent with those used in Davis, Fama, and French (2000), Novy-Marx (2013), and Hou, Xue, and Zhang (2014) to construct stockholders' equity and book value of preferred stock. Stockholders equity is as given in Compustat (SEQ) if available, or else common equity (CEQ) plus the book value of preferred stock, or else total assets minus total liabilities (AT–LT). Book value of preferred stock is redemption value (PSTKRV) if available, or else liquidating value (PSTKL) if available, or else par value (PSTK). Book-to-market ratio in year *t*-1 is computed as book equity for the fiscal year ending in calendar year *t*-1 divided by the market capitalization at the end of December of year *t*-1. Stocks with missing book values or negative book-values are deleted.
2. Gross Profit to Asset (GP). Following Novy-Marx (2013), we measure gross profits-to-assets in year *t*-1 as gross profit in year *t*-1 (Compustat item GP) divided by total assets in year *t*-1 (AT).
3. Operating Profit (OP). Following Fama and French (2015), we measure operating profit in year *t*-1 as year *t*-1 gross profit (Compustat item GP), minus selling, general, and administrative expenses (XSGA) if available, minus interest expense (XINT) if available, all divided by year *t*-1 book equity. Stocks with missing book value or negative book-value are deleted.

4. Momentum (MOM). Similar to Jegadeesh and Titman (1993), at the end of March, June, September, and December (month *t*), we compute each stock's cumulative return from month *t*-13 to *t*-2, and form quintile portfolios for the next three months. We compute equal-weighted monthly returns in each portfolio for month *t*+1 to *t*+3, and the portfolio is rebalanced at the end of month *t*+3.
5. Market Capitalization (MC). Following Fama and French (2008), MC is defined as the market capitalization at the end of June in each year. It is the product of the number of shares outstanding and share price from the CRSP. This MC is used for the following four quarters.
6. Asset Growth (AG). Following Cooper, Gulen, and Schill (2008), we compute asset growth in year *t*-1 as total assets (AT) for the fiscal year ending in calendar year *t*-1 divided by total assets for the fiscal year ending in calendar year *t*-2, minus one.
7. Investment growth (IK). Following Xing (2008), we measure investment growth for year *t*-1 as the growth rate in capital expenditure (CAPX) from the fiscal year ending in calendar year *t*-2 to the fiscal year ending in *t*-1.
8. Net stock issues (NS). Following Fama and French (2008), we compute net stock issues in year *t*-1, as the split-adjusted shares outstanding for fiscal year ending in calendar year *t*-1 divided by the split-adjusted shares outstanding for fiscal year ending in calendar year *t*-2, minus one. The split-adjusted shares outstanding are calculated as shares outstanding (CSHO) times the adjustment factor (AJEX).
9. Accrual (AC). Accruals in year *t*-1 are defined following Fama and French (2008), as the change in operating working capital per split-adjusted share from *t*-2 to *t*-1 divided by book equity per split-adjusted share at *t*-1. Operating working capital is computed as current assets (ACT) minus cash and short-term investments (CHE), minus the difference of current liability (LCT) and debt in current liabilities (DLC) if available.
10. Net Operating Assets (NOA). Following Hirshleifer et al. (2004), we define net operating assets (NOA) in year *t*-1, as operating assets minus operating liabilities in year *t*-1 scaled by total assets in year *t*-2 (Compustat item AT). Operating assets are total assets (AT) minus cash and short-term investment (CHE). Operating liabilities are total assets minus debt included in current liabilities (item DLC, zero if missing), minus long-term debt (item DLTT, zero if missing), minus minority interests (item MIB, zero if missing),

minus book value of preferred stocks as described in the definition of book equity (zero if missing), and minus common equity (CEQ).

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Table 1. Summary Statistics

This table presents summary statistics for the following variables: hedge fund holdings (HF), defined as the ratio between shares owned by hedge funds and the number of outstanding shares; short interest (SR), defined as the ratio between shares shorted and the number of shares outstanding; the difference between HF and SR (HFSR); abnormal hedge fund holdings (AHF), defined as the percentage change of current HF from the average HF in the previous four quarters; abnormal short ratio (ASR), defined as the percentage change of current SR from the average SR in the previous four quarters; and the difference between AHF and ASR (AHFSR). Panel A reports the summary statistics including the mean, 5th percentile, 25th percentile, median, 75th percentile, 95th percentile, standard deviation, and quarterly autocorrelation coefficient. At the end of each quarter, we first compute the variables across stocks, and then take average across quarters. % of CRSP represents the total market capitalization of our sample stocks as a fraction of the market capitalization of the full CRSP universe. In each quarter, we delete firms with market capitalizations below the 20th percentile size breakpoint of NYSE firms. Panel B presents average correlations between HF, SR, HFSR, AHF, ASR, AHFSR and stock characteristics over quarters. We consider the following stock characteristics: book-to-market ratio (BM) of Fama and French (2008); gross profitability (GP) of Novy-Marx (2013); operating profit (OP) of Fama and French (2015); momentum (MOM) of Jegadeesh and Titman (1993); market capitalization (MC) of Fama and French (2008); asset growth (AG) of Cooper, Gulen, and Schill (2008), Hou, Xue, and Zhang (2014), and Fama and French (2015); investment-to-capital ratio (IK) of Xing (2008); net stock issues (NS) of Fama and French (2008); accrual (AC) of Fama and French (2008); and net operating assets (NOA) of Hirshleifer, Hou, Teoh, and Zhang (2004). Monthly stock returns are from the CRSP. Annual accounting data used for calculating the stock characteristics are from COMPUSTAT. The characteristics of each firm from July of year t to June of year t+1 are based on its accounting information of the last fiscal year that ends in calendar year t-1. The sample period is from 1990Q1 to 2012Q4.

Table 1, continued.

Panel A: Summary (in percentage)								
	Mean	P5	P25	P50	P75	P95	STD	AR(1)
HF	3.72	0.34	1.12	2.37	4.90	12.01	3.97	64.11
SR	3.49	0.38	1.12	2.35	4.44	11.20	3.66	58.60
HFSR	0.23	-7.42	-1.63	0.13	1.88	8.23	4.69	59.94
AHF	0.19	-2.67	-0.55	0.04	0.75	3.63	1.90	45.25
ASR	0.18	-2.37	-0.52	0.02	0.69	3.38	1.83	40.86
AHFSR	0.00	-4.50	-1.03	0.02	1.06	4.45	2.66	41.53
% of CRSP	86.73	74.87	85.50	87.29	89.26	92.22	4.50	

Panel B: Correlation																
	HF	SR	HFSR	AHF	ASR	AHFSR	BM	GP	OP	MOM	MC	AG	IK	NS	AC	NOA
HF	1.00	0.23	0.63	0.42	0.06	0.24	0.00	0.06	-0.04	0.06	-0.17	0.08	0.06	0.08	-0.01	0.06
SR	0.23	1.00	-0.59	0.04	0.45	-0.30	-0.09	0.08	-0.08	-0.04	-0.20	0.19	0.11	0.11	0.05	0.10
HFSR	0.63	-0.59	1.00	0.30	-0.31	0.45	0.08	-0.02	0.03	0.07	0.00	-0.09	-0.04	-0.02	-0.05	-0.03
AHF	0.42	0.04	0.30	1.00	0.07	0.64	0.01	0.01	-0.01	0.02	-0.03	-0.02	0.00	-0.02	-0.01	-0.01
ASR	0.06	0.45	-0.31	0.07	1.00	-0.68	-0.03	0.01	-0.02	-0.02	-0.05	0.05	0.03	0.02	0.02	0.02
AHFSR	0.24	-0.30	0.45	0.64	-0.68	1.00	0.03	0.00	0.01	0.02	0.01	-0.04	-0.03	-0.03	-0.02	-0.02

Table 2. Stock Returns and Alphas of Portfolios Formed on Arbitrage Capital

At the end of each quarter, we form quintile portfolios based on AHF, ASR, or AHFSR, and track each portfolio's monthly excess returns (in percentage) in the next quarter, which are the equal-weighted average of excess returns on stocks in each portfolio. Quintile 5 has the highest AHF, ASR or AHFSR. We adjust risk exposures using the three factors of Fama and French (1996), the Fama-French three factors and the Carhart (1997) momentum factor, and the five factors of Fama and French (2015) that are labelled as FF3, FF4, and FF5, respectively. Table 2A uses our base sample that deletes the firms with market capitalizations below the NYSE 20th percentile size breakpoint at the end of each quarter. Panel A presents results for the portfolios formed on AHF, Panel B presents results for the portfolios formed on ASR, Panel C presents results for the portfolios formed on AHFSR, and Panel D presents return spreads of these portfolios in the next four quarters. The left panels present excess returns and alphas, and the right panels report their t-values. Table 2B presents results from using a sample without applying the firm size filter. Table 2C uses firms that have strictly positive HF and SR in our base sample. Table 2D uses the first half of the sample period. Table 2E uses the second half of the sample period. Table 2F presents results from tercile portfolios independently formed on AHF and ASR in our base sample. Stock excess return and alpha are reported in percent per month. Table 2G (Panel A) repeats the quintile AHFSR sorting but with HF and SR scaled by total institutional ownership. The variable AHFSRIO represents the AHFSR constructed using scaled HF and SR. Table 2G (Panel B) presents next four quarters returns for AHFSRIO sorting. Table 2H, similar to table 2F, presents double sorting result from AIO and ASR, where AIO is abnormal IO defined similarly to abnormal HF. Panel A through D in table 2H presents next quarter returns and various alphas and their t-values. Panel E in table 2H presents the next four quarter returns of portfolios formed on AIO and ASR. The sample period is from 1990Q1 to 2012Q4.

Table 2A. Base Sample

	Return and Alpha				t-value			
	Ret.	FF3	FF4	FF5	Ret.	FF3	FF4	FF5
Panel A: Quintile Portfolios Formed on AHF								
AHF1	0.61	-0.12	-0.04	-0.16	1.77	-1.23	-0.41	-1.65
AHF2	0.57	-0.12	-0.05	-0.23	1.95	-1.53	-0.61	-3.03
AHF3	0.62	-0.02	0.05	-0.19	2.36	-0.26	0.66	-2.51
AHF4	0.81	0.11	0.16	-0.04	2.76	1.43	2.01	-0.47
AHF5	1.05	0.28	0.34	0.19	2.97	3.11	3.92	2.12
AHF-HML	0.44	0.40	0.38	0.35	4.98	4.50	4.27	3.80
Panel B: Quintile Portfolios Formed on ASR								
ASR1	0.90	0.18	0.24	0.09	2.70	2.08	2.91	1.05
ASR2	0.86	0.18	0.21	0.01	3.05	2.38	2.68	0.10
ASR3	0.75	0.09	0.13	-0.05	2.79	1.19	1.73	-0.65
ASR4	0.68	0.00	0.07	-0.11	2.32	0.05	0.77	-1.27
ASR5	0.49	-0.32	-0.17	-0.35	1.32	-3.09	-1.91	-3.31
ASR-HML	-0.41	-0.50	-0.42	-0.44	-4.21	-5.42	-4.71	-4.58
Panel C: Quintile Portfolios Formed on AHFSR								
AHFSR1	0.43	-0.34	-0.22	-0.38	1.20	-3.53	-2.48	-3.80
AHFSR2	0.61	-0.08	-0.01	-0.20	2.07	-0.98	-0.06	-2.40
AHFSR3	0.69	0.06	0.10	-0.09	2.65	0.74	1.40	-1.21
AHFSR4	0.81	0.14	0.17	-0.04	2.85	1.75	2.07	-0.48
AHFSR5	1.11	0.36	0.42	0.27	3.23	4.26	5.02	3.23
AHFSR-HML	0.68	0.70	0.64	0.65	7.93	8.17	7.57	7.20
Panel D: Subsequent-quarter Returns and t-values after Portfolio Formation								
	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4
AHF-HML	0.44	0.22	0.17	-0.04	4.98	2.77	2.14	-0.56
ASR-HML	-0.41	-0.26	-0.12	-0.11	-4.21	-2.57	-1.15	-1.21
AHFSR-HML	0.68	0.42	0.18	0.01	7.93	4.90	1.90	0.18

Table 2B. Full Sample								
	Return and Alpha				t-value			
	Ret.	FF3	FF4	FF5	Ret.	FF3	FF4	FF5
Panel A: Quintile Portfolios Formed on AHF								
AHF1	0.57	-0.17	-0.04	-0.20	1.66	-1.84	-0.46	-2.14
AHF2	0.61	-0.08	0.02	-0.18	2.13	-1.09	0.23	-2.48
AHF3	0.66	0.07	0.14	-0.05	2.79	0.85	1.74	-0.64
AHF4	0.80	0.13	0.19	0.00	2.90	1.82	2.58	-0.01
AHF5	0.96	0.21	0.31	0.12	2.87	2.56	4.01	1.44
AHF-HML	0.39	0.38	0.35	0.32	5.34	5.19	4.68	4.18
Panel B: Quintile Portfolios Formed on ASR								
ASR1	0.80	0.04	0.18	-0.01	2.32	0.41	2.27	-0.15
ASR2	0.83	0.18	0.23	0.03	3.13	2.27	2.94	0.47
ASR3	0.84	0.26	0.32	0.14	3.63	3.40	4.23	1.83
ASR4	0.69	0.04	0.10	-0.08	2.50	0.51	1.15	-0.99
ASR5	0.43	-0.36	-0.21	-0.38	1.21	-3.76	-2.60	-3.91
ASR-HML	-0.36	-0.40	-0.39	-0.37	-4.58	-5.02	-4.83	-4.39
Panel C: Quintile Portfolios Formed on AHFSR								
AHFSR1	0.41	-0.37	-0.21	-0.39	1.17	-3.89	-2.74	-4.07
AHFSR2	0.62	-0.05	0.04	-0.15	2.22	-0.63	0.53	-2.06
AHFSR3	0.77	0.19	0.24	0.06	3.34	2.53	3.16	0.87
AHFSR4	0.81	0.15	0.21	0.01	2.98	2.07	3.02	0.16
AHFSR5	0.99	0.23	0.34	0.15	2.92	2.81	4.55	1.86
AHFSR-HML	0.58	0.60	0.55	0.54	7.74	7.94	7.39	6.88

Table 2C. HF>0, SR>0, Base Sample								
	Return and Alpha				t-value			
	Ret.	FF3	FF4	FF5	Ret.	FF3	FF4	FF5
Panel A: Quintile Portfolios Formed on AHF								
AHF1	0.63	-0.10	-0.02	-0.13	1.81	-0.98	-0.17	-1.37
AHF2	0.61	-0.08	0.00	-0.18	2.06	-1.02	-0.06	-2.40
AHF3	0.69	0.05	0.12	-0.13	2.58	0.63	1.52	-1.80
AHF4	0.81	0.10	0.15	-0.05	2.69	1.26	1.79	-0.65
AHF5	1.08	0.30	0.36	0.20	2.99	3.07	3.76	2.04
AHF-HML	0.45	0.40	0.38	0.33	4.76	4.23	3.99	3.40
Panel B: Quintile Portfolios Formed on ASR								
ASR1	0.96	0.24	0.30	0.15	2.85	2.61	3.37	1.65
ASR2	0.86	0.19	0.21	0.01	3.01	2.38	2.67	0.17
ASR3	0.79	0.12	0.16	-0.03	2.85	1.57	2.07	-0.48
ASR4	0.71	0.03	0.09	-0.09	2.37	0.31	1.03	-1.02
ASR5	0.50	-0.30	-0.16	-0.34	1.35	-2.81	-1.67	-3.09
ASR-HML	-0.45	-0.54	-0.46	-0.49	-4.47	-5.63	-4.96	-4.86
Panel C: Quintile Portfolios Formed on AHFSR								
AHFSR1	0.47	-0.30	-0.18	-0.34	1.30	-3.03	-1.98	-3.35
AHFSR2	0.61	-0.08	0.00	-0.20	2.04	-0.94	-0.01	-2.31
AHFSR3	0.76	0.12	0.16	-0.04	2.82	1.53	2.15	-0.54
AHFSR4	0.83	0.16	0.19	-0.02	2.87	1.90	2.25	-0.25
AHFSR5	1.15	0.39	0.44	0.30	3.26	4.31	4.90	3.30
AHFSR-HML	0.67	0.69	0.62	0.64	7.25	7.36	6.75	6.46

Table 2D. First Half of the Sample Period, 1990Q1–2000Q2								
	Return and Alpha				t-value			
	Ret.	FF3	FF4	FF5	Ret.	FF3	FF4	FF5
Panel A: Quintile Portfolios Formed on AHF								
AHF1	0.77	-0.19	-0.01	-0.18	1.67	-1.28	-0.04	-1.21
AHF2	0.69	-0.23	-0.03	-0.28	1.91	-1.79	-0.29	-2.52
AHF3	0.70	-0.14	0.03	-0.21	2.24	-1.06	0.28	-1.82
AHF4	0.94	0.01	0.15	-0.05	2.64	0.12	1.33	-0.43
AHF5	1.15	0.10	0.19	0.05	2.45	0.72	1.34	0.37
AHF-HML	0.38	0.29	0.20	0.23	3.10	2.39	1.62	1.76
Panel B: Quintile Portfolios Formed on ASR								
ASR1	1.05	0.09	0.27	0.09	2.42	0.66	2.05	0.71
ASR2	1.04	0.14	0.26	0.05	3.00	1.19	2.20	0.46
ASR3	0.83	-0.03	0.08	-0.10	2.58	-0.26	0.70	-0.94
ASR4	0.72	-0.21	-0.04	-0.23	1.94	-1.61	-0.34	-1.94
ASR5	0.63	-0.41	-0.21	-0.45	1.32	-2.62	-1.41	-2.93
ASR-HML	-0.41	-0.50	-0.47	-0.55	-3.44	-4.44	-4.03	-4.56
Panel C: Quintile Portfolios Formed on AHFSR								
AHFSR1	0.54	-0.47	-0.27	-0.48	1.14	-3.10	-1.91	-3.15
AHFSR2	0.72	-0.21	-0.01	-0.24	1.98	-1.59	-0.07	-2.04
AHFSR3	0.85	0.02	0.17	-0.06	2.73	0.19	1.54	-0.58
AHFSR4	0.94	0.02	0.14	-0.05	2.65	0.20	1.12	-0.49
AHFSR5	1.21	0.20	0.31	0.17	2.65	1.46	2.29	1.35
AHFSR-HML	0.67	0.67	0.57	0.65	5.93	5.77	4.99	5.27

Table 2E. Second Half of the Sample Period, 2000Q3–2012Q4								
	Return and Alpha				t-value			
	Ret.	FF3	FF4	FF5	Ret.	FF3	FF4	FF5
Panel A: Quintile Portfolios Formed on AHF								
AHF1	0.47	-0.14	-0.13	-0.10	0.90	-1.26	-1.17	-0.89
AHF2	0.48	-0.05	-0.05	-0.08	1.04	-0.62	-0.57	-0.88
AHF3	0.54	0.07	0.08	-0.04	1.30	1.02	1.04	-0.56
AHF4	0.69	0.15	0.15	0.08	1.48	1.96	1.89	0.98
AHF5	0.96	0.38	0.40	0.44	1.84	4.12	4.60	4.52
AHF-HML	0.50	0.52	0.53	0.54	3.99	4.22	4.29	4.27
Panel B: Quintile Portfolios Formed on ASR								
ASR1	0.75	0.21	0.21	0.20	1.50	2.36	2.36	2.18
ASR2	0.69	0.17	0.16	0.06	1.57	2.09	2.00	0.74
ASR3	0.69	0.19	0.18	0.09	1.61	2.24	2.20	1.10
ASR4	0.66	0.15	0.15	0.12	1.45	1.65	1.63	1.22
ASR5	0.35	-0.30	-0.26	-0.16	0.62	-2.38	-2.51	-1.25
ASR-HML	-0.41	-0.51	-0.46	-0.37	-2.67	-3.47	-3.65	-2.40
Panel C: Quintile Portfolios Formed on AHFSR								
AHFSR1	0.34	-0.30	-0.27	-0.22	0.62	-2.66	-2.72	-1.85
AHFSR2	0.51	-0.01	-0.01	-0.04	1.12	-0.12	-0.09	-0.51
AHFSR3	0.56	0.08	0.08	-0.01	1.35	0.97	0.92	-0.10
AHFSR4	0.69	0.19	0.18	0.09	1.56	2.56	2.48	1.17
AHFSR5	1.03	0.45	0.46	0.49	2.00	5.09	5.29	5.13
AHFSR-HML	0.69	0.75	0.73	0.70	5.38	5.85	5.93	5.18

Table 2F. Double Sorting on AHF and ASR								
	Return and Alpha				t-value			
	AHF1	AHF2	AHF3	AHF-HML	AHF1	AHF2	AHF3	AHF-HML
Panel A: Excess Returns								
ASR1	0.71	0.72	1.18	0.47	2.12	2.55	3.47	4.41
ASR2	0.67	0.67	0.98	0.30	2.29	2.74	3.26	3.73
ASR3	0.40	0.45	0.81	0.42	1.13	1.48	2.25	4.75
ASR-HML	-0.31	-0.27	-0.36		-3.43	-2.80	-3.73	
Panel B: FF3 Alpha								
ASR1	0.01	0.05	0.42	0.41	0.11	0.56	4.36	3.91
ASR2	-0.02	0.07	0.28	0.30	-0.22	0.86	2.88	3.60
ASR3	-0.37	-0.26	0.03	0.40	-3.51	-2.72	0.31	4.56
ASR-HML	-0.38	-0.31	-0.39		-4.35	-3.31	-4.09	
Panel C: FF4 Alpha								
ASR1	0.08	0.08	0.47	0.39	0.88	0.87	4.94	3.66
ASR2	0.02	0.12	0.30	0.28	0.27	1.52	3.10	3.33
ASR3	-0.25	-0.14	0.12	0.38	-2.57	-1.60	1.32	4.25
ASR-HML	-0.34	-0.22	-0.35		-3.86	-2.43	-3.65	
Panel D: FF5 Alpha								
ASR1	-0.04	-0.13	0.29	0.33	-0.42	-1.52	2.93	3.04
ASR2	-0.11	-0.11	0.12	0.23	-1.24	-1.46	1.27	2.64
ASR3	-0.41	-0.38	-0.02	0.39	-3.97	-3.84	-0.22	4.25
ASR-HML	-0.37	-0.25	-0.31		-3.99	-2.49	-3.12	

Table 2G. One Dimensional Sorting from AHFSRIO								
	Return and Alpha				t-value			
	Ret.	FF3	FF4	FF5	Ret.	FF3	FF4	FF5
Panel A: Quintile Portfolios Formed on AHFSRIO								
AHFSRIO1	0.42	-0.34	-0.23	-0.35	1.19	-3.82	-2.81	-3.87
AHFSRIO2	0.62	-0.08	0.00	-0.21	2.09	-0.94	-0.02	-2.49
AHFSRIO3	0.71	0.05	0.11	-0.11	2.60	0.68	1.48	-1.49
AHFSRIO4	0.86	0.18	0.22	0.02	2.98	2.25	2.65	0.27
AHFSRIO5	1.06	0.32	0.37	0.23	3.16	3.94	4.60	2.83
AHFSRIO-HML	0.64	0.66	0.60	0.58	7.46	7.74	7.14	6.54
Panel B: Subsequent-quarter Returns and t-values after Portfolio Formation								
	Ret				t-value			
Quarters	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4
AHFSRIO-HML	0.64	0.42	0.22	0.03	7.46	4.85	2.35	0.32

Table 2H. Double Sorting from AIO and ASR								
	Ret. and Alpha				t-value			
	AIO1	AIO2	AIO3	AIO-HML	AIO1	AIO2	AIO3	AIO-HML
Panel A: Excess Returns								
ASR1	0.89	0.82	0.80	-0.09	2.72	2.88	2.36	-0.74
ASR2	0.84	0.71	0.76	-0.08	3.03	2.75	2.50	-0.80
ASR3	0.59	0.58	0.60	0.00	1.62	1.84	1.65	0.03
ASR-HML	-0.30	-0.24	-0.21		-2.83	-2.42	-2.04	
Panel B: FF3 Alpha								
ASR1	0.17	0.16	0.08	-0.09	1.74	1.75	0.80	-0.76
ASR2	0.18	0.07	0.06	-0.12	1.99	0.89	0.68	-1.25
ASR3	-0.19	-0.16	-0.17	0.02	-1.41	-1.41	-1.90	0.17
ASR-HML	-0.36	-0.32	-0.25		-3.50	-3.20	-2.54	
Panel C: FF4 Alpha								
ASR1	0.28	0.18	0.04	-0.25	3.16	1.93	0.37	-2.40
ASR2	0.28	0.11	0.05	-0.23	3.31	1.39	0.57	-2.61
ASR3	0.05	-0.01	-0.15	-0.20	0.49	-0.09	-1.64	-1.85
ASR-HML	-0.23	-0.19	-0.19		-2.47	-2.12	-1.92	
Panel D: FF5 Alpha								
ASR1	0.05	-0.01	0.02	-0.03	0.51	-0.16	0.21	-0.23
ASR2	0.07	-0.12	-0.06	-0.13	0.78	-1.64	-0.60	-1.28
ASR3	-0.23	-0.29	-0.20	0.02	-1.61	-2.58	-2.22	0.17
ASR-HML	-0.28	-0.27	-0.23		-2.55	-2.63	-2.15	
Panel E: Subsequent quarter returns and t-values								
	Ret				t-value			
Quarters	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4
AIO3, ASR1	0.80	0.81	0.74	1.02	2.36	2.29	2.03	2.74
AIO1, ASR3	0.59	0.87	0.81	1.08	1.62	2.31	2.15	2.82
Diff.	0.21	-0.06	-0.07	-0.06	1.35	-0.37	-0.46	-0.42
	Alpha				t-value			
AIO3, ASR1	0.02	0.01	-0.04	0.09	0.21	0.11	-0.33	0.62
AIO1, ASR3	-0.23	0.05	-0.09	0.00	-1.61	0.35	-0.67	-0.02
Diff.	0.25	-0.04	0.05	0.09	1.51	-0.25	0.38	0.63

Table 3. Fama-MacBeth Regressions of Monthly Excess Returns

This table presents the Fama-MacBeth regression results from regressing average monthly stock excess returns over the next quarter on AHF, ASR, or AHFSR of the current quarter. The control variables include book-to-market ratio (BM) of Fama and French (2008); gross profitability (GP) of Novy-Marx (2013); operating profit (OP) of Fama and French (2015); momentum (MOM) of Jegadeesh and Titman (1993); market capitalization (MC) of Fama and French (2008); asset growth (AG) of Cooper, Gulen, and Schill (2008), Hou, Xue, and Zhang (2014), and Fama and French (2015); investment growth (IK) of Xing (2008); net stock issues (NS) of Fama and French (2008); accrual (AC) of Fama and French (2008); and net operating assets (NOA) of Hirshleifer, Hou, Teoh, and Zhang (2004). We take natural logs for BM and MC. All explanatory variables are winsorized at 1% and 99% and standardized at the end of each quarter. Stock excess returns are in percent per month. The t-values use Newey-West standard errors with four lags. The sample period is from 1990Q1 to 2012Q4.

Table 3, continued.

Fama-MacBeth Regression of Future Stock Excess Returns on AHF, ASR, or AHFSR												
	Panel A: 1990Q1–2012Q4			Panel B: 1990Q1–2012Q4, HF>0,SR>0			Panel C: 1990Q1–2000Q2			Panel D: 2000Q3–2012Q4		
AHF	0.15***			0.16***			0.12***			0.17***		
t-value	5.39			5.46			2.81			6.31		
ASR		-0.14***			-0.16***			-0.18***			-0.12***	
t-value		-4.10			-4.23			-2.81			-3.38	
AHFSR			0.22***			0.24***			0.23***			0.22***
t-value			5.82			6.17			3.24			6.87
BM	0.12	0.11	0.11	0.12	0.11	0.11	0.01	-0.01	-0.01	0.12	0.21	0.21
t-value	1.35	1.22	1.21	1.26	1.12	1.12	0.09	-0.02	-0.04	1.59	1.54	1.55
OP	0.08	0.08	0.08	0.09	0.07	0.08	-0.05	-0.06	-0.06	0.20*	0.20*	0.21*
t-value	0.95	0.87	0.91	0.94	0.83	0.88	-0.33	-0.41	-0.4	1.75	1.71	1.74
MOM	0.01	0.01	0.01	-0.02	-0.01	-0.01	0.32***	0.34***	0.33***	-0.26	-0.27	-0.26
t-value	0.01	0.04	0.03	-0.14	-0.09	-0.11	3.16	3.29	3.25	-1.48	-1.55	-1.51
MC	-0.08	-0.09	-0.09	-0.10	-0.12*	-0.11*	-0.02	-0.04	-0.03	-0.13**	-0.15***	-0.15***
t-value	-1.24	-1.57	-1.45	-1.55	-1.93	-1.74	-0.21	-0.34	-0.25	-2.36	-2.90	-2.81
AG	0.02	0.03	0.03	0.04	0.04	0.04	0.08	0.09	0.09	-0.05	-0.05	-0.05
t-value	0.35	0.45	0.44	0.54	0.61	0.62	0.77	0.82	0.81	-0.63	-0.56	-0.56
IK	-0.01	-0.01	-0.01	-0.02	-0.02	-0.02	0.01	0.01	0.01	-0.04	-0.04	-0.04
t-value	-0.47	-0.36	-0.42	-0.57	-0.47	-0.53	0.2	0.31	0.31	-1.05	-0.99	-1.07
GP	0.03	0.03	0.03	0.03	0.03*	0.03	0.04	0.04	0.04	0.02	0.02	0.02
t-value	1.49	1.48	1.44	1.66	1.67	1.62	1.61	1.54	1.53	0.54	0.57	0.53
NS	-0.05	-0.06	-0.05	-0.05	-0.06	-0.06	-0.05	-0.05	-0.05	-0.05	-0.05	-0.05
t-value	-1.26	-1.4	-1.35	-1.15	-1.23	-1.21	-0.86	-0.95	-0.98	-0.88	-0.97	-0.89
AC	0.02	0.03	0.03	0.03	0.03	0.03	-0.01	-0.00	0.01	0.03	0.04	0.04
t-value	1.02	1.17	1.14	1.34	1.55	1.48	-0.09	0.03	0.06	1.14	1.24	1.19
NOA	-0.20**	-0.20**	-0.20**	-0.20**	-0.20**	-0.20**	-0.34**	-0.34**	-0.34**	-0.05	-0.06	-0.06
t-value	-2.43	-2.46	-2.44	-2.49	-2.53	-2.50	-2.46	-2.48	-2.44	-0.83	-0.86	-0.87
Const.	0.79***	0.79***	0.79***	0.82***	0.82***	0.82***	0.84***	0.84***	0.84***	0.72	0.72	0.72
t-value	2.85	2.85	2.84	2.94	2.93	2.93	3.01	3.00	3.00	1.62	1.61	1.61
Adj. R^2	0.083	0.083	0.084	0.088	0.089	0.089	0.073	0.074	0.074	0.090	0.090	0.091
Obs.	115,461	115,461	115,461	101,993	101,993	101,993	55,355	55,355	55,355	61,512	61,512	61,512

Table 4. Returns around Earnings Announcements and Changes in Non-Hedge Fund Holdings by AHFSR Portfolios

In Panel A, for each stock, we compute its returns (in percentage) for the three days around earnings announcements (i.e., a three-day window) in the next four quarters. Ret_EA1 is the return around earnings announcement in the next quarter after portfolio formation, and Ret_EA2, Ret_EA3, and Ret_EA4 are the returns around earnings announcement in the second, third, and fourth quarters after portfolio formation, respectively. In Panel B, at the end of each quarter *t*, for each stock in each AHFSR portfolio, we compute the percentage changes of non-hedge fund holdings in the current and next four quarters. CNHF0 is the change of non-hedge fund holdings in the current quarter, defined as the difference in non-hedge fund holdings between the end of quarter *t* and the end of quarter *t*–1. CNHF1 is the change of non-hedge fund holdings in the next quarter, defined as the difference in non-hedge fund holdings between quarter *t*+1 and *t*. CNHF2 is the change of non-hedge fund holdings in the next two quarters, defined as the difference in non-hedge fund holdings between quarter *t*+2 and *t*. CNHF3 and CNHF4 are similarly defined for the next three and four quarters, respectively. Portfolio-level earnings-announcement-window returns and changes in non-hedge fund holdings are averages across stocks. The t-values for the CNHFs are Newey-West with four lags.

	Panel A: Returns around EA				Panel B: Changes in Non-Hedge Fund Holdings				
	Ret_EA1	Ret_EA2	Ret_EA3	Ret_EA4	CNHF0	CNHF1	CNHF2	CNHF3	CNHF4
AHFSR1	0.12	0.12	0.14	0.17	1.76	0.07	0.10	0.12	0.22
AHFSR2	0.11	0.14	0.16	0.14	0.77	0.28	0.52	0.74	1.01
AHFSR3	0.10	0.13	0.10	0.12	0.34	0.28	0.53	0.82	1.05
AHFSR4	0.14	0.13	0.14	0.14	0.10	0.34	0.67	1.05	1.39
AHFSR5	0.23	0.20	0.18	0.18	-0.70	0.49	1.08	1.61	2.12
AHFSR-HML	0.11	0.08	0.04	0.00	-2.46	0.42	0.98	1.49	1.90
t-value	4.10	3.22	1.73	0.16	-3.84	3.55	4.09	4.14	4.12

Table 5. Net Arbitrage Trading and Stock Anomaly Returns in the Following Year

For each return anomaly, at the end of each quarter, we construct quintile portfolios and compute monthly portfolio returns in the next four quarters (Q1, Q2, Q3 and Q4). In Panel A, LMS is the return spread between the long- and the short-legs of the stock anomalies. The column "Avg." reports results for a portfolio equally-investing in the 10 anomalies. We also report the alpha of the long-minus-short of these composite portfolios, Alpha(LMS), as well as the alphas of the long portfolio Alpha(L) and the short portfolio Alpha(S), based on the Fama-French (2015) five-factor model. Next, we independently form three AHFSR portfolios using the 30% and 70% AHFSR cutoff values. At the end of each quarter, in the long leg, we identify stocks that belong to the AHFSR group 3 (Trading) and that do not belong to AHFSR group 3 (Not Trading). Similarly, in the short leg, we identify those stocks that belong to the AHFSR group 1 (Trading) and that do not belong to the AHFSR group 1 (Not Trading). We track the monthly equal-weighted averages of these four portfolios. In Panel B, "return of trading" is the return spread between the long- and the short-legs when arbitrage capital trades. In Panel C, "return of not trading" is the return spread between the long- and short-legs when arbitrage capital does not trade. Panel D reports the difference between the groups of trading and not-trading. Table 5A presents the returns, and Table 5B presents corresponding t-values. Table 5C presents, for each return anomaly, the total number of stocks on the long- or the short-leg, and the numbers and fractions of stocks that are traded by the arbitrage capital on the long- or the short-leg. We consider the following anomalies: book-to-market ratio (BM) of Fama and French (2008); gross profitability (GP) of Novy-Marx (2013); operating profit (OP) of Fama and French (2015); momentum (MOM) of Jegadeesh and Titman (1993); market capitalization (MC) of Fama and French (2008); asset growth (AG) of Cooper, Gulen, and Schill (2008), Hou, Xue, and Zhang (2014), and Fama and French (2015); investment growth (IK) of Xing (2008); net stock issues (NS) of Fama and French (2008); accrual (AC) of Fama and French (2008); and net operating assets (NOA) of Hirshleifer, Hou, Teoh, and Zhang (2004). The sample period is from 1990Q1 to 2012Q4.

Table 5A: Returns

	BM	GP	OP	MOM	MC	AG	IK	NS	AC	NOA	Avg.	Alpha(LMS)	Alpha(L)	Alpha(S)
Panel A: LMS Returns														
Q1	0.18	0.32	0.35	0.17	0.20	0.35	0.22	0.46	0.16	0.38	0.28	0.14	-0.03	-0.17
Q2	0.21	0.24	0.27	0.06	0.25	0.36	0.28	0.38	0.08	0.39	0.25	0.13	-0.02	-0.15
Q3	0.17	0.22	0.19	-0.15	0.19	0.32	0.25	0.33	0.14	0.38	0.20	0.11	-0.01	-0.11
Q4	0.11	0.18	0.18	-0.22	0.20	0.16	0.22	0.24	0.13	0.29	0.15	0.08	0.02	-0.07
Panel B: Return of Trading														
Q1	0.69	1.06	1.03	0.85	0.73	1.00	0.78	0.99	0.69	1.00	0.88	0.70	0.22	-0.48
Q2	0.59	0.69	0.65	0.43	0.60	0.69	0.58	0.67	0.39	0.77	0.61	0.45	0.13	-0.32
Q3	0.21	0.50	0.49	0.02	0.15	0.42	0.33	0.57	0.22	0.52	0.34	0.25	0.09	-0.16
Q4	0.16	0.27	0.41	-0.09	0.26	0.30	0.35	0.35	0.17	0.49	0.27	0.22	0.06	-0.15
Panel C: Return of Not Trading														
Q1	-0.07	0.02	0.04	-0.20	0.04	-0.01	-0.05	0.19	-0.12	0.11	-0.01	-0.12	-0.14	-0.02
Q2	0.05	0.06	0.09	-0.15	0.15	0.19	0.12	0.24	-0.10	0.22	0.09	-0.02	-0.09	-0.07
Q3	0.16	0.12	0.07	-0.25	0.20	0.26	0.20	0.22	0.10	0.32	0.14	0.04	-0.04	-0.08
Q4	0.09	0.15	0.07	-0.30	0.21	0.07	0.16	0.20	0.11	0.21	0.10	0.02	0.00	-0.02
Panel D: Difference between Trading and Not Trading														
Q1	0.76	1.04	0.99	1.05	0.69	1.01	0.83	0.80	0.82	0.89	0.89	0.82	0.36	-0.46
Q2	0.54	0.63	0.56	0.57	0.46	0.50	0.46	0.43	0.49	0.55	0.52	0.47	0.22	-0.25
Q3	0.06	0.38	0.41	0.27	-0.05	0.16	0.13	0.35	0.11	0.21	0.20	0.21	0.13	-0.08
Q4	0.07	0.12	0.33	0.21	0.04	0.24	0.19	0.15	0.07	0.28	0.17	0.20	0.07	-0.13

Table 5B: t-values

	BM	GP	OP	MOM	MC	AG	IK	NS	AC	NOA	Avg.	Alpha(LMS)	Alpha(L)	Alpha(S)
Panel A: LMS Returns														
Q1	0.82	1.86	2.03	0.54	0.97	2.25	1.92	2.70	1.71	2.50	3.47	2.27	-0.49	-1.92
Q2	0.99	1.37	1.44	0.20	1.30	2.31	2.32	2.19	0.86	2.53	3.19	1.99	-0.36	-1.58
Q3	0.78	1.21	1.11	-0.62	0.99	1.90	1.82	1.85	1.51	2.45	2.48	1.46	-0.07	-1.04
Q4	0.55	0.99	1.02	-0.96	0.99	0.97	1.64	1.36	1.41	1.86	1.97	1.18	0.19	-0.62
Panel B: Return of Trading														
Q1	2.68	5.12	4.11	2.51	3.09	5.22	4.63	4.47	5.10	5.13	7.10	6.31	2.99	-4.37
Q2	2.29	3.24	2.70	1.33	2.59	3.54	3.43	2.99	2.71	4.29	4.88	3.90	1.54	-2.63
Q3	0.83	2.24	2.19	0.08	0.65	2.00	1.86	2.52	1.47	2.78	2.68	1.98	0.99	-1.20
Q4	0.64	1.15	1.76	-0.34	1.04	1.49	1.96	1.51	1.17	2.78	2.18	1.73	0.60	-1.16
Panel C: Return of Not Trading														
Q1	-0.35	0.11	0.25	-0.64	0.21	-0.07	-0.44	1.23	-1.21	0.72	-0.07	-1.75	-2.36	-0.21
Q2	0.25	0.33	0.54	-0.52	0.76	1.22	0.98	1.50	-1.04	1.39	1.16	-0.30	-1.36	-0.75
Q3	0.74	0.65	0.44	-1.02	1.06	1.54	1.46	1.26	1.04	1.94	1.72	0.55	-0.57	-0.81
Q4	0.44	0.84	0.44	-1.34	1.12	0.39	1.13	1.18	1.09	1.21	1.27	0.28	-0.03	-0.22
Panel D: Difference between Trading and Not Trading														
Q1	5.19	6.48	5.76	7.25	4.41	6.98	5.11	5.19	5.81	5.57	7.85	6.92	5.52	-5.93
Q2	3.84	3.93	3.53	3.74	3.12	3.62	2.85	3.03	3.36	3.61	4.69	3.99	3.33	-3.27
Q3	0.38	2.23	2.73	1.66	-0.33	1.02	0.82	2.28	0.74	1.26	1.72	1.67	1.96	-1.00
Q4	0.47	0.65	2.13	1.33	0.29	1.45	1.14	0.90	0.44	1.66	1.44	1.54	0.98	-1.55

Table 5C: Number and Fraction of Stocks Traded by Arbitrage Capital										
	BM	GP	OP	MOM	MC	AG	IK	NS	AC	NOA
# of Stocks Traded by Arbitrage Capital, Long Leg	92	102	95	106	99	104	92	91	87	89
Fraction of Stocks Traded by Arbitrage Capital, Long Leg	0.29	0.32	0.30	0.33	0.31	0.33	0.33	0.29	0.34	0.28
# of Stocks Traded by Arbitrage Capital, Short Leg	95	83	108	102	71	116	101	113	90	109
Fraction of Stocks Traded by Arbitrage Capital, Short Leg	0.30	0.26	0.33	0.31	0.22	0.37	0.36	0.36	0.35	0.34
# of Stocks on the Long or the Short Leg	322	322	322	322	322	315	281	315	254	314

Table 6. Differences in Characteristics of Anomaly Stocks Traded and Not Traded by Arbitrage Capital

At the end of each quarter, on the long leg of each anomaly, we identify a portfolio of stocks that have high AHFSR (ranked among the top 30%) as stocks traded by arbitrageurs. Similarly, we identify a portfolio of stocks that have low or medium AHFSR (not ranked among the top 30%) as stocks not traded by arbitrageurs. For these two portfolios, we compute portfolio-level price, idiosyncratic volatility, the Amihud (2002) illiquidity measure, and anomaly characteristic, by equal-averaging stocks in each portfolio. The Amihud measure is transformed into percentiles among NYSE/AMEX or NASDAQ firms separately. Panel A presents the difference in these characteristics between the "Trading" portfolio and "Not Trading" portfolio for the long-leg of each anomaly. The difference of "Anomaly Char." in each anomaly is normalized by the average of cross-sectional standard deviation of the anomaly variable. Panel B repeats this analysis for the short-leg. Panels C and D report corresponding Newey-West t-values with four lags.

Variable	BM	GP	OP	MOM	MC	AG	IK	NS	AC	NOA	Average
Panel A: Trading - Not Trading, Long Leg											
Price	-3.48	-1.94	-1.22	-0.61	-1.62	-1.80	-1.98	-2.26	-1.70	0.11	-1.65
IVOL	0.01	0.01	0.01	0.00	0.02	0.01	0.01	0.01	0.01	0.02	0.01
Amihud	15.94	25.65	26.55	26.88	10.90	19.78	20.64	21.48	22.78	26.94	21.75
Char.	-0.05	-0.03	-0.03	-0.05	0.00	0.02	0.01	0.04	0.10	0.00	
Panel B: Trading - Not Trading, Short Leg											
Price	-4.64	-3.91	-2.84	-0.21	-3.15	-3.04	-1.92	-2.13	-1.10	-1.58	-2.45
IVOL	0.02	0.02	0.02	0.01	0.01	0.01	0.01	0.02	0.01	0.01	0.01
Amihud	34.34	23.74	21.62	20.56	39.38	27.96	23.51	25.99	20.86	22.75	26.07
Char.	0.01	0.05	0.13	0.09	0.03	-0.17	-0.13	-0.11	-0.06	-0.12	
Panel C: Trading - Not Trading, Long Leg, t-values											
Price	-2.39	-2.60	-1.68	-1.02	-1.98	-2.43	-1.92	-2.29	-2.02	0.12	-2.43
IVOL	2.56	2.58	2.61	2.29	2.51	2.55	2.63	2.56	2.53	2.43	2.58
Amihud	2.68	2.71	2.71	2.71	2.59	2.67	2.68	2.69	2.70	2.69	2.71
Char.	-2.20	-1.46	-1.28	-2.16	1.40	2.21	2.30	2.41	2.44	0.09	
Panel D: Trading - Not Trading, Short Leg, t-values											
Price	-2.44	-2.26	-2.22	-0.44	-1.95	-1.72	-2.16	-2.01	-2.05	-1.88	-2.30
IVOL	2.62	2.41	2.62	2.25	2.51	2.58	2.68	2.65	2.62	2.65	2.63
Amihud	2.70	2.69	2.66	2.68	2.72	2.69	2.71	2.70	2.68	2.69	2.71
Char.	1.49	2.17	2.58	2.61	2.66	-2.38	-2.37	-2.33	-2.05	-2.50	

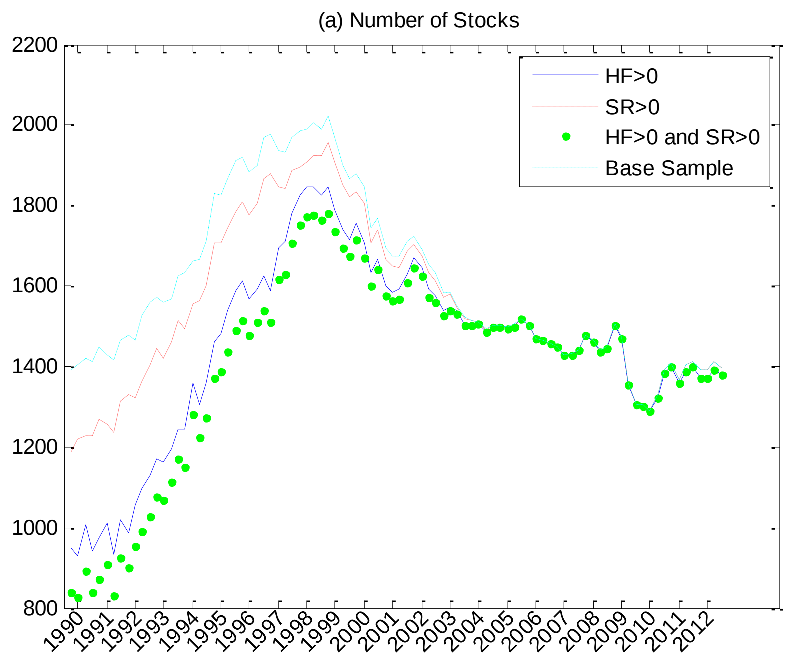
Table 7. Returns around Earnings Announcements and Changes in Non-Hedge Fund Holdings by Traded vs. Not-Traded Group

In Panel A, for each stock, we compute its returns (in percentage) for the three days around earnings announcements (i.e., a three-day window) in the next four quarters. Ret_EA1 is the return around earnings announcement in the next quarter after portfolio formation, and Ret_EA2, Ret_EA3 and Ret_EA4 are the returns around earnings announcement in the second, third, and fourth quarters after portfolio formation, respectively. In Panel B, at the end of each quarter *t*, in each return anomaly, for each stock that belongs to the long leg (L) and short leg (S) of the traded and not traded portfolios, we compute the changes of non-hedge fund holdings in the current and next four quarters. CNHF0 is the change of non-hedge fund holdings in the current quarter, defined as the difference in non-hedge fund holdings between the end of quarter *t* and the end of quarter *t*–1. CNHF1 is the change of non-hedge fund holdings in the next quarter, defined as the difference in non-hedge fund holdings between quarter *t*+1 and *t*. CNHF2 is the change of non-hedge fund holdings in the next two quarters, defined as the difference in non-hedge fund holdings between quarter *t*+2 and *t*. CNHF3 and CNHF4 are similarly defined for the next three and four quarters, respectively. Portfolio-level earnings-announcement-window returns and changes in non-hedge fund holdings are averages across stocks. The statistics are based on a composite portfolio equally investing in the 10 anomalies. We also report the return difference between the long- and short-legs for the traded and not-traded groups (Traded L–S, and Not Trade L–S) and their t-values. The t-values for the CNHFs are Newey-West with four lags.

	Panel A: Returns around EA				Panel B: Changes in Non-Hedge Fund Holdings				
	Ret_EA1	Ret_EA2	Ret_EA3	Ret_EA4	CNHF0	CNHF1	CNHF2	CNHF3	CNHF4
Traded L	0.23	0.20	0.19	0.17	-0.28	0.52	1.07	1.57	2.01
Traded S	0.06	0.10	0.12	0.12	1.37	0.04	0.06	0.13	0.27
Traded L–S	0.17	0.10	0.07	0.05	-1.65	0.48	1.01	1.44	1.74
t-value	5.96	3.56	2.52	1.63	-3.42	3.75	4.04	4.15	4.18
Not Traded L	0.12	0.14	0.15	0.17	1.00	0.28	0.51	0.72	0.95
Not Traded S	0.14	0.12	0.12	0.13	-0.06	0.38	0.75	1.13	1.52
Not Traded L–S	-0.02	0.02	0.03	0.04	1.05	-0.10	-0.24	-0.41	-0.57
t-value	-1.10	1.17	1.89	2.55	4.09	-2.43	-3.21	-3.68	-3.70

Figure 1. Number of Stocks and Sample Coverage

At the end of each quarter, we count the number of firms that have positive values of hedge fund holdings (HF), positive values of short interest (SR), positive values of both HF and SR, and the total number of stocks in our base sample, and plot them over quarters in figure (a). We compute the market capitalization of these firms as a fraction of market capitalization of the CRSP universe, and plot them in figure (b). Our sample does not include firms with market capitalization below the 20th percentile size breakpoint of NYSE firms. The sample period is from 1990Q1 to 2012Q4.



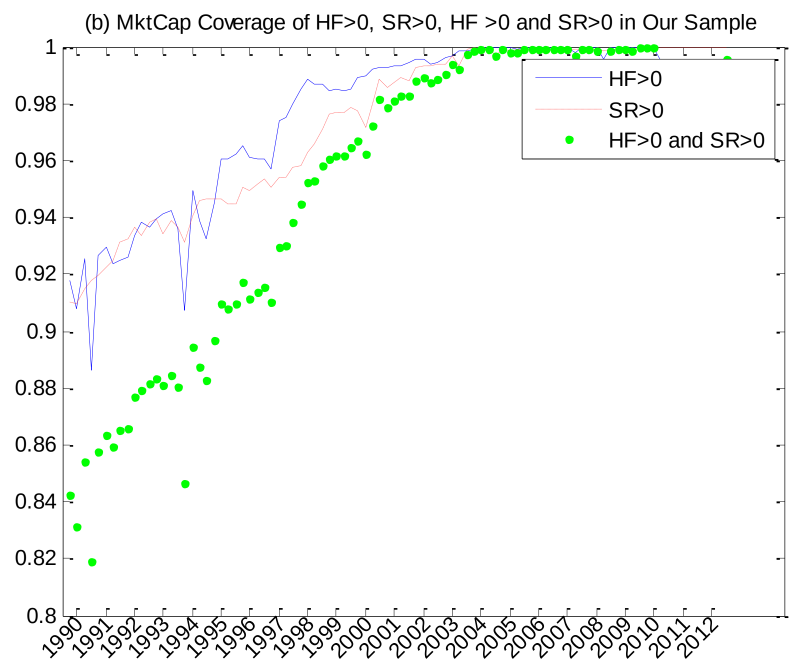


Figure 2. Aggregate Variables about Hedge Fund Holdings and Short Interest

We plot value-weighted averages of the following variables: hedge fund holdings (HF), defined as the ratio between shares owned by hedge funds and the number of outstanding shares; short interest (SR), defined as the ratio between shares shorted and the number of shares outstanding; the difference between HF and SR (HFSR); abnormal hedge fund holdings (AHF), defined as the percentage change of current HF from the average of HF in the previous four quarters; abnormal short ratio (ASR), defined as the percentage change of current SR from the average of SR in the previous four quarters; and the difference between AHF and ASR (AHFSR). The sample period is from 1990Q1 to 2012Q4.

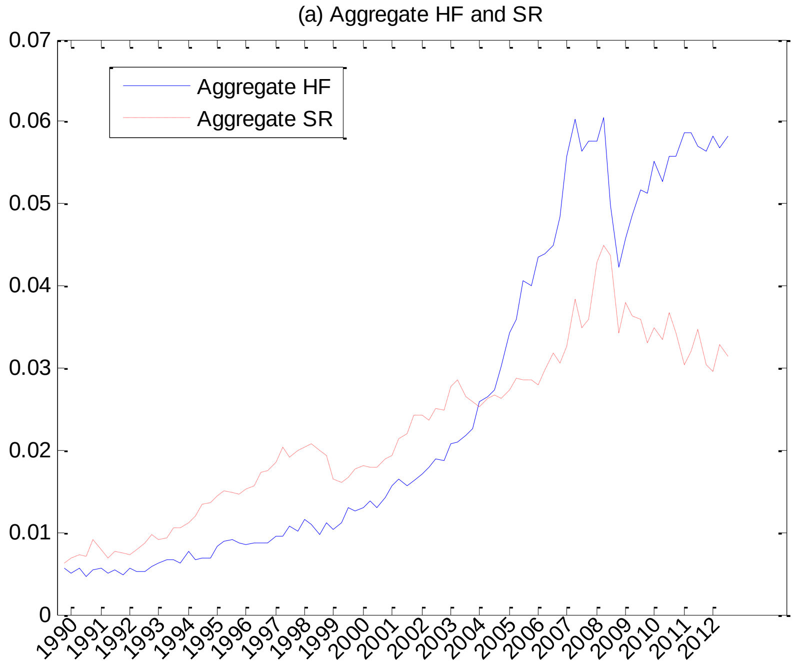
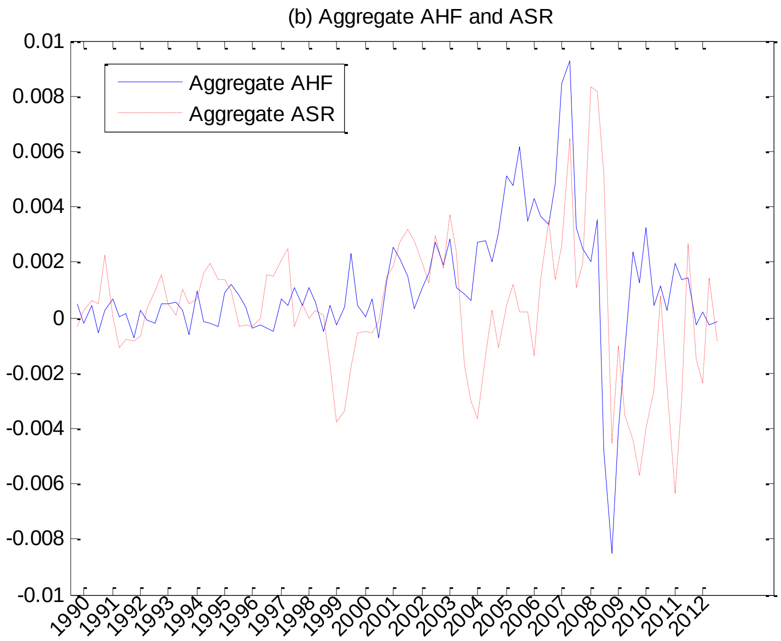


Figure 2, continued.



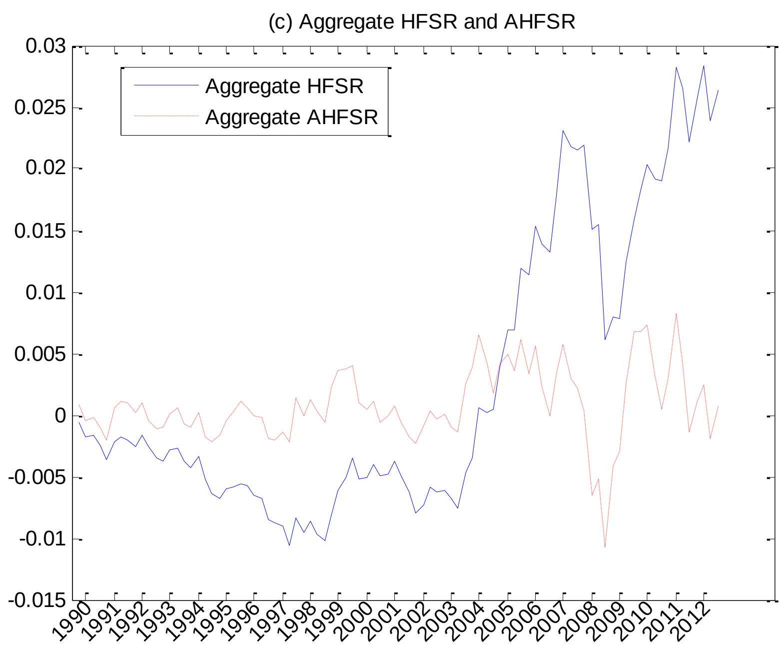


Figure 3. Return Spreads of the AHFSR Portfolios

At the end of each quarter, we form quintile portfolios based on AHFSR and track their monthly excess returns in the following eight quarters (i.e., from quarter 1 up to quarter 8). LMS returns are the return difference between the portfolio with high AHFSR and the portfolio with low AHFSR. The upper chart (a) reports excess returns and the CAPM alphas, and the lower chart (b) reports their t-values. The sample period is from 1990Q1 to 2012Q4.