Informed Trading and Expected Returns

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Abstract

Does asymmetric information affect a stock's expected return? Using stock-level daily institutional ownership percentage data from the Shanghai Stock Exchange, we first show that institutions have a strong information advantage when they trade. We then show that stocks in which institutions' trading profits during the past year were in the top quintile outperform bottom-quintile stocks by 6.6% per year going forward, consistent with increasing information asymmetry raising the cost of capital. Past institutional trading profits predict future returns more strongly in stocks where institutional trading profitability is more persistent.

Does asymmetric information affect a stock's expected return? In the model of Easley and O'Hara (2004), investors demand a return premium from stocks in which there is more private information. This higher expected return compensates uninformed investors for the losses they suffer from trading against informed investors. However, Hughes, Liu, and Liu (2007) argue that the relationship between asymmetric information and expected returns disappears in large economies because of diversification. Lambert, Leuz, and Verrecchia (2011) argue that the relationship will only be present in financial markets that are not perfectly competitive. Thus, the question is theoretically controversial.

In this paper, we empirically test the cross-sectional relationship between information asymmetry and expected returns inthe Shanghai Stock Exchange. Testing this relationship in the Chinese market has two advantages. First, we have daily stock ownership data from a representative sample of investors in the Shanghai Stock Exchange. In most other markets, ownership data are either available only at much lower frequencies or come from a non-representative investor sample. High-frequency ownership data from a representative investor sample allows us to more accurately measure the prevalence of informed trading. Second, due to the less-developed state of Chinese legal institutions and regulations, there is likely to be greater cross-sectional variation in how much private company information is shared with select outside investors than in developed markets. Greater variation gives us morestatistical power to detect information asymmetry effects.

We identify one large group of investors in the Shanghai Stock Exchange that hasan information advantage when trading: institutions.If each week during our 1996 to 2007 sample period, one bought stocks whose institutional ownership percentage change in the prior week was in the top quintile and sold short stocks whose institutional ownership change in the prior week was in the bottom quintile, the resulting four-factor portfolio alpha was 126 basis points per month, or 15.1% per year (t = 5.42).Although institutional trades are most predictive of future returns in large-cap stocks (four-factor alpha of 158 basis points per month, t = 5.76), they are also strongly predictive in mid-cap stocks (four-factor alpha of 138 basis points per month, t = 4.07) and small-cap stocks (four-factor alpha of 108 basis points per month, t = 4.11).

Having established that institutions are informed traders in this market, we measure the size of the information advantage they have in each stockby measuring the excess profitability of their trades over the past year. Each week, we multiply the stock's return in excess of the market during the week by the change in the stock's institutional holding percentage during the prior week.At each month-end, we sum the fifty most recent such products to obtain a measure of institutions' past excess trading profits in that stock.Larger past excess trading profits should correspond to greater institutional information advantage.

Of course, past excess trading profits should predict future returns only to the extent that they are correlated with current and future information asymmetry. We validate our measure by using it to forecast excess institutional trading profits at the next earnings announcement date, when trading profits are particularly likely to be due to the possession of information. We find that institutions significantly outperform in stocks where their past excess trading profits are in the top quintile, indicating that information advantage is persistent at the stock level. Conversely, institutions do not underperform the market in stocks where their past excess trading profits are in the bottom four quintiles, indicating that any information disadvantage they had in these stocks is not persistent. This lack of future underperformance in the bottom four quintiles allows us to judge stocks in which past institutional excess profits are low as having relatively symmetric information going forward, rather than high degrees of asymmetric information that disadvantages institutions. Thus, Easley and O'Hara (2004) would predict that each of the bottom four quintiles would underperform the top quintile. The fact that future institutional trading performance does not significantly differ among the bottom four quintiles causes us to expect any asymmetric information effect on expected returns to have little differential impact among the bottom four quintiles.

Consistent with Easley and O'Hara (2004), we find that stocks in the top quintile of prior institutional trading performance have positive one-, three-, and four-factor alphas of 57, 66, and 50 basis points per month (6.8%, 7.9%, and 6.0% annualized), which are all significant at the 1% level. These alphas are respectively 66, 70, and 55 basis points higher than that of their bottom-quintile counterparts (7.9%, 8.4%, and 6.6% annualized); the differences are significant at the 1%, 1%, and 5% level. The alphas of the bottom four quintiles are mostly not significantly different from zero. The exception is the third quintile, whose one-factor alpha is insignificant but whose three-and four-factor alphas are negative and significant at the 5% and 10% levels, respectively. However, the third-quintile four-factor alpha is not significantly different from the bottom-quintile four-factor alpha, and the three-factor alphas' difference is only significant at the 10% level.

Examining the results separately by size category, we find that even though institutions have an information advantage in all size categories, past institutional excess trading profits predict future excess trading profits at earnings announcements only among large-cap stocks. Correspondingly, past institutional trading profits significantly predict future stock returns only among large-cap stocks.

In sum, companies face a higher cost of capital when the asymmetry in the information available about them rises. The market appearsquite sophisticated in recognizing which stocks have a high level of information asymmetry going forward. The market does not apply the same discount to all stocks in which institutions have had recent trading success, nor does it naively infer that institutions will beinformationally disadvantaged in stocks where they have recently lost money. In robustness checks, we find that differences in liquidity or price pressure from future institutional buys and sells are not responsible for our main results.

Our paper contributes to a literature that tries to empirically identify the impact of asymmetric information on the cross-section of expected stock returns. Easley, Hvidkjaer, and O'Hara (2002) use the temporal clustering of buy and sell orders to estimate the probability of informed trading (PIN) and find that high-PIN stocks have higher returns than low-PIN stocks. However, Duarte and Young (2009) argue that PIN is priced due to its correlation with liquidity rather than asymmetric information, a claim that Easley, Hvidkjaer, and O'Hara (2010) dispute.Mohanram and Rajgopal (2009) argue that the PIN-return relationship is not robust to alternative specifications and time periods, whileAslan et al. (2011) argue the opposite. Kelly and Ljungqvist (2012) use changes in sell-side analyst coverage to identify changes in the amount of information asymmetry and find that stock prices drop when the asymmetry of information increases.

Our paper is distinguished from this prior work in that we directly observe the presence and activity of informed traders in each stock, rather than inferring them from proxies. In this sense, our approach is closest to that of Berkman, Koch, and Westerholm (forthcoming), who use Finnish data to show that trades by children's accounts are unusually successful, indicating that the children's guardians are informed. They construct a measure called BABYPIN that is the proportion of trading activity in a stock that occurs through children's accounts, and find that high BABYPIN stocks have higher returns. However, due to the small size of the Finnish stock market, the average number of stocks in their cross-sections is only 46. Therefore, they are unable to address the theoretical argument of Hughes, Liu, and Liu (2007) that the effect of asymmetric information will disappear in large economies. In our data, the average number of stocks in a given year is 573, so our estimates should reflect most of the effects of diversification.

The paper proceeds as follows. Section I gives a brief background on the Shanghai Stock Exchange. Section II describes our data, and Section III establishes that institutions have an information advantage when they trade. Section IV details our methodology for identifying in which stocks institutions have a greater information advantage and validates this measure by showing it predicts institutional trading profits on future earnings announcement dates. Section V contains our main empirical test of whether greater asymmetric information increases expected returns, and Section VI runs these tests separately by market capitalization tercile. Section VII and VIII investigate whether price pressure from institutional trading and differences in liquidity are responsible for the results we find in Section V. Section IX concludes.

I. Background on the Shanghai Stock Exchange

At the end of 2007—the last year of our sample period—the 860 stocks traded on the Shanghai Stock Exchange (SSE)had a total market capitalization of $3.7 trillion, making it the world's sixth-largest stock exchange behind NYSE, Tokyo, Euronext, Nasdaq, and London. Mainland China's other stock exchange, the Shenzhen Stock Exchange, had a $785 billion market capitalization at year-end 2007. By year-end 2011, mainlandChina's collective stock market had the second-largest market capitalization among all countries of the world, behind only the U.S.

Almost all SSE shares are A shares, which only domestic investors could hold until 2003. At year-end 2007, A shares constituted over 99% of SSE market capitalization. B shares are quoted in U.S. dollars and can be held by foreign and (since 2001) domestic investors. Shares are further classified into tradable and non-tradable shares. Non-tradable shares have the same voting and cashflow rights as tradable shares and are typically owned directly by the Chinese government ("state-owned shares") or by government-controlled domestic financial institutions and corporations ("legal person shares").[1] We use the term "tradable market capitalization" to refer to the value of tradable A shares, and "total market capitalization" to refer to the combined value of tradable and non-tradable A shares.During our sample period, about 27% of SSE market capitalization was tradable.

There is minimal equity derivatives activity in the Chinese markets. Prior to the end of 2005, there were no equity derivatives at all. From 2005 to 2007, eleven SSE companies were allowed to issue put warrants (Xiong and Yu, 2011). Therefore, nearly all trading on company information must happen via the stock market.Short-sales are not allowed, so whenever we mention "shorting" a portfolio, it should be understood as a hypothetical position.

II. Data description

We obtain stock return, market capitalization, earnings announcement date, and accounting data from the China Stock Market & Accounting Research Database (CSMAR).

Our institutional ownership data come from the SSE. To trade on the SSE, both retail and institutional investorsare required to open an account with the Exchange, at which point they must identify themselves to the Exchange as an individual or an institution. Each account uniquely and permanently identifies an investor, even if the

[1] Beginning in April 2005, non-tradable shares began to be converted to tradable status, although the conversion process was slow enough that as of year-end 2007, 72% of total Chinese market capitalization remained non-tradable. Converted tradable shares were subject to a one-year lockup, and investors holding more than a 5% stake were subject to selling restrictions for an additional two years.

account later becomes empty. Investors cannot have multiple accounts. The data assembled by the Exchange for this paper consists of the entire history of SSE tradable A-share holdings from January 1996 to May 2007 for a representative random sample of all accounts that existed at the end of May 2007.[2] Since there are far fewer institutional accounts than retail accounts, the Exchange over-sampled institutional investors in order to ensure that a meaningful number of institutional accounts were extracted.The market-wide statistics computed from these account data are reweighted to adjust for the over-sampling of institutional investors.

The sample contains both currently active and inactive accounts, so there is no survivorship bias, and in expectation, a constant fraction of the accounts extant at any date are represented. The number of accounts in the sample grows from 36,349 retail accounts and 360 institutional accounts to 384,709 retail accounts and 20,727 institutional accounts from January 1996 to May 2007. Holdings data are aggregated at the Exchange into daily stock-levelinstitutional ownership percentage measures. The aggregation is carried out under arrangements that maintain strict confidentiality requirements to ensure that no individual account data are disclosed.

Table 1 shows year-by-year summary statistics on the fraction of tradable A shares owned by institutions. Over our sample period, the weight of the SSE investor base has shifted from individuals to institutions. From 1996 to 2007, institutional ownership in the average stock rose from 4.3% to 19.2%, and the across-stock standard deviation in institutional ownership rose from 9.3% to 24.9%. Weighting across stocks by tradable market capitalization, the average institutional ownership grew even more quickly—from 4.6% to 46.7%—indicating that the expansion of institutional ownership occurred disproportionately in large stocks. The number of stocks in our sample rises from 186 to 802.[3]

[2] This is the same sample used by Choi, Jin, and Yan (forthcoming).
[3] The number of stocks in our sample is slightly smaller than the total number of SSE stocks because of gaps in CSMAR's coverage.

III. Do institutions have an information advantage?

We begin our analysis by establishing that institutions have an information advantage that they trade on.We do this by showing that stocks that institutions have bought heavily subsequently outperform stocks that institutions have sold heavily.

On each Friday that is a trading day, we compute the change in institutional holding percentage since the prior Friday that was a trading day.[4] We sort stocks into quintiles based on this change, weight them by their tradable market capitalization, and hold them until the next Friday that is a trading day. Henceforth, we will refer to a trading Friday to trading Friday period as a "week," even though market holidays sometimes make this period much longer thanseven days.

The first five columns in Panel A of Table 2 show the average raw monthly returns of these portfolios in excess of the demand deposit rate, which we use as our riskfree return proxy. The four portfolios holding the bottom 80 percentiles of institutional-ownership-change stocks have excess returns between 1.53% and 1.90% per month that do not rise monotonically with institutional ownership change. However, the top quintile portfolio's average excess return of 3.08% per month is markedly higher than the rest. The last column shows that the difference between the top and bottom quintile portfolios' excess raw returns is 1.46% per month and highly significant (t = 6.74). Judging from the pattern of raw returns, it appears that heavy buying by Chinese institutions is a signal of good company news, but anything from heavy selling to moderate buying by institutions has little information content about future returns.

We estimate these institutional-ownership-change portfolios' one-, three-, and four-factor alphas using monthly return regressions, where the factor portfolio returns capture CAPM beta, size, value, and momentum effects. The market portfolio return is the composite Shanghai and Shenzhen market return, weighted by tradable market capitalization. We construct size and value factor returns (SMB and HML, respectively) for the Chinese stock market according to the methodology of Fama and French (1993), but using the entire Shanghai/Shenzhen stock universe to calculate percentile breakpoints. We form SMB based on total market capitalization and HML based on the ratio of book

[4] We compute the difference, not the difference as a proportion of the initial ownership level. In other words, a change from 20% to 21% is a 1% change.

equity to total market capitalization, weighting stocks within component sub-portfolios by their tradable market capitalization.[5] We construct the momentum factor portfolio MOM following the methodology described on Kenneth French's website. We calculate the 50th percentile total market capitalization at month-end $t - 1$ and the 30th and 70th percentile cumulative stock returns over months $t - 12$ to $t - 2$, again using the entire Shanghai/Shenzhen stock universe to calculate percentile breakpoints. The intersections of these breakpoints delineate six tradable-market-capitalization-weighted sub-portfolios for which we compute month t returns. MOM is the equally weighted average of the two recent-winner sub-portfolio returns minus the equally weighted average of the two recent-loser sub-portfolio returns.

The alphas are consistent with the story suggested by the raw returns. There are no significant abnormal returns for the portfolios containing the bottom 80 percentiles of institutional ownership change stocks, except perhaps for the second quintile portfolio, whose one-factor alpha is negative and significant at the 10% level but whose three- and four-factor alphas are insignificant. The top quintile portfolio has alphas that are large and highly significant: one-, three-, and four-factor alphas of 1.09%, 1.28%, and 1.28% per month with *t*-statistics of 4.78, 6.16, and 6.10, respectively. The alphas of the portfolio that buys the top-quintile portfolio and shorts the bottom-quintile portfolio are similar in magnitude and statistical significance:one-, three-, and four-factor alphas of 1.35%, 1.26%, and 1.26% per month with *t*-statistics of 6.15, 5.74, and 5.72.

Figure 1 plots the average raw monthly return of the long-short portfolio by calendar year. Although the average return during the 2003-2007 period is lower than the average return during the 1996-2002 period—1.16% versus 1.80%, perhaps indicating stricter regulation of disclosure and stricter enforcement of these regulations—the returns after 2002 are less volatile.

IV. Measuring stock-level information asymmetry

[5] Whenever possible, we use the book equity value that was originally released to investors. If this is unavailable, we use book equity that has been restated to conform to revised Chinese accounting standards.

Section III showed that institutions have an information advantage on average across stocks. In this section, we identify in which stocks institutions have a greater information advantage.

In both the monopolistic setting of Kyle (1985) and the competitive setting of Easley and O'Hara (2004), informed trader profits are increasing in his/their information advantage. Therefore, we use past institutional trading profits in the stock as a measure of how large institutions' information advantage is in the company.[6]Let $q_{i,t}$ be the percent of tradable shares owned by institutions in stock i at the end of week t, $R_{i,t}$ be stock i's return during week t, and $R_{m,t}$ be the market return during week t. We compute past institutional excess trading profit in stock i as

$$\sum_{\tau=t-49}^{t}(q_{i,\tau-1}-q_{i,\tau-2})(R_{i,\tau}-R_{m,\tau}). \tag{1}$$

Theexpressioninside the summation operator corresponds to the extra profit (as a fraction of the stock's tradable market capitalization at the end of week $\tau - 1$) institutions accrued during week τ because of their net trades during week $\tau - 1$, assuming that the alternative investment was the market portfolio and that institutions held their positions at the end of week $\tau - 1$ until the end of week τ.[7] We sum these terms over the prior 50 trading weeks in order to improve the statistical precision of our excess trading profit measure.On the last day of each calendar month, we use the most recentpast excess trading profit measure available to sort stocks into quintile portfolios and hold them for the following month.

Table 3 shows the average past institutional excess trading profits in each quintile as of the beginning of each calendar year in the sample. Average excess profits are close to zero but almost always positive in the middle quintile. In almost every year, the average excess profit in the fourth quintile has a larger magnitude than the average excess loss in the second quintile, and the average excess profit in the fifth quintile has a larger

[6] The slope coefficient from regressing future returns on informed trader order flow is also increasing in the informed trader's information advantage in Kyle (1985) and Easley and O'Hara (2004). However, when we sort stocks by their estimated slope coefficient from regressing week t excess returns on week $t - 1$ institutional ownership change, the extreme quintiles are predominantly populated by stocks in which institutions did not trade particularly actively but which experienced returns of large magnitude. The fact that institutions were relatively passive in these stocks suggests that they do not have much private information about these companies.

[7] Although this measure only counts profits from information that is revealed in the week following the trade, it has the advantage of not crediting institutions for returns that occur following a long passive holding period, which is less likely to be motivated by private information.

magnitude than the average excess loss in the first quintile. Across years, the average excess trading loss in the first quintile is 0.69%, and the average excess trading gain in the fifth quintile is 1.11%.

Table 4 displays summary statistics for the stocks in each excess trading profit quintile. Because the number of stocks listed on the SSE expanded rapidly during our sample period, we adopt the following procedure in order to keep later time periods from dominating the summary statistics. We calculate separately for each month the mean of each variable. The table reports the time-series average of these monthly means. In general, stocks in the extreme quintiles are more similar to each other than to stocks in the middle quintiles. Extreme-quintile stocks have large market capitalizations, low book-to-market ratios, high past returns, and high prior-month share turnover and Amivest liquidity ratios (measured as the sum of the stock's yuan trading volume over one month divided by the sum of the stock's absolute daily returns over that month; higher values correspond to lower price impacts of trading, and hence higher liquidity). Middle-quintile stocks have the opposite characteristics. Over the prior 50 weeks, the average absolute weekly change in institutional ownership is higher in the extreme quintiles than the middlequintiles, indicating that institutions traded more aggressively in stocks in which their realized excess profit magnitudes were larger. Comparing the highest quintile to the lowest quintile, highest-quintile stocks are larger, have higher past returns, and are more liquid than lowest-quintile stocks. Institutions also traded more aggressively in highest-quintile stocks than lowest-quintile stocks.

Past institutional excess trading profit would not be expected to predict future stock returns unless it was correlated with current and future information asymmetry. We test past institutional trading profit's relationship with future institutional information advantage by examining past institutional trading profit's ability to predict future institutional trading profit. However, we are sensitive to the concern that persistence in institutional trading profits need not be due to persistence in information advantage, but rather to institutions persistently providing liquidity in some stocks and demanding liquidity in others. Therefore, we restrict our attention to past institutional profit's ability to predict future institutional trading profits on earnings announcement days. Expected trading profits on these days are likely to be due predominantly to the possession of information rather than liquidity provision or consumption.

If a company announced its earnings on a trading day, we define the earnings announcement excess return as being the stock's return in excess of the market return cumulated over the earnings announcement day and the following trading day. We cumulate over these two days because we do not know if the announcement occurred during trading hours or after the market close. If the announcement was on a non-trading day, we define the earnings announcement excess return as being the stock's return in excess of the market return on the first trading day after the announcement. We define the institutional excess trading profit during the announcement period as the earnings announcement excess return multiplied by the change in institutional ownership percentage from five days before the announcement to one day before the announcement.

Table 5 shows the results from regressing institutional excess trading profit during the announcement period on dummies for the stock'spast institutional excess trading profit quintile as of the previous month-end.If a stock is in the top quintile of past institutional excess trading profit, then at the next earnings announcement, institutions will earn 42 basis pointsmore excess trading profit in the stockas a percent of its tradable market capitalization (p = 0.046). Hence, institutional information advantage is persistent at the stock level. The constant term is close to zero and statistically insignificant (p = 0.947), indicating that institutions do not suffer an information disadvantage going forward in profit quintile 1 stocks, which they previously lost the most money in. Therefore, we judge stocks in the lowest quintile of past institutional excess trading profit as being stocks in which information asymmetry going forward is relatively low, rather than stocks in which institutions are at a large information disadvantage and information asymmetry is high. The profit quintile 2 through 4 dummy coefficients are small in magnitude and statistically insignificant, which leads us to assess stocks in these quintiles as alsohaving low levels of information asymmetry going forward, similar to stocks in quintile 1.

V. Does greater asymmetric information increase expected returns?

Having shown that past institutional excess trading profit in a stock predicts future institutional information advantage in the same stock, we now analyze the relationship between past institutional excess trading profit and expected returns. We sort stocks into quintiles by their past institutional excess trading profit at the end of each month. We hold stocks in each portfolio in proportion to their tradable market capitalization for one month before re-sorting them into new portfolios.

The first four columns of Panel A in Table 6 show the raw returns in excess of the riskfree rate of each past institutional excess trading profit portfolio. The bottom four quintile excess returns are similar to each other: 1.39% per month for Portfolio 2 and 1.23% to 1.26% per month for the other three portfolios. The top quintile portfolio has considerably higher returns of 1.88% per month. The last column shows that the 0.65% per month (7.8% per year) difference between the top and bottom quintile portfolios is statistically significant at the 1% level.

Panels B through D contain results from regressions that estimate one-, three-, and four-factor alphas for the past institutional excess trading profit portfolios. The alphas for the bottomfour quintile portfolios are mostly insignificant. The exception is Portfolio 3, whose one-factor alpha is insignificant but whose three-factor alpha is negative and significant at the 5% level, and whose four-factor alpha is negative and significant at the 10% level. However, the difference between Portfolio 3 and Portfolio 1 is barely significant at the 10% level for the three-factor alphas (p = 0.099) and insignificant for the four-factor alphas (p = 0.188). Consistent with information asymmetries being similar across the bottom four quintiles, their alphas are by and large not statistically distinguishable from each other.

In contrast, the top-quintile portfolio alphas are large and positive, ranging from 50 to 66 basis points per month (6.0% to 7.9% per year) with significance always at the 1% level. The difference between the top and bottom quintile one-, three-, and four-factor alphas is 66, 70, and 55 basis points with p-values of 0.008, 0.005, and 0.020, respectively. Therefore, exactly in the one portfolio where our analysis in Section IV indicated there are greater information asymmetries going forward, we find significantly higher abnormal returns.

Examining the factor loadings of the portfolios in the four-factor regression, we find that top-quintile stocks load much more heavily on the momentum factor than bottom-quintile stocks; the difference in the loadings is significant at the 1% level. This difference mayindicate that institutions more intensely gather information on stocks that are doing well.

VI. Analysis by sizetercile

How does the relationship between past institutional excess trading profits and future expected returns differ by company size? To answer this question, we divide stocks into terciles by tradable market capitalization at the end of each month, and then sort stocks within each size tercile into past institutional excess trading profit quintiles. The past profit quintile breakpoints differ by size tercile, so that each size × past profit portfolio contains approximately the same number of stocks. We weight stocks by their tradable market capitalization and hold them until the end of the following month, when the portfolios are reconstituted.

Table 7 shows how returns and alphas differ between the top and bottom past profit quintiles by size tercile. In the first and second columns, we see that across both raw excess returns and alphas, the difference between the extreme quintiles is insignificant among small- and mid-cap stocks. If we average together the small-cap and mid-cap long-short returns to reduce noise, we obtain three- and four-factor alphas of 30 basis points per month that are barely significant at the 10% level (p = 0.094 for three-factor, p = 0.099 for four-factor). On the other hand, the alphas are much larger in magnitude and more significant among large-cap stocks, where the one- and three-factor alphas are 85 and 87 basis points respectively and significant at the 5% level, and the four-factor alpha is 62 basis points and significant at the 10% level (p = 0.068).

The weak relationship between past institutional excess trading profits and future expected returns among small- and mid-cap stocks could be due to institutions having no information advantage in these companies.To explore this hypothesis, wecreate portfolios using sequential sorts on size and prior-week institutional ownership change. At the end of each week, we sort stocks into terciles based on tradable market capitalization, and then within each size tercile, we sort stocks into quintiles based on their institutional ownership percentage change since the end of the prior week. Stocks within each portfolio are weighted by their tradable market capitalization and held until the end of the following week. Table 8 reports monthly raw excess returns and alphasof long-short portfolios that hold the highest institutional ownership change quintile portfolio of a given size tercile long and the lowest institutional ownership change quintile portfolio of the same size tercile short.

We find that institutions have an information advantage in every size tercile. The long-short alphas do increase with size tercile; for example, the four-factor alphas grow from 108 basis points to 138 basis points to 158 basis points as we move from small- to mid- to large-cap stocks. However, the raw returns and one-, three-, and four-factor alphas are significant at the 1% level for all size groups, with *t*-statistics almost always above 4. The weak relationship between past institutional excess trading profits and future expected returns in small- and mid-cap stocks is therefore unlikely to be due to weakness of institutions' information advantage in these stocks.

Instead, it appears that it is the persistence of institutions' information advantage in a given stock that explains the difference across size groups. Table 9 shows how the ability of past institutional excess trading profit to predict future institutional excess trading profit during earnings announcements varies with size. The analysis is identical to that in Table 5, except the regressions are run separately by size tercile. We find that only in large-cap stocks does past institutional excess trading profit significantly predict future institutional excess trading profit during earnings announcements.This is consistent with institutions' information advantage being persistent at the company level in large stocks but transient at the company level in smaller stocks.Therefore, sorting by past institutional excess trading profits creates a large spread incurrent and futureasymmetric information only amonglarge-cap stocks.The model of Easley and O'Hara (2004) would not predict much of an expected return spread across portfolios formed by this sort among small- and mid-cap stocks.

In sum, it appears that the market is quite sophisticated in assessing the level of asymmetric information in a stock going forward and adjusting the stock's expected return. Past institutional excess trading profit has a stronger relationship with future expected returns in stocks where institutional information advantage is persistent than in stocks where that advantage is transient.Nonetheless, there is some evidence that thecorrelation between past institutional excess trading profit and expected returns isnot zero among small- and mid-cap stocks, even though institutional excess trading profit in these stocks appears to be transient. This possibly non-zero correlation may indicate that the market is not perfect in discerning in which stocks institutional information advantage does and does not persist. Alternatively,there may be a small amount of persistence in institutional information advantage among small- and mid-cap stocks that our tests are not sensitive enough to detect, in which case the market is not making a mistake in varying these stocks' expected returns with past institutional excess trading profit.

VII. Does price pressure from institutional trading explain our results?

When institutions observe from their past trading profits that they have an information advantage in a particular stock, they might be expected to subsequently increase their position in the stock on average, since their subjective uncertainty about the stock's intrinsic value is lower.Price pressure from institutional trading is a mechanism unrelated to the Easley and O'Hara (2004) hypothesis that could generate a positive relationship between past institutional excess trading profit and expected returns.[8]

We look for an institutional price pressure effect on our portfolio returns by running a Fama-MacBeth (1973) regression.The dependent variable is the change in a stock's institutional ownership percentage during month t,and the explanatory variables are dummies for the past institutional excess trading profit quintile the stock belongs to at the end of month $t - 1$.Table 10 shows that the top and bottom quintiles do not experience significantly different institutional demand in the month following portfolio formation. Institutional ownership increases by 4 basis points for the average stock in the bottom quintile, and this increase is 1 basis point *lower*($p = 0.914$) for the average stock in the top quintile. Therefore, it is unlikely that institutional price pressure can explain why the top quintile experiences higher returns than the bottom quintile during the month after portfolio formation.

[8] See Gompers and Metrick (2001), Coval and Stafford (2007), Frazzini and Lamont (2008), and Lou (forthcoming) for evidence that institutional demand shocks affect U.S. security prices.

VIII. Does liquidity explain our results?

A stock's liquidity should affect its expected return due to the expected transactions costs its investors will have to pay (Amihud and Mendelson, 1986), and a stock's liquidity should also be affected by asymmetric information about the company (Kyle, 1985). If the relationship between expected returns and asymmetric information is entirely explained by differences in liquidity, the Amihud and Mendelson (1986) mechanism may be responsible for the relationship rather than the Easley and O'Hara (2004) mechanism.

We use two measures of stock liquidity: share turnover during the prior month, and the Amivest liquidity ratio during the prior month. Table 11 displays Fama-MacBeth regression results, where the dependent variable is the stock's month t return. The first column controls only for month $t - 1$ log total market capitalization, book-to-market,[9] and prior eleven-month return lagged one month. During the February 1997 to June 2007 sample period, these variables predict returns in a manner consistent with the U.S. market: returns are decreasing in size and increasing in book-to-market and momentum, although the momentum effect barely misses 5% significance ($p = 0.0505$). The second column adds prior-month return, turnover, and liquidity ratio controls, which causes the size, book-to-market, and momentum coefficients to strengthen in magnitude and statistical significance. Turnover is negatively associated with future returns, whereas liquidity ratio and prior-month returnare not significant.

The final column adds dummies for the stock'spast institutional excess trading profit quintile as of month-end $t - 1$. The coefficient on the quintile 5 dummy indicates that the average stock in the top quintile has a 32 basis point higher abnormal monthly return than the average stock in the bottom quintile, a difference that is significant at the 5% level.[10] Therefore, it does not appear that liquidity alone can explain the expected return differences between the top and bottom quintiles of past institutional excess trading profit.

[9] The value at year-end $\tau - 1$ is used as the predictor from July of year τ through June of year $\tau + 1$.

[10] This magnitude is not directly comparable to the alpha differences estimated in the factor regressions because the test portfolios in the factor regressions were value-weighted, whereas the Fama-MacBeth procedure equally weights each stock.

We also note that in this regression specification, stocks in the middle quintile portfolio have an average return that is significantly (at the 5% level) lowerthan that of stocks in the bottom quintile portfolio. Although we do not want to over-interpret this result in light of the weak significance of the difference between these portfolios' alphas in Section V, we offer here one possible explanation for the middle quintile's low returns. Table 4 showed that institutions trade least aggressively in middle-quintile stocks. The lower return of stocks in this portfolio could be due to investors interpreting low institutional trading activity in these stocks as indicatinglower institutional information advantage in these stocks going forward, causing them to decrease these stocks' required rate of return. Recall, however, that future institutional excess trading profits upon earnings announcements do not significantly differ between bottom- and middle-quintile stocks (the point estimate for middle-quintile stocks is actually higher than that of bottom-quintile stocks in Table 5), so such an interpretation by investors appears to be incorrect.

IX. Conclusion

We use daily institutional ownership data from the Shanghai Stock Exchange to demonstrate that institutions have an information advantage in the Chinese stock market, and the stronger this advantage is for a given stock, the higher is the stock's expected return. The value-weighted portfolio of stocks in which institutional excess trading profits over the past year were in the top quintile outperforms the bottom-quintile value-weighted portfolio by 6.6% per year on a four-factor-adjusted basis. This cross-sectional relationship is consistent with the model of Easley and O'Hara (2004), suggesting that companies could decrease their cost of capital by leveling the informational playing field among their investors. Neither future price pressure from institutional trades nor differences in liquidity explain these results.

The market appears quite sophisticated in distinguishing between stocks in which past institutional trading resultsdo and do not predict future institutional information advantage. Institutions do nothave a future information disadvantage in stocks they have had the largest past trading losses in, and the alphas of these stocks are correspondingly not significantly different from zero. Past institutional excess trading profits do not predict future institutional success in small- and mid-cap stocks, and the relationship between past institutional excess trading profits and expected returns is correspondingly weaker in small- and mid-cap stocks than in large-cap stocks. There are some hints that the market is not perfect at making these distinctions, although this evidence is not very robust: Past institutional excess trading profits and expected returns have a weakly significant positive relationship among small- and mid-cap stocks, andin some specifications, stocks in the middle quintile of past institutional excess trading profits have significantly lower expected returns, even though institutions have no lesser information advantage in these stocks.

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Table 1. Institutional ownership percentage summary statistics

This table shows, as of the beginning of each year, the average percent of each Shanghai Stock Exchange stock's tradable A shares owned by institutions when equally weighting across stocks, the across-stock standard deviation of institutional ownership percentage, the average when weighting across stocks by their tradable market capitalization, and the number of stocks in the sample.

Year	Equal-weighted mean	Standard deviation	Value-weighted mean	Number of stocks
1996	4.3%	9.3%	4.6%	186
1997	3.1%	9.1%	4.0%	291
1998	2.1%	4.8%	2.4%	376
1999	4.1%	9.5%	5.2%	429
2000	7.6%	14.2%	10.0%	474
2001	7.8%	13.9%	10.0%	571
2002	7.5%	12.3%	10.1%	639
2003	9.9%	14.5%	14.5%	708
2004	8.4%	16.8%	21.5%	772
2005	11.4%	19.6%	26.5%	826
2006	14.1%	22.2%	35.5%	805
2007	19.2%	24.9%	46.7%	802

Table 2. Returns and alphas of prior institutional ownership change portfolios

Wesort stocks into quintiles by their institutional ownership change in the prior weekand hold themfor the next week. Portfolio 1 contains stocks in the lowest 20 percentiles of institutional ownership change, and Portfolio 5 contains stocks in the highest 20 percentiles. All stocks are weighted by tradable market capitalization. "5 – 1" holds Portfolio 5 long and Portfolio 1 short. PanelA shows raw average monthly returns in excess of the riskfree ratefor the long-only portfolios, and raw average monthly returns for the long-short portfolio. Panels B through D show regression results that estimate one-, three-, and four-factor monthly alphas. $R_m - R_f$ is the Chinese market return in excess of the riskfree rate, SMB is the Chinese size factor return, HML is the Chinese value factor return, and UMD is the Chinese momentum factor return. The numbers in parentheses are *t*-statistics.

	(lowest) Portfolio 1	Portfolio 2	Portfolio 3	Portfolio 4	(highest) Portfolio 5	5 – 1
Panel A: Raw excess returns						
Constant	1.62*	1.53*	1.90*	1.74*	3.08**	1.46**
	(2.20)	(2.04)	(2.37)	(2.34)	(3.99)	(6.74)
Panel B: One-factor alphas						
Constant	-0.25	-0.39^{+}	-0.08	-0.18	1.09**	1.35**
	(1.05)	(1.69)	(0.23)	(0.79)	(4.78)	(6.15)
$R_m - R_f$	0.91**	0.93**	0.96**	0.93**	0.96**	0.06*
	(34.48)	(36.83)	(26.20)	(38.48)	(38.57)	(2.31)
Panel C: Three-factor alphas						
Constant	0.02	-0.20	0.01	0.00	1.28**	1.26**
	(0.12)	(0.98)	(0.03)	(0.02)	(6.16)	(5.74)
$R_m - R_f$	0.97**	0.97**	0.97**	0.96**	1.00**	0.04
	(43.47)	(42.44)	(31.68)	(42.14)	(42.50)	(1.51)
SMB	-0.21**	0.16**	0.50**	0.08^{+}	-0.16**	0.05
	(4.93)	(3.55)	(8.38)	(1.90)	(3.56)	(1.03)
HML	-0.27**	-0.35**	-0.37**	-0.29**	-0.18**	0.09^{+}
	(5.60)	(6.94)	(5.52)	(5.81)	(3.48)	(1.70)
Panel D: Four-factor alphas						
Constant	0.01	-0.14	0.09	0.06	1.28**	1.26**
	(0.07)	(0.78)	(0.36)	(0.31)	(6.10)	(5.72)
$R_m - R_f$	0.97**	0.97**	0.97**	0.97**	1.00**	0.04
	(43.38)	(48.67)	(36.04)	(46.41)	(42.35)	(1.51)
SMB	-0.20**	0.08*	0.40**	0.02	-0.15**	0.05
	(4.46)	(2.09)	(7.37)	(0.52)	(3.21)	(0.93)
HML	-0.29**	-0.25**	-0.25**	-0.21**	-0.19**	0.10^{+}
	(5.62)	(5.49)	(3.98)	(4.38)	(3.52)	(1.67)
UMD	0.05	-0.31**	-0.40**	-0.26**	0.04	-0.01
	(0.97)	(6.40)	(6.13)	(5.28)	(0.71)	(0.20)

** Significant at the 1% level. * Significant at the 5% level. $^{+}$ Significant at the 10% level.

Table 3. Average prior institutional excess trading profits by quintile

In each week for each stock, we sum the past fifty realizations of institutional ownership change in the stock during week $\tau - 1$ multiplied by the stock's week τ return in excess of the Chinese market return. We sort stocks by this prior institutional excess trading profit measure into quintiles. The table shows the average prior institutional excess trading profit in each quintile as of the beginning of each year.

Year	(lowest) Quintile 1	Quintile 2	Quintile 3	Quintile 4	(highest) Quintile 5
1997	-0.98%	-0.11%	0.02%	0.23%	1.36%
1998	-0.65%	-0.10%	-0.01%	0.08%	0.68%
1999	-0.52%	-0.05%	0.00%	0.06%	1.10%
2000	-0.88%	-0.07%	0.03%	0.21%	2.26%
2001	-0.97%	-0.08%	0.02%	0.16%	1.67%
2002	-0.35%	-0.04%	0.00%	0.03%	0.40%
2003	-0.37%	-0.06%	0.00%	0.05%	0.36%
2004	-0.57%	-0.02%	0.01%	0.07%	0.53%
2005	-0.41%	-0.03%	0.00%	0.06%	0.78%
2006	-0.37%	-0.02%	0.01%	0.10%	0.96%
2007	-1.52%	-0.22%	0.00%	0.29%	2.07%

Table 4. Summary statistics on prior institutional excess trading profit quintiles

This table shows the average total and tradable market capitalizations in thousands of RMB, book-to-market ratio, prior eleven-month return lagged one month, prior-month return, prior-month share turnover, prior-month Amivest liquidity ratio, and the average weekly absolute institutional ownership change over the prior 50 weeks for each ofthe prior institutional excess trading profit quintiles, which are formed as in Table 3. Averages are computed cross-sectionally at the end of each month, and then the monthly time-series average of these cross-sectional month-end averages is computed and reported in the table. The sample is restricted to stocks for which all the variable values are available.

	(lowest) Quintile 1	Quintile 2	Quintile 3	Quintile 4	(highest) Quintile 5
Total market cap	4,280,878	3,123,984	2,587,709	3,621,973	4,863,585
Tradable market cap	1,242,408	982,294	814,620	1,131,168	1,414,942
Book-to-market	0.373	0.402	0.404	0.388	0.369
$\text{Return}_{t-12,\ t-2}$	24.68%	14.02%	8.47%	14.19%	33.30%
Return_{t-1}	1.90%	1.78%	1.70%	1.91%	2.70%
Prior-month turnover	0.373	0.359	0.340	0.356	0.393
Liquidity ratio	1.103	0.834	0.666	0.984	1.314
Avg. weekly absolute institutional ownership change	0.79%	0.27%	0.15%	0.37%	1.07%

Table 5. Institutional trading excess profits during next earnings announcement, by prior institutional excess trading profit

If the earnings announcement was made on a trading day, the dependent variable is the announcing stock's return in excess of the market return cumulated over the announcement day and the first trading day after the announcement, multiplied by the change in institutional ownership during the five trading days prior to the announcement date. If the earnings announcement was made on a non-trading day, the dependent variable is the announcing stock's return in excess of the market return on the first trading day after the announcement multiplied by the change in institutional ownership during the five trading days prior to the announcement date. We discard earnings announcements that are not the first announcement of the calendar month for the firm. The dependent variable's units are basis points. The explanatory variables are dummies for which prior institutional excess trading profit quintile the stock was put in at the end of the previous month.The numbers in parentheses are *t*-statistics.

Constant	-0.01
	(0.07)
Profit quintile 2	-0.06
	(0.27)
Profit quintile 3	0.07
	(0.31)
Profit quintile 4	0.01
	(0.05)
Profit quintile 5	0.42*
(highest)	(2.00)
Observations	17,121

** Significant at the 1% level. * Significant at the 5% level. + Significant at the 10% level.

Table 6. Returns and alphas of prior institutional excess trading profitportfolios

Wesort stocks into quintiles by their prior institutional excess trading profit at the end of each month and hold them for the next month. Portfolio 1 contains stocks in the lowest 20 percentiles of prior institutional excess trading profit, and Portfolio 5 contains stocks in the highest 20 percentiles. All stocks are weighted by tradable market capitalization. "5 – 1" holds Portfolio 5 long and Portfolio 1 short. Panel A shows raw average monthly returns in excess of the riskfree rate for the long-only portfolios, and raw average monthly returns for the long-short portfolio. Panels B through D show regression results that estimate one-, three-, and four-factor monthly alphas. $R_m - R_f$ is the Chinese market return in excess of the riskfree rate, SMB is the Chinese size factor return, HML is the Chinese value factor return, and UMD is the Chinese momentum factor return. The numbers in parentheses are *t*-statistics.

	(lowest) Portfolio 1	Portfolio 2	Portfolio 3	Portfolio 4	(highest) Portfolio 5	5 – 1
Panel A: Raw excess returns						
Constant	1.23	1.39$^+$	1.26	1.25$^+$	1.88*	0.65**
	(1.68)	(1.86)	(1.53)	(1.70)	(2.55)	(2.69)
Panel B: One-factor alphas						
Constant	-0.08	0.07	-0.17	-0.06	0.57**	0.66**
	(0.53)	(0.33)	(0.64)	(0.33)	(2.93)	(2.69)
$R_m - R_f$	0.98**	0.98**	1.06**	0.97**	0.97**	-0.01
	(51.06)	(40.72)	(32.55)	(45.63)	(41.18)	(0.28)
Panel C: Three-factor alphas						
Constant	-0.05	-0.09	-0.45*	-0.04	0.66**	0.70**
	(0.29)	(0.54)	(2.33)	(0.24)	(3.49)	(2.88)
$R_m - R_f$	0.98**	0.96**	1.02**	0.97**	0.98**	0.00
	(50.71)	(47.68)	(44.04)	(44.85)	(43.26)	(0.04)
SMB	-0.03	0.28**	0.46**	0.02	-0.16**	-0.13*
	(0.71)	(7.09)	(10.03)	(0.39)	(3.50)	(2.23)
HML	-0.07	0.12*	0.24**	-0.06	-0.06	0.02
	(1.28)	(2.00)	(3.50)	(0.96)	(0.85)	(0.19)
Panel D: Four-factor alphas						
Constant	-0.05	0.00	-0.37$^+$	-0.01	0.50**	0.55*
	(0.32)	(0.02)	(1.95)	(0.08)	(2.95)	(2.36)
$R_m - R_f$	0.98**	0.96**	1.02**	0.97**	0.98**	-0.00
	(50.48)	(50.11)	(45.03)	(44.85)	(0.02)	(0.09)
SMB	-0.02	0.21**	0.40**	-0.00	-0.04	-0.02
	(0.53)	(5.01)	(8.02)	(0.09)	(0.91)	(0.29)
HML	-0.07	0.11$^+$	0.23**	-0.07	-0.03	0.04
	(1.26)	(1.85)	(3.40)	(1.02)	(0.57)	(0.47)
UMD	0.01	-0.20**	-0.16*	-0.06	0.33**	0.32**
	(0.21)	(3.62)	(2.49)	(0.98)	(5.78)	(4.04)

** Significant at the 1% level. * Significant at the 5% level. $^+$ Significant at the 10% level.

Table 8.Returns and alphas of prior institutional excess trading profit long-short portfolios by size tercile

At the end of each month, wesort stocks by their tradable market capitalization into terciles, and then sort them into quintileswithin each size tercileby their prior institutional excess trading profit. For each size group, stocks in the highest prior institutional excess trading profit quintile are held long for the next month, and stocks in the lowest prior institutional excess trading profit quintile are held shortfor the next month, each in proportion to its tradable market capitalization. The panels show raw average monthly returns and regression results that estimate one-, three-, and four-factor monthly alphas. $R_m - R_f$ is the Chinese market return in excess of the riskfree rate, SMB is the Chinese size factor return, HML is the Chinese value factor return, and UMD is the Chinese momentum factor return. The numbers in parentheses are *t*-statistics.

	Small-cap	Mid-cap	Large-cap
Panel A: Raw excess returns			
Constant	0.27	0.11	0.87*
	(1.05)	(0.45)	(2.51)
Panel B: One-factor alphas			
Constant	0.28	0.17	0.85*
	(1.08)	(0.73)	(2.39)
$R_m - R_f$	-0.01	-0.04	0.02
	(0.30)	(1.61)	(0.38)
Panel C: Three-factor alphas			
Constant	0.29	0.31	0.87*
	(1.11)	(1.39)	(2.43)
$R_m - R_f$	-0.01	-0.03	0.03
	(0.37)	(0.98)	(0.59)
SMB	0.07	-0.11*	-0.15^{+}
	(1.08)	(2.02)	(1.77)
HML	-0.10	-0.25**	0.11
	(1.04)	(3.03)	(0.85)
Panel D: Four-factor alphas			
Constant	0.31	0.30	0.62^{+}
	(1.13)	(1.31)	(1.85)
$R_m - R_f$	-0.01	-0.03	0.01
	(0.36)	(1.00)	(0.37)
SMB	0.06	-0.10^{+}	0.02
	(0.84)	(1.68)	(0.23)
HML	-0.10	-0.24**	0.14
	(1.05)	(2.99)	(1.17)
UMD	-0.03	0.02	0.50**
	(0.28)	(0.29)	(4.43)

** Significant at the 1% level. * Significant at the 5% level. $^{+}$ Significant at the 10% level.

Table 9. Returns and alphas of prior institutional ownership change long-shortportfolios by size tercile

At the end of each week, we sort stocks by their tradable market capitalization into terciles, and then sort them into quintiles within each size tercile by their prior-week institutional ownership change. For each size group, stocks in the highest institutional ownership change quintile are held long for the next month, and stocks in the lowest institutional ownership change quintile are held shortfor the next month, each in proportion to its tradable market capitalization. The panels show raw average monthly returns and regression results that estimate one-, three-, and four-factor monthly alphas. $R_m - R_f$ is the Chinese market return in excess of the riskfree rate, SMB is the Chinese size factor return, HML is the Chinese value factor return, and UMD is the Chinese momentum factor return. The numbers in parentheses are *t*-statistics.

	Small-cap	Mid-cap	Large-cap
	Panel A: Raw returns		
Constant	1.27**	1.35**	1.94**
	(4.95)	(4.13)	(6.92)
	Panel B: One-factor alphas		
Constant	1.10**	1.27**	1.78**
	(4.28)	(3.77)	(6.30)
$R_m - R_f$	0.09**	0.04	0.08*
	(3.05)	(1.15)	(2.54)
	Panel C: Three-factor alphas		
Constant	1.09**	1.39**	1.59**
	(4.17)	(4.12)	(5.82)
$R_m - R_f$	0.09**	0.07^{+}	0.04
	(2.86)	(1.75)	(1.33)
SMB	-0.00	-0.01	0.04
	(0.00)	(0.14)	(0.63)
HML	0.00	-0.17*	0.24**
	(0.04)	(2.02)	(3.48)
	Panel D: Four-factor alphas		
Constant	1.08**	1.38**	1.58**
	(4.11)	(4.07)	(5.76)
$R_m - R_f$	0.08**	0.07^{+}	0.04
	(2.82)	(1.72)	(1.30)
SMB	0.02	0.01	0.05
	(0.27)	(0.08)	(0.77)
HML	-0.02	-0.19*	0.22**
	(0.26)	(2.15)	(3.11)
UMD	0.07	0.07	0.04
	(0.96)	(0.75)	(0.58)

** Significant at the 1% level. * Significant at the 5% level. $^{+}$ Significant at the 10% level.

Table 10. Institutional excess trading profits during next earnings announcement by prior institutional trading profit and size

If the earnings announcement was made on a trading day, the dependent variable is the announcing stock's return in excess of the market return cumulated over the announcement day and the first trading day after the announcement, multiplied by the change in institutional ownership during the five trading days prior to the announcement date. If the earnings announcement was made on a non-trading day, the dependent variable is the announcing stock's return in excess of the market return on the first trading day after the announcement multiplied by the change in institutional ownership during the five trading days prior to the announcement date. We discard earnings announcements that are not the first announcement of the calendar month for the firm. The dependent variable's units are basis points. The explanatory variables are dummies for which prior institutional excess trading profit quintile the stock was put in at the end of the previous month. We run regressions separately for each tradable market capitalization tercile, as measured at the end of the previous month. The numbers in parentheses are *t*-statistics.

	Small-cap	Mid-cap	Large-cap
Constant	0.02	-0.148	0.24
	(0.08)	(0.63)	(0.73)
Profit quintile 2	-0.03	0.09	-0.41
	(0.12)	(0.27)	(0.90)
Profit quintile 3	0.01	0.20	-0.20
	(0.05)	(0.61)	(0.44)
Profit quintile 4	0.09	0.04	0.05
	(0.29)	(0.10)	(0.10)
Profit quintile 5	-0.12	-0.08	1.01*
(highest)	(0.40)	(0.24)	(2.20)
Observations	5,502	5,820	5,799

** Significant at the 1% level. * Significant at the 5% level. + Significant at the 10% level.

Table 12. Fama-MacBeth return prediction regressions

This table shows Fama-MacBeth regression coefficients. The dependent variable is next month's return. The explanatory variables, which are measured at the end of the current month, are the log total market capitalization, book-to-market ratio, prior eleven-month return lagged one month, prior-month return, prior-month share turnover, prior-month Amivest liquidity ratio, and dummies for which prior institutional excess trading profit the stock belongs to. The sample consists of 125 months.

Constant	10.647**	12.947**	13.723**
	(3.139)	(3.986)	(4.307)
log(Total market value)	-0.622**	-0.703**	-0.754**
	(2.978)	(3.538)	(3.879)
Book-to-market	1.115*	1.432**	1.548**
	(1.963)	(2.659)	(2.868)
$\text{Return}_{t-12,\,t-2}$	0.010^{+}	0.012*	0.010*
	(1.956)	(2.418)	(2.254)
Return_{t-1}		0.004	0.004
		(0.318)	(0.329)
Turnover		-3.251**	-3.387**
		(5.745)	(5.981)
Amivest liquidity ratio		0.006	0.002
		(0.044)	(0.014)
Profit quintile 2			-0.059
			(0.352)
Profit quintile 3			-0.393*
			(2.260)
Profit quintile 4			-0.099
			(0.066)
Profit quintile 5			0.315*
			(2.182)

** Significant at the 1% level. * Significant at the 5% level. $^{+}$ Significant at the 10% level.

Table 13. Institutional ownership change next month by prior institutional trading profit quintile

This table shows Fama-MacBeth regression coefficients. The dependent variable is next month's change in institutional ownership percentage. The explanatory variables, which are measured at the end of the current month, are dummies for which prior institutional excess trading profit the stock belongs to. The sample consists of 124 months.

Constant	0.04
	(0.58)
Profit quintile 2	0.19**
	(3.38)
Profit quintile 3	0.13*
	(2.21)
Profit quintile 4	0.17**
	(3.02)
Profit quintile 5	-0.01
(highest)	(0.11)

** Significant at the 1% level. * Significant at the 5% level. + Significant at the 10% level.

Figure 1. Institutional ownership change long-short portfolio monthly returns by year

This figure shows the average monthly return of a long-short portfolio by calendar year. We sort stocks into quintiles by their institutional ownership change in the prior week and hold the highest 20 percentiles long and the lowest 20 percentiles short for the next week, weighting each stock by its tradable market capitalization.