Institutional Investors and Stock Return Anomalies[#]

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Abstract

We examine institutional demand prior to well-known stock return anomalies and find that institutions have a strong tendency to buy stocks classified as overvalued (short leg of anomaly), and that these stocks have particularly negative ex-post abnormal returns. Our results differ from numerous studies documenting a positive relation between institutional demand and future returns. We trace the difference to measurement horizon. We also find a positive relation at a quarterly horizon. However, the relation turns strongly negative at the one-year horizon used in anomaly studies. We consider several explanations for institutions' tendency to trade contrary to anomaly prescriptions. Our evidence largely rules out explanations based on flow and limits of arbitrage, but is more consistent with agency-induced preferences for stock characteristics that relate to poor long-run performance.

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1. Introduction

A longstanding debate in finance concerns whether institutional money managers are skilled investors.[1] A recent study in this literature, Lewellen (2011), examines the aggregate holdings of institutional investors and finds that they essentially hold the market portfolio, with no discernable tilt to take advantage of well-known stock return anomalies. This analysis of how institutions' holdings relate to stock return anomalies puts aside the general question of whether or not they are informed and focuses on a simpler question: do they exploit well-known sources of predictability in returns? That institutions fail to use such information is more than a little puzzling. Irrespective of whether anomalies represent mispricing or benchmarking errors, they provide a statistically reliable means of favorably biasing assessed performance against standard benchmarks. As discussed below, a skilled agent (investment manager) can be expected to exploit such an opportunity.

Our study conducts a detailed and comprehensive analysis of the relation between institutional investors and stock return anomalies, from the perspective of both asset management and asset pricing. In particular, we examine how institutions modify their portfolios as stocks take on their anomaly-defining characteristics, and how anomaly returns relate to those actions. Because anomaly characteristics tend to be transient, we focus on changes in institutional holdings during the anomaly portfolio formation period. By contrast, Lewellen (2011) examines the mean-variance efficiency of institutional portfolios, which focuses on the level of institutional holdings.

[1]For a sampling of studies that conclude institutional investors are skilled, see Coval and Moskowitz (2001), Badrinath and Wahal (2002), Cohen, Gompers, and Vuolteenaho (2002), Parrino, Sias, and Starks (2003), Gibson, Safieddine, and Sonti (2004), and Alti and Sulaeman (2012). For a sampling of evidence against this conclusion see Jensen (1968), Carhart (1997), and Fama and French (2010).

Our analysis also focuses on new and closed positions (changes in number of institutional holders) as they are more likely to reflect explicit portfolio decisions than adjustments to ongoing positions (i.e., percent held), which often reflect operational trades relating to flow or portfolio rebalancing. However, we find similar results with changes in the percent of shares held by institutions.

We frame our analysis around the sophisticated institutions hypothesis (SIH). The SIH asserts that agents trade in a way that exploits anomaly return predictability. In cases where aggregate changes in institutional ownership are orthogonal to anomaly predicted returns, the SIH requires that these changes do not negatively impact performance.[2] However, the SIH does not require that institutions be informed in the usual (private) sense. Our analysis explores two questions that relate to the SIH: (i) Do institutions trade according to anomaly prescriptions (i.e., buy long-leg anomaly stocks and sell short-leg anomaly stocks)? (ii) Does their residual trading predict future returns? Of particular interest with regard to the second question is a special case motivated by our findings: When institutions trade contrary to anomaly prescriptions do future returns defy anomaly predictions?

Our evidence rejects the sophisticated institutions hypothesis on all counts. First, we find that not only do institutional investors fail to tilt their portfolios to take advantage of anomalies, they trade contrary to anomaly prescriptions. Most notably, they have a strong propensity to buy stocks classified as 'overvalued' (i.e., the short leg of anomaly portfolios). For example, during the anomaly portfolio formation window (prior to anomaly returns) there is a net increase in both the number of institutional investors and fraction of shares held by institutional investors in short-leg stocks for all seven of the anomalies we consider. In four of the seven anomalies there is

[2] The analyses we perform are gross of performance using portfolio holdings (i.e., transaction costs are not a factor) hence this condition imposes minimal restriction.

significantly greater institutional buying in short-leg stocks than in long-leg stocks. There is significantly greater buying in long-leg stocks in only one case.

Second, cross-sectional regressions reveal a significant negative relation between changes in number of institutional holders (Δ#Insts), and future returns orthogonalized to anomalies. Thus, aggregate institutional demand is negatively related to both predicted and residual anomaly returns. When these two effects are combined (e.g., short-leg stocks that institutions buy, or long-leg stocks they sell), anomalous returns are particularly large. This result is most pronounced in the short leg stocks with widespread institutional buying (i.e., top quintile of Δ#Insts), which earn abnormal returns of -74 basis points per month (t-statistic = -5.0) versus -27 basis points per month (t-statistic = -1.9) for short leg stocks with widespread institutional selling (bottom quintile of Δ#Insts).

The negative relation between changes in institutional holdings and future returns we document is in sharp contrast to the positive relation between changes in institutional holdings and future returns documented in several previous studies (see footnote 1). We trace this difference to the length of the horizon over which returns and changes in holdings are measured. In particular, the literature suggests that this relation tends to be positive for shorter horizons (3-12 months in aforementioned studies) and turns negative for longer horizons (12+ months in Gutierrez and Kelly (2009), and Dasgupta, Prat, and Verardo (2011).[3]

We confirm this horizon effect in the context of our study. In particular, we find a significant positive relation between quarterly changes in institutional holdings and next-quarter returns that turns significantly negative as the horizon extends to a year or longer. Thus, while institutional

[3] The relation generally turns insignificant or negative after six months. See, i.e., Grinblatt Titman and Wermers (1995), Wermers (1999), Chen Hong and Stein (2002), Chen Jagadeesh and Wermers (2000), and Sias (2004).

trades seem to be informed when evaluated over short horizons, that assessment seems premature when evaluated over a longer horizon. Whatever the reason behind the positive short-horizon relation between institutional trading and returns, a long horizon is more relevant to our study. Our central hypothesis concerns how institutional investors modify their portfolios as stocks take on anomaly-defining characteristics. Both the standard anomaly portfolio formation period and anomaly return window span a year (or longer). Additionally, the changes in institutional holdings we document persist through the entire anomaly return window.

A natural question concerns why institutions trade contrary to anomaly prescriptions. While a full accounting for this behavior is beyond the scope of this study, we provide some insights. As a starting point, we examine the potential role of investor flow (Edelen, 2009). Evidence suggests that the effects of correlated investor flow on both institutional trading and security returns can be relatively protracted (see, e.g., Coval and Stafford, 2007; Frazzini and Lamont, 2008; and Khan, Kogan, and Serafeim, 2012). Thus, the negative relation between changes in institutional holdings and future anomaly returns that we document is potentially driven by price reversals from investor flow. Our evidence largely rules out this explanation. For example, our results are not due to changes in ownership by mutual funds. Likewise, our results are nearly identical when we control for mutual fund trades motivated by flow as well as when we exclude stocks that had been subject to considerable mutual fund flow using the methodology in Coval and Stafford (2007).

Our finding that anomaly returns are concentrated in 'overvalued' (short-leg) stocks that institutions buy has a number of implications regarding the role of institutional investors and limits-of-arbitrage in stock return anomalies. For example, the fact that they increase their holdings in short-leg stocks suggests that institutions' failure to capitalize on anomalies is not due to an unwillingness to take on idiosyncratic risk (see also Lewellen, 2011). It also casts doubt on friction-based limits-of-arbitrage such as transaction costs and short-sale constraints. More generally, the negative relation between institutional demand and future returns that we document is inconsistent with the argument (Shleifer and Vishny, 1997) that rational but constrained investors should at least trade in the right direction.

A large body of literature portrays institutions as relatively sophisticated investors who play the role of arbitrageurs, except where limited by frictions. Our evidence is more consistent with institutions playing a causal role with mispricing, and suggests that the real limit to arbitrage may be the prospect of shorting against widespread institutional buying. While contradictory to the SIH, the notion that institutions may contribute to mispricing has precedence in studies that suggest institutional herding can be destabilizing (see Coval and Stafford, 2007; Frazzini and Lamont, 2008; Gutierrez and Kelly, 2009; and Dasgupta, Prat, and Verardo, 2011).

To further investigate this potential causal role, we examine earnings announcement returns as in Bernard and Thomas (1990). The idea is that expected returns during a narrow window around earnings announcements are essentially zero, hence any variable that systematically identifies positive (negative) returns during that window likely identifies under- (over-) valuation that is partially corrected by the announcement.[4] We find a statistically significant negative relation between changes in institutional holdings and subsequent announcement-period returns, which is consistent with a causal influence of institutional demand on anomaly returns.

The motive behind a causal role is unclear. A bias in managers' cash flow expectations offers a straightforward interpretation of the earnings announcement evidence; but it also represents a particularly strong contradiction of the notion that institutions are sophisticated. A

[4] See Lewellen (2010) for a discussion of tests of short-horizon return predictability around future earnings announcements.

plausible alternative explanation lies with the underlying premise of the SIH – that fund managers' only concern is outperforming standard performance benchmarks). Lakonishok, Shleifer, and Vishny (1992) conjecture a schmoozing motive[5] that causes portfolio managers to seek stocks of good companies, rather than stocks with good value, because the former is more tangible, objective, and easily communicated.

Standard performance benchmarks do not capture preferences for 'good companies.' If these agency-induced preferences drive rational portfolio managers to seek characteristics associated with the short leg of anomalies, this could appear as causal mispricing *vis à vis* standard performance benchmarks. Consider, for example, net operating assets (NOA) which identifies the accumulation of operating income less free-cash flow. One could argue that high NOA (the short leg of one anomaly) superficially suggests strong past performance and good positioning for the future. A similar argument applies to several other anomalies we consider; investment-to-assets (e.g., high growth in assets suggests a strong company); book-to-market (growth prospects are good); and under-minus-over valued (net stock and debt issuance, which implies growth, over repurchases, which imply atrophy). In each case, the short leg of the anomaly portfolio potentially offers a tangible identification of good companies (though evidently bad investments). Interestingly, the two anomaly characteristics we consider that make *long* leg stocks look like good companies (gross profitability and momentum) are precisely the two cases where institutions buy the long leg relatively heavily (significantly so in the case of momentum).

Benchmarking errors provide another possible explanation for our results. If the positive abnormal returns of anomalies are associated with risk that beneficial investors are particularly averse to (despite the return premium), then trading contrary to anomalies serves investors'

[5] Their terminology (see pg. 375).

interests. There are three problems with this hypothesis. First, it does not clarify how those preferences are communicated to investment managers or performance on this dimension is monitored. Standard performance benchmarks reward anomaly return premia but do not penalize their risks, leaving managers a strong incentive to trade *with* anomalies. Thus, to make the benchmarking hypothesis plausible there must be some other mechanism that investors employ to override this return-based incentive. Second, what do we make of the revealed preferences implied by flow chasing benchmark-adjusted returns? Third, if aversion to these risks is so strong as to drive aggregate institutional demand, why don't standard benchmarks reflect those risks to better align managers' incentives?

Finally, it is important to place our findings in the proper context regarding institutional performance. One might be tempted to infer from our evidence gross underperformance for the average institutional portfolio. However, the trades we examine constitute but a fraction of the portfolio; we do not directly evaluate portfolio performance. It is possible that their overall portfolio yields sufficient alpha to offset the negative effects we document.

In what follows, Section 2 describes the data and variables used. Section 3 documents changes in institutional investors prior to anomaly portfolio formation and examines anomalies conditional on changes in institutional investors. Section 4 discusses possible explanations and implications. Section 5 conducts robustness checks and Section 6 concludes the study.

2. Sample, data, and variable definitions

This section describes the data used in examining the sophisticated institutions hypothesis.

2.1. Stock return anomalies

Our study employs seven well-known return anomalies in the literature. Our initial set includes the eleven anomalies in Stambaugh, Yu, and Yuan (2012) plus book-to-market and the undervalued-minus-overvalued anomaly of Hirshleifer and Jiang (2010). Some of these anomaly characteristics are highly correlated with each other. To reduce redundancy, we assign anomalies to seven broad categories (profitability, corporate investment, earnings quality, financing, financial distress, momentum), choosing the relatively encompassing case where possible, which also picks the anomaly from each category with the most reliable alpha (highest t-statistic) during our sample period (1981-2012).[6] Our final set of anomalies includes: net operating performance, gross profitability, investment-to-assets, O-Score, book-to-market, undervalued-minus-overvalued, and momentum. The magnitude and significance of results for those excluded are nearly identical to those reported. Table 1 presents a detailed description of the anomalies we examine along with a primary literature reference.

[Table 1 around here]

Data on the defining anomaly characteristics and stock returns is obtained from CRSP, Compustat, and SDC Global New Issues databases. Our initial sample includes US common stocks (CRSP share codes of 10 or 11) traded on the NYSE, AMEX, and Nasdaq from January 1977 through June 2012. We exclude utilities, financials, and stocks priced under $5—results are nearly

[6] For example, Net Operating Assets represents accumulated accruals plus investment in operating assets (consumption of free cash flow); Undervalued Minus Overvalued is similarly a combination of various issuance studies. In an internet appendix we provide results for the full initial set of anomalies.

identical if we include them. To avoid survivorship bias, we adjust monthly stock returns for delistings using the CRSP monthly delisting file following Shumway (1997). Quarterly data on institutional holdings (13F) and mutual fund holdings is obtained from Thomson-Reuters starting in December 1980 and ending June 2011.

We follow the conventions in the literature for constructing anomaly portfolios, except for the case of momentum where we deviate somewhat to accommodate our analysis of changes in institutional holdings. For each anomaly except momentum, we rank stocks on June 30th of year *t* using data observed either at calendar year-end *t*-1 or the fiscal year-end in year *t*-1, and hold the stocks for twelve months from July *t* through June *t*+1. In the case of momentum, we rank stocks on a quarterly basis using stock returns from the previous four calendar quarters and hold them for three months after skipping one month.[7] We use the Fama and French (1993) methodology to construct the anomaly portfolios. Specifically, for each anomaly, we construct six portfolios from the intersection of the two size groups (< > NYSE median) and three anomaly-characteristic groups (long, short, neutral).[8] We calculate monthly value-weighted returns for each portfolio from July year *t* through June year *t*+1. The returns of the long-leg (short-leg) of each anomaly are an equal-weighted average of the returns of the two size portfolios with the anomaly characteristic associated with high (low) future returns. Taking an equal-weighted average of portfolios of stocks above and below the NYSE median and value-weighting returns ensures that anomaly portfolio returns are not driven primarily by the performance of the large number of micro-cap stocks. We

[7] The results are robust to using more conventional specifications of momentum strategies that sort stocks on returns over the prior three to twelve months and hold stocks for three to twelve months with monthly rebalancing.

Long correspond to the highest performing (as reported by previous studies and confirmed in our sample) 30% according to the ranking variable; neutral is the middle 40% and short is the bottom 30%.

use this portfolio formation methodology in calculating returns for the anomaly portfolios. All other results reflect an equal weighting of observations.

[Table 2 around here]

Table 2 documents the magnitude and statistical significance of abnormal returns for each of the seven anomalies, confirming the presence of each during our sample period. In particular, the Fama-French (1993) three-factor abnormal returns for the long-short portfolio are economically and statistically significant in all cases. The monthly abnormal returns range from 40 bps per month (t-stat=4.5) for the O-Score anomaly to 76 bps (t-stat=6.8) for the gross profitability anomaly. The overall anomaly portfolio ("AVG") that takes an equal position across all seven anomalies earns a three-factor alpha of 60 bps (t-stat= 8.6).[9] Table 2 also confirms the well-documented asymmetry in anomaly returns – the fact that anomalies derive most of their abnormal returns from short-leg ('overvalued') stocks (see Miller, 1977; Diether, Malloy, and Scherbina, 2002; and Stambaugh, Yu, and Yuan, 2012).

2.2. Changes in institutional investors

Institutional investor demand is measured in various ways in the literature. The primary differences in these measures lie in the choice between levels versus changes and the choice between the number of institutions versus percent shares held by institutions. Table 3 provides summary characteristics of institutional ownership in our sample.

[Table 3 around here]

[9] The alphas for the "AVG" portfolio do not necessarily equal the mean of the alphas for the seven anomalies because the alpha for the B/M anomaly is estimated using a two-factor model that omits the HML factor whereas the alphas for the "AVG" portfolio as well as the other six anomalies are estimated using the three-factor model.

Because our central hypothesis centers around how institutional investors modify their portfolios as stocks take on anomaly characteristics, we examine changes in holdings rather than levels. We focus on the number of institutions holding a stock rather than percent shares held, for several reasons. First, the change in number of institutions provides an equal weighted account of institutions' actions whereas percent shares held can be heavily influenced by a few large institutions. Second, the change in number of institutions is more likely to reflect alpha-motivated trades (e.g., anomalies) because it tracks new and closed positions whereas the change in shares held includes adjustments to ongoing positions and thus often reflects operational motives such as investor flow and portfolio rebalancing (Khan et al., 2012). Finally, several empirical studies find that the quantity of shares traded contains little incremental information for stock returns relative to number of trades (see, e.g., Jones, Kaul, and Lipson, 1994; and Sias, Starks, and Titman, 2006). Nevertheless, it is worth noting that the results are always qualitatively similar (though sometimes less significant) when we use changes in the percent of shares held as our measure of institutional demand.

Figure 1 depicts the time line for anomaly portfolio construction, institutional trading, and returns for the seven anomalies. Our aim is to measure changes in institutional ownership during a window that runs from the realization of anomaly ranking variables (January *t*-1 to December *t*-1) to the beginning of the anomaly return window (June 30, year *t*).[10] Doing so insures that we capture all institutional trading leading up to the realization of anomaly returns, and that institutions have access to all information used in constructing the anomaly portfolios (i.e., annual

[10] Because of momentum's time sensitivity (Jegadeesh and Titman, 1993), we form momentum portfolios each January, April, July, and October using stock returns from the previous 12 months and institutional holdings from the previous 6 calendar quarters, and hold the portfolios for 3 months.

10-K). Note that institutional trading during the quarter immediately prior to the anomaly return window may impart a positive bias in the relation between institutional demand and future returns due to price pressure from serially correlated institutional trades (see, e.g., Sias et al., 2006). Thus, for some tests we examine trading in the quarter prior to the anomaly return window separately.

[Figure 1 around here]

We face a choice as to how to scale changes in number of institutions. One alternative is to divide by the beginning period value, but this is problematic when the beginning value is zero, and induces skewness when the beginning value is small. To address these issues we divide changes in number of institutional investors by the average number of institutional shareholders holding stocks in the same market capitalization decile as of the beginning of the trading window (denoted Δ#Inst). This latter approach is similar to that used in Chen, Hong, and Stein (2002), who evaluate changes in number of institutions within each stock's market capitalization decile.

To differentiate between competing hypotheses, we include the change in fraction of shares held by institutional investors (Δ%Inst); the change in fraction of shares held by mutual funds (Δ%MF); and the difference, i.e., the change in fraction of shares held by non-mutual-funds (Δ%NMF).[11] All measures are winsorized at the 1% level in both tails.

[11] Due to the way institutional holdings are reported by Thomson-Reuters, an absence of holdings can indicate zero institutional ownership, an inactive company, or missing data. We set missing observations to zero if the company's permno is listed as active in CRSP on that date. The results are stronger if we set all missing observations to zero.

3. Anomalies and changes in institutional ownership

3.1. Changes in institutional ownership around the anomalies

Table 4 documents changes in number of institutional investors and fraction of shares held by institutional investors during the anomaly portfolio formation window. Recall this window encompasses six quarters; the four-quarters over which anomaly ranking variables are measured (December of year *t*-2 through December of *t*-1) plus the two-quarter gap (January of year *t* through June of *t*) prior to the measurement of anomaly returns. To streamline our discussion we focus on changes in number of institutions (Δ#Inst, our primary metric) but note that changes in fraction of shares held (Δ%Inst) closely mirror those results.

For each anomaly we report the average annualized change in number of institutional investors for stocks in the long and short legs of the anomaly portfolio as well as for stocks in the neutral portfolio (middle 40% of stocks for anomaly ranking variable), which provide a benchmark for evaluating changes in the long and short portfolios. From Table 4, neutral stocks have an average annualized Δ#Inst of 11.4% during the portfolio formation window, reflecting a general increase in number of institutional investors during our sample period. This average change in Δ#Inst is somewhat higher than the change in the average of all CRSP stocks during the sample period (7% annualized), but in line with the change in median (12%).

According to the sophisticated institutions hypothesis we should observe relatively strong demand for long-leg anomaly stocks and relatively weak demand for short-leg anomaly stocks. The evidence of Table 4 is inconsistent with this prediction. Not only do institutions generally fail to trade according to anomaly prescriptions, in four of the seven anomalies they trade substantially contrary to anomaly prescriptions. Most notably, institutions have a strong propensity to *buy* stocks classified as ‘overvalued’ (i.e., short leg of anomaly portfolio). From Table 4, there is a net increase in both number of institutional investors and fraction of shares held by institutional investors in short-leg stocks for all seven anomalies. In four out of the seven anomalies there is significantly greater institutional buying in short-leg stocks than in long-leg stocks (p-value < 1%), whereas trading is aligned with only one anomaly at a 1% or 5% significance level. Across all seven anomalies the average Δ#Inst for short-leg stocks (15.1%) is significantly greater than the Δ#Inst for long-leg stocks (12.1%) at a 1% level. We conclude that, in aggregate, institutions generally do not exploit anomalies. Rather, in the majority of cases their trading runs contrary to anomaly prescriptions.

[Table 4 around here]

As mentioned above, we find isolated support for the sophisticated institutions hypothesis in the case of momentum (MOM). The long leg of the momentum portfolio exhibits a Δ#Inst that is greater than that of the neutral portfolio (19.7% vs 9.5%, p-value of difference < 0.001) while the short-leg of the momentum portfolio exhibits a Δ#Inst that is less than that of the neutral portfolio (4.0% vs. 9.5%, p-value of difference < 0.001). In the case of gross profitability (GP) Δ#Inst is larger for long leg stocks with marginal significance, consistent with the sophisticated investor hypothesis, and in the case of O-score (OSC) the long and short legs do not reliably differ. It is interesting to note that institutions' well-known tendency to chase past returns would tend to place them on the "right side" of these anomalies given their anomaly ranking variables' high correlation with past returns (see, e.g., Falkenstein, 1996).

3.2. Anomaly returns conditional on institutional ownership

The fact that institutions trade contrary to anomaly prescriptions does not necessarily imply that these positions underperform. Perhaps institutions' stock-picking skill allows them to identify stocks that defy anomaly predictions. That is, maybe the short-leg stocks they buy earn positive abnormal returns and the long-leg stocks they sell earn negative abnormal returns – yielding a positive abnormal return to their contrary positions.[12] More generally, a second prediction of the sophisticated institution hypothesis is that institutional trades should be non-negatively related to future anomaly returns. This section examines the relation between pre-anomaly changes in institutional investors and future anomaly returns.

On each portfolio formation date, we conduct independent double sorts of all stocks on the basis of the anomaly ranking variable and Δ#Inst. We then take the intersection of the long leg (top 30%) and short leg (bottom 30%) of each anomaly with the top and bottom quintiles of Δ#Inst.[13] That is, for each anomaly we partition the long and short leg portfolios into stocks that institutions bought (highest Δ#Inst) and stocks that institutions sold (lowest Δ#Inst). Table 5 reports monthly Fama-French (1993) three-factor alphas for each of the four portfolios for each anomaly (Panel A) as well as the average alphas across the seven anomalies (Panel B).

[Table 5 around here]

Two striking patterns emerge from Table 5. First, from Panel A, anomaly stocks that institutions buy underperform those they sell in 11 out of 14 portfolios. Overall, the difference between buys and sells averages -34 bps per month (t-statistic = -2.5; untabulated). Second, this poor performance is concentrated in short-leg stocks that institutions buy, which earn significantly

[12] For example, Gibson, Safieddine, and Sonti (2004) find that SEOs experiencing the greatest increase in institutional investors outperform over the 3 months following the offering.

[13] We sort stocks into Δ#Inst quintiles to ensure that all stocks in the lowest Δ#Inst group exhibit a decrease in number of institutional investors to allow us to frame the discussion of changes in terms of buys and sells. The results are very similar if we use the top and bottom 30% sorts.

negative abnormal returns for all seven anomalies. From Panel B, the average alpha for short-leg stocks bought is -74 bps monthly (t-statistic= -5.0) versus -27 bps monthly (t-stat= -1.9) for short-leg stocks sold. The difference of -47 bps has a t-statistic of -3.3. By contrast, the average abnormal return of stocks in the long-leg anomaly portfolios are 10 bps (stocks bought) and 16 bps (stocks sold). Thus, almost all of the anomalies' abnormal returns come from "overvalued" (short-leg) stocks that institutions buy (rather than sell). As discussed later, this result has interesting implications for institutions' role in limits-of-arbitrage arguments.

Table 5, Panel B provides evidence using three alternative measures of institutional demand (besides Δ#Inst). In particular, we consider the change in percent of shares held (Δ%Inst) as well as parallel measures that focus on mutual funds (number of: Δ#MF, and shares held by: Δ%MF). In all cases the results are similar in direction, magnitude, and statistical significance. In addition to confirming the results for Δ#Inst, these provide an additional insight: a statistically reliable concentration of positive abnormal returns in long-leg stocks sold by institutions. For example, the average alpha in the Long-leg Sell portfolio ranges from 19 to 23 bps (t-statistics 2.1 to 3.0) using Δ%Inst, Δ#MF, and Δ%MF.

[Table 6 around here]

The Table 5 portfolios condition on extreme-quintile changes in Δ#Inst as well as anomaly characteristics. A natural question – addressed in Table 6, Panel A – concerns the magnitude of buying/selling within each Δ#Inst-anomaly portfolio. The first rows of Panel A shows that short-leg buying is similar to, though slightly more extensive, than long-leg buying (difference generally not significant). The second set of rows provides similar inferences regarding selling: long-leg selling is generally similar in magnitude to short-leg selling, though slightly less extensive. However, from the first column, institutions bought a significantly greater number of short-leg stocks than long-leg stocks (selling is not significantly different comparing across anomaly legs). Panel B presents characteristics of stocks in the conditional portfolios. The average stock in the overall sample is fairly large (average market cap of $1.1 billion) and widely held by institutions (e.g., average number of institutions is 64.8; and average percent of shares held by institutions is 43.3%). Short-leg stocks that institutions buy do not significantly differ from the long-leg stocks they buy on any dimension examined. However, long-leg stocks sold by institutions are significantly less liquid than short-leg stocks sold (Amihud measure); with marginally fewer beginning-of-period institutional investors; and marginally lower market capitalization (p-values 0.000, 0.07, and 0.06, respectively). But, overall, Table 6 Panel B does not offer a compelling explanation for the contrary trading pattern – or resulting returns – of institutions.

3.3. Institutional holding periods

An important consideration is the extent to which changes during the portfolio formation window are maintained over the anomaly return window. If institutions reverse their positions sometime prior to the realization of anomaly returns, they might capture shorter-horizon positive abnormal returns while avoiding the longer horizon negative abnormal returns – leaving little to puzzle over regarding their behavior.

[Figure 2 around here]

Figure 2 examines potential reversals in changes in number of institutional investors. Panel A tracks stocks in the highest Δ#Inst quintile during the anomaly portfolio formation window ("stocks bought") while Panel B tracks stocks in the lowest Δ#Inst quintile during the anomaly portfolio formation window ("stocks sold"). Recall that quarters -5 to 0 represents the portfolio formation window whereas quarters 1 through 4 reflect the anomaly return window.[14] Each Panel tracks cumulative Δ#Inst separately for the long and short legs of anomaly portfolios, averaged across the seven anomalies. We detrend Δ#Inst for each portfolio by subtracting the concurrent Δ#Inst of stocks in the neutral leg (middle 40%) for each anomaly. From Panel A, short-leg stocks in the highest Δ#Inst quintile (stocks bought) experience a 67% increase in Δ#Inst (relative to the trend) prior to the anomaly return window, with a statistically insignificant (t-statistic: -0.8) reversal to 63% by the end of the return window. From Panel B, long-leg stocks in the lowest Δ#Inst quintile (stocks sold) experience a 49% decrease in Δ#Inst prior to the anomaly return window followed by a statistically insignificant (t-statistic: -0.8) reversal to -45%. Thus, in both cases there is no statistically reliable evidence of reversal in Δ#Inst during, or immediately preceding, the anomaly return window.

3.4. Reconciling with prior studies

The negative relation between changes in institutional holdings and future returns we document is in sharp contrast to the positive relation between changes in institutional holdings and future stock returns found in other studies (see e.g., Grinblatt, Titman, and Wermers, 1995; Wermers, 1999; Chen, Hong, and Stein, 2002; Chen, Jegadeesh, and Wermers, 2000; Bennett, Sias, and Starks, 2003; Sias, 2004; and Sias, Starks, and Titman, 2006]. We trace this discrepancy to differences in time horizon.[15] The horizons we examine (12-18 months) are generally longer

[14] Since momentum portfolios are constructed quarterly with a 3-month holding period, Δ#Inst for momentum is measured and included in Figure 2 only until the end of quarter 1.

[15] These studies also differ in the metric for institutional demand (number of institutions vs percent of shares held); the scaling methodology; and the type of institution (all institutions or mutual funds). We find these differences to be less important.

than that of the above studies (3-12 months) with regards to both institutional trading and performance evaluation. As suggested in Jain (2010), the relation between institutional trading and future returns depends critically on the horizon over which trading and returns are measured. For example, the literature indicates that institutional trading is negatively related to future returns for horizons longer than one year (see e.g., Gutierrez and Kelly, 2009; and Dasgupta, Prat, and Verardo, 2011).[16]

Table 7 documents the relation between Δ#Inst and anomaly returns during each of the four quarters of the anomaly return window, and over the entire (one year) window. We separately compute average monthly three factor alphas of institutions' buy-minus-sell portfolios for the long and the short leg of each anomaly portfolio, and then take the average alpha across the seven anomalies. Panel A shows that the negative relation between Δ#Inst (*q*-5:*q*) and abnormal returns (*q*+1:*q*+4) in Table 5 is concentrated in the third and fourth quarters of the return window.[17] From Panel B, this seems to be due to a significantly positive short-run relation between Δ#Inst (*q*) and future abnormal returns, which dissipates after two quarters. Combining the two, Panel C shows that the negative relation between long-horizon changes in institutional ownership (*q*-5:*q*-1) and future abnormal returns is considerably stronger when a one-quarter gap is inserted between the ranking and return periods, as is typical of the anomaly literature.[18]

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[16] The relation generally turns insignificant or negative after six months. See, e.g., Grinblatt Titman and Wermers (1995), Wermers (1999), Chen Hong and Stein (2002), Chen Jagadeesh and Wermers (2000), and Sias (2004).

[17] An intriguing aspect of this result is that the third quarter generally represents the first calendar quarter (with anomaly return windows beginning in July).

[18] Companies have 90 days after their fiscal-year end to file the 10-K annual report that contains fourth quarter financial and accounting data. Thus, the latest possible filing date is March 31st in calendar year *t*+1 for companies

[Table 7 around here]

Table 7 demonstrates the central role that the measurement interval plays in reconciling our results with those of the literature. The fact that the negative long-horizon relation subsumes the positive short-horizon relation – particularly for the short-leg of anomaly portfolios – suggests that the short-horizon positive relation may reflect price pressure associated with persistent institutional trading, as opposed to informed trading. Whatever the case may be, a long horizon is more relevant to our study. Our central hypothesis concerns how institutional investors modify their portfolios as stocks take on anomaly-defining characteristics. Both the standard anomaly portfolio formation period and the anomaly return window span a year (or longer). Additionally, as shown in Figure 2, the changes in institutional holdings that we document persists through the anomaly return window, suggesting that a longer horizon is more relevant to typical institutional holding periods.

3.5. Fama-MacBeth Regressions

The portfolio sorts in Tables 4 and 5 demonstrate a negative long-horizon relation between Δ#Inst and future stock returns via two distinct channels: adverse exposure to anomaly characteristics and negative predictive power for future returns controlling for anomalies. In this section, we investigate these two effects using cross-sectional Fama-MacBeth regressions that control for the full set of anomaly characteristics simultaneously. This provides a more robust examination of the predictive power of changes in institutional ownership, and it accounts for the possibility that institutions' trading behavior varies across anomalies (e.g., trading on the wrong side of one anomaly but on the right side of another).

with a fiscal-year ending in December of t, and earlier for those with earlier fiscal-year ends. As a result, the shorter Δ#Inst (q-5:q-1) trading window contains substantially all of the data required to calculate anomaly variables.

Table 8 reports the Fama-MacBeth regression results using future monthly returns across all (long, neutral, and short leg) stocks as the dependent variable. Independent variables are observed as of the most recent June and updated annually, with the exception of Δ#Inst (prior quarter), which is updated quarterly to capture the short-horizon relation between Δ#Inst and stock returns documented in Table 7. Thus, in most cases the independent variables are the same for all twelve regressions for year *t*. Coefficient estimates and *t*-statistics are based on the time-series average and variability of the monthly estimates, with Newey-West adjusted standard errors using six lags.

[Table 8 around here]

Table 8 column 1 examines the predictive power of changes in number of institutions using Δ#Inst (*q*-5:*q*) as the sole explanatory variable. The overall long-horizon relation is negative with an average coefficient of -0.50 and *t*-statistic of -3.3. To examine the horizon effect revealed in Table 7, column 2 splits Δ#Inst (*q*-5:*q*) into Δ#Inst (*q*-5:*q*-1) and Δ#Inst (*q*). The long-horizon changes remain significantly negatively related to returns (t-statistic of -3.7) whereas the short-horizon changes are positive and statistically insignificant (t-statistic of 1.1).

To better capture the short-horizon relation between Δ#Inst and subsequent stock returns, column 3 replaces Δ#Inst (*q*) with Δ#Inst (prior quarter). Δ#Inst (prior quarter) is significantly positively related to returns during the following three months (t-statistic of 2.0) while Δ#Inst (*q*-5:*q*-1) remains significantly negatively related to future long-horizon returns, confirming that the positive predictive power of institutional demand for future stock returns documented in earlier studies is short-lived.

In Table 8 column 4 we investigate the marginal predictive power of changes in number of institutions for future stock returns after controlling for the seven anomaly characteristics along with the natural logarithm of market capitalization and Amihud's illiquidity ratio as of June of year *t* (coefficient estimates untabulated). Both Δ#Inst (*q*-5:*q*-1) and Δ#Inst (prior quarter) remain statistically significantly related to returns (negatively and positively, respectively). Notably, the average coefficient on Δ#Inst (*q*-5:*q*-1) drops from -0.60 (t-statistic of -3.7) to -0.23 (t-statistic of -2.5) after controlling for anomaly characteristics. This indicates that much (but not all) of the predictive power of Δ#Inst for returns at the long-horizon is due to institutions' adverse exposure to characteristics associated with anomaly returns.

To explore this further, we decompose stock returns into 'predicted anomaly returns' and 'residual returns' using the regression presented in Table 8 column 4, and regress each component separately on Δ#Inst.[19] The 'predicted anomaly return' regression (column 5) explores institutional demand for firm characteristics associated with anomalies. The `residual return' regression (column 6) essentially replicates column 4 without controls. Column 5 reveals that Δ#Inst (*q*-5:*q*-1) is significantly negatively related to predicted anomaly returns (t-statistic of -3.0), confirming institutions' adverse exposure to ex-ante anomaly returns. In contrast, the short-horizon change in institutional demand, as measured by Δ#Inst in the quarter prior to returns, is insignificantly related to ex-ante anomaly returns, consistent with the evidence in Figure 2 that institutions do not change their exposure significantly during the anomaly return window.

Altogether, the cross-sectional regressions in Table 8 confirm the results from portfolio sorts. Long-horizon changes in number of institutional investors are negatively related to future stock returns, due both to institutions' adverse exposure to anomaly characteristics and to a direct

[19] Predicted anomaly returns are calculated as the sum of the products of the nine firm characteristics added to column 4 with their estimated regression coefficients. The residual component equals returns minus the predicted anomaly returns. Note that predicted anomaly returns do not exactly equate to predicted values from the regression in column 4 due to the omission of institutional demand values in the predicted anomaly component.

negative effect independent from the anomalies. We also find that the positive relation between institutional demand and stock returns documented by earlier studies is largely orthogonal to anomalies and short-lived.

4. Explanations and Implications

The evidence in Section 3 indicates that institutions' pre-anomaly trades are on the wrong side of both ex-ante anomaly prescriptions and ex-post realized anomaly returns. Moreover, our analysis reveals a strong horizon effect for the relation between changes in institutional ownership and future stock returns – the relation is positive for short horizons and negative for long horizons. In this section we consider potential explanations for our findings.

4.1. Mutual funds and flow

An important consideration when interpreting institutional trading activity is the potential effects of investor flow. Edelen (1999) finds that roughly 30% of all mutual fund trades are in response to investor flow. Moreover, trading in response to flow can cause price-pressure in the underlying stocks of institutional portfolios. For example, Khan, Kogan, and Serafeim (2012) argue that mispricing prior to SEOs is related to price pressures by mutual funds experiencing large investor inflows. Likewise, Frazzini and Lamont (2008) argue that the value effect is due, in part, to mispricing from investor flows into mutual funds holding growth stocks. More generally, Coval and Stafford (2007) show that correlated investor flows into institutional portfolios with common investment objects (particularly highly specialized) can cause relatively protracted price-pressures and subsequent reversals. Thus, the puzzling institutional trading that we find conceivably originates with beneficial investors rather than portfolio managers.

Table 9 provides evidence on the potential role of flow using several regression specifications of anomaly returns on institutional demand and various proxies for investor flows.

First, following Sias, Starks, and Titman (2006), we compare two different measures of institutional trading: the change in number of institutions (Δ#Inst) and the change in the fraction of shares held by institutions (Δ%Inst). Columns 1 and 2 present the baseline result that both measures are significantly negatively related to returns. However, as Khan et al. (2012) show, mutual fund inflows typically go towards expansion of existing positions rather than new positions. Hence, flow-induced price pressure should be more closely related to Δ%Inst (which reflects both adjustments to existing positions as well as new and closed positions) than Δ#Inst (which reflects only new and closed positions). From column 3 of Table 9, when both Δ#Inst and Δ%Inst are included in the regressions only Δ#Inst is significant (t-statistic= -3.2). Thus, new and closed positions appear more relevant to future returns than adjustments to ongoing positions, casting doubt on flow as a factor behind these trades.

[Table 9 around here]

Second, the effects of flow are likely to be most pronounced in the context of mutual funds. In column 4, we decompose Δ%Inst into the change in percent shares held by mutual funds (Δ%MF), versus non-mutual funds (Δ%NMF). Neither regression coefficient is statistically significant, though the relation is strongest among non-mutual funds where the t-statistic is -1.9. Third, we use the methodology of Coval and Stafford (2007) to partition Δ%MF into its Δ%MF(Flow-induced) and Δ%MF(Non-flow) components and include them in the regression along with Δ%NMF.[20] Δ%MF (Flow-induced) is the change in fraction of stock held by mutual funds having in-flow buying pressure or out-flow selling pressure and Δ%MF(Non-flow) is the

[20] Due to the incompleteness of mutual fund flow data prior to 1990 we limit this analysis to 1991-2012.

change in the fraction of the stock held by mutual funds that are not under flow pressure.[21] From column 5, Δ%MF (Flow-induced) is negatively related to future stock returns, but marginally significant with a t-statistic of -1.8 whereas Δ%NMF remains significantly negative with a t-statistic of -2.2. In column 6, we include Δ#Inst in the regression rather than Δ%Inst to examine the impact of flow-induced mutual fund demand on our main result. We find that Δ#Inst remains significantly negatively related to stock returns (t-statistic of -2.8) while Δ%NMF, Δ%MF (Flow-induced), and Δ%MF (Non-flow) are statistically insignificant.

Finally, as an alternative to the linear specifications for flow-induced buying and selling pressure, we examine the relation between Δ#Inst and future stocks returns excluding stocks under flow-induced buying or selling pressure from the sample. Following Khan et al. (2012), we classify a stock as under flow-driven buying (selling) pressure if it is in the top (bottom) decile of Δ%MF(Flow-induced) and in the middle three deciles of Δ%MF(Non-flow). In the univariate regression in Table 9 column 7, the coefficient on Δ#Inst is -0.67 with a t-statistic of -3.1. In column 8 we estimate the marginal predictive power of Δ#Inst for future stock returns controlling for all anomaly characteristics (as in Table 8), again restricting to stocks not under flow pressure. Similar to Table 8, the coefficient on Δ#Inst declines considerably from -0.67 to -0.29 but remains statistically significant with a t-statistic of -2.3. Thus, by all counts, the long-horizon negative relation between institutional demand and future returns does not appear to be due to investor flow.

[21] Following Coval and Stafford (2007), a mutual fund is classified as having in-flow driven buying pressure (out-flow driven selling pressure) during the year if the fund was subject to capital flows in the top (bottom) 10% of all mutual funds in at least one quarter during that year.

4.2. Limits-of-Arbitrage

Our findings have implications regarding the role of institutional investors and limits-of-arbitrage in stock return anomalies. Shleifer and Vishny (1997) argue that idiosyncratic risk can cause institutions to be reluctant to bet heavily against mispricing. Lewellen's (2011) evidence that the aggregate institutional portfolio does not deviate efficiently from the market portfolio vis-à-vis anomalies suggests that institutions' failure to capitalize on anomalies is not due to their unwillingness to take on idiosyncratic risk. Our evidence that anomaly returns are heavily concentrated in stocks with substantial institutional buying further supports this conclusion. They do place significant bets, but on the wrong side of the mispricing. Furthermore, the fact that anomaly returns are concentrated in stocks heavily traded by institutions also casts doubt on transaction costs as an explanation for why institutions fail to exploit these opportunities.

Finally, several studies argue that institutions' inability to engage in short sales contributes to persistence in overpricing (Stambaugh, Yu, and Yuan, 2013). Our evidence challenges this view. To the extent that institutional investors are aware of anomaly overvaluation but constrained from exploiting it due to short-sale restrictions, we would expect institutions that hold these stocks to sell them and institutions that don't hold these stock to abstain from buying them – yielding a net decrease in institutional holdings (as argued in Chen, Hong, and Stein, 2002). Yet we find just the opposite—short-leg anomaly returns are concentrated primarily in stocks with a net increase in institutional holdings. Note from Table 5 that when institutions in aggregate plausibly face short-sale constraints – i.e., 'sell' stocks – we still see strong anomaly returns (e.g., 0.43% per month with a t-statistic of 5.4 for the AVG portfolio), but they are not particularly biased to the short leg – contrary to what one would expect if anomalies' survival depended on institutions facing aggregate short-sale constraints. Thus, while short sale constraints may inhibit the arbitrage of these anomalies, these constraints are clearly not binding for institutions in aggregate.

Why do the anomalies persist? Our results suggest that not only do institutions fail to arbitrage them away, but that persistent institutional demand itself might be an important source of arbitrage risk. This notion is consistent with De Long, Shleifer, Summers, and Waldman (1990) who argue that positive feedback trading by noise traders poses an arbitrage risk for arbitrageurs. Our results suggest that institutions might be the noise traders in their model. This might also explain why mispricing is concentrated in overpriced stocks bought by institutions. It may be that the real limits-of-arbitrage is the reluctance of other parties to take a short position against a tidal wave of persistent institutional buying. While speculative, our results are consistent with aggregate institutional trading forming a key impediment to arbitrage, rather than the stabilizing force against mispricing that is often conjectured.

4.3. Biased cash flow forecasts?

Several studies examine returns around earnings announcements in an attempt to distinguish between mispricing and risk-based explanations of financial anomalies (see, e.g., Bernard and Thomas, 1990; Chopra et al., 1992; La Porta et al. 1997). The basic idea is that valuation errors caused by biased expectations about future cash flows should be corrected, in part, during subsequent earnings announcements (Lewellen, 2010). We use this approach to explore whether the negative long-horizon relation between Δ#Inst and future stock returns is due to biased expectations about future cash flows. If so, Δ#Inst during the portfolio formation window should be negatively related to earnings announcement returns during the anomaly return window.

In untabulated results we estimate monthly Fama-MacBeth regressions of abnormal earnings announcement returns in the anomaly return window on Δ#Inst (q-5:q-1) and Δ#Inst(q), controlling for anomaly characteristics. Following convention, we compute abnormal earnings announcement returns as the average daily return during the three-day earnings announcement window (event days -1 and +1) minus the average daily return of the same stock during the anomaly return window, but outside the announcement window.[22] Thus, each month, July t – June t+1 where quarter q corresponds to April – June of t, we have an observation for those stocks with an earnings announcement that month. The estimated relation (t-statistics in parenthesis, intercept and controls suppressed) is:

Abnormal earnings announcement return =

$$\underset{(-4.5)}{-\,0.11}\ \Delta\#\text{Inst}\,(q\text{-}5{:}q\text{-}1) \underset{(-0.9)}{-\,0.06}\ \Delta\#\text{Inst}(q) \tag{1}$$

Thus, the long-horizon Δ#Inst that negatively relate to abnormal returns in Tables 7 and 8 also negatively relate to earnings announcement returns. This suggests that institutions' (long-run) contrary demand for anomaly characteristics may be partly due to faulty earnings expectations.

5. Robustness Checks

5.1. Small capitalization stocks

A natural question concerns the extent to which our results are driven by small capitalization stocks. Our empirical methodology limits the effect of small stocks in several ways. First, we restrict our sample to stocks with a share price of at least $5 at the time of portfolio formation. Second, anomaly portfolio returns in Table 5 are value-weighted using the market capitalization of stocks at the time of portfolio formation. Third, the Fama-MacBeth regressions control for size by including the natural logarithm of market capitalization as an independent variable.

In Table 10 Panel A, we address the potential influence of size more directly by repeating the Fama-MacBeth regressions from Table 8 in sub-samples of larger firms. First, we limit the sample to stocks with 20 or more institutional investors at the time of portfolio formation. Second,

[22] Results are almost identical using market-adjusted returns.

we separate stocks by their market capitalization at the time of portfolio formation to explore the robustness of our results for larger stocks. Following Fama and French (2008) and Lewellen (2014), we use the 20^{th} and 50^{th} percentiles of market capitalization for NYSE stocks, which separates micro-cap, small, and large stocks.

[Table 10 around here]

Table 10 Panel A shows that institutions' contrary preference for anomaly stocks is strongly present among large stocks. Predicted anomaly returns are significantly negatively related to Δ#Inst(q-5:q-1) in all three sub-samples. With regards to residual returns, both the negative long-horizon and positive short-horizon relation with Δ#Inst are still observed in the sub-sample that excludes stocks with fewer than 20 institutional investors. However, both Δ#Inst measures become insignificantly related to future residual returns once micro-cap stocks are excluded. Nevertheless, the evidence does not support the prediction of the sophisticated institutions hypothesis that institutions select stocks contrary to anomaly portfolios in a way that avoids anomaly predicted returns. In sum, institutions' contrary preference for anomaly stocks extends to large-cap stocks, whereas both the short-term continuation and long-term price reversals from their trading orthogonal to anomaly characteristics appears to be limited to micro-cap stocks.

5.2. Sub-period results

While it is difficult to precisely date institutions' awareness of anomaly-based trading strategies, it is likely that some of the anomalies we consider were not widely known during the early part of our sample period. To the extent that the institutional trading patterns we document are due to a lack of awareness, our results should be weaker in the latter part of the sample period, after academic studies document the profitability of anomaly trading strategies (McLean and

Pontiff, 2013).

In Table 10 Panel B, we compare the cross-sectional regression results from Table 8 across sub-periods by splitting our sample into an early period (1982-1996) and late (1997-2011) period by the year of portfolio formation. The first two columns reveal that the anomaly component of future stock returns is significantly negative related to Δ#Inst(*q*-5:*q*-1) and insignificantly related to Δ#Inst(prior quarter) in both periods. In contrast, in the last two columns, the residual component of future stock returns is significantly negatively related to Δ#Inst(*q*-5:*q*-1) only during the second half of the sample period, and positively related to Δ#Inst(prior quarter) only during the first half of the sample period. In summary, institutions' contrary preference for anomaly stocks has not diminished over time despite increasing awareness of the anomalies. Notably, the positive predictive power of short-horizon institutional demand on stock returns documented by several earlier studies seems to have dissipated over time.

6. Conclusion

Our findings have important implications regarding the role that institutional investors and limits-of-arbitrage play in widely documented stock return anomalies. A large body of literature portrays institutions as relatively sophisticated investors who, in the absence of frictions, correct mispricing. The negative relation between institutional demand and anomaly returns we document is more consistent with a causal role than an arbitrager role. At a minimum, the fact that anomaly returns are concentrated almost entirely in "overvalued" stocks that institutions buy rather than sell suggests that idiosyncratic risk, transaction costs, and restrictions on institutional short sales cannot account for why institutions fail to arbitrage these anomalies away.

A new and perhaps bigger question that emerges from our findings concerns why institutions trade contrary to anomaly prescriptions. While a full accounting for this behavior is beyond the scope of this study we provide some insights. We find no evidence that our results reflect investor flow, but some evidence that behavioral biases and/or agency conflicts relating to tracking of common characteristics play a role, as in Lakonishok, Shleifer, and Vishny (1992).

A behavioral interpretation of our results seems odd because institutions are generally thought of as being 'smart,' which should at a minimum subsume knowledge of the widely cited anomalies literature. An agency interpretation seems more plausible because institutional investing entails known agency conflicts such as excessive turnover [Chalmers, Edelen, and Kadlec (1999)], risk taking (Brown, Harlow, and Starks, 1996; and Chevalier and Ellison, 1997) and herding for reputational reasons [Del Guercio, 1996; Falkenstein, 1996; Gompers and Metrick, 2001; Barberis and Shleifer, 2003; Bennett, Sias, and Starks, 2003). Moreover, if anomalous returns are a consequence of mispricing, then the most obvious place to look for an economic force big enough to distort asset prices is the elephant in the room– institutions.

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Figure 1. Time line for the construction of anomaly portfolios

Figure 1 depicts the portfolio construction time line for the seven stock return anomalies of Table 1. For all anomalies except momentum, portfolios are constructed annually at the end of June of each year t based on stock characteristics as of fiscal year-end in year t-1 and changes in institutional ownership during the previous six calendar quarters (q-5 to q), and held for the next twelve months. For momentum, portfolios are constructed quarterly based on stock returns during the previous 12 months and changes in institutional ownership during the previous six calendar quarters (q-5 to q), and held for the next three months. "FYE t indicates the fiscal year-end in calendar year t-1.

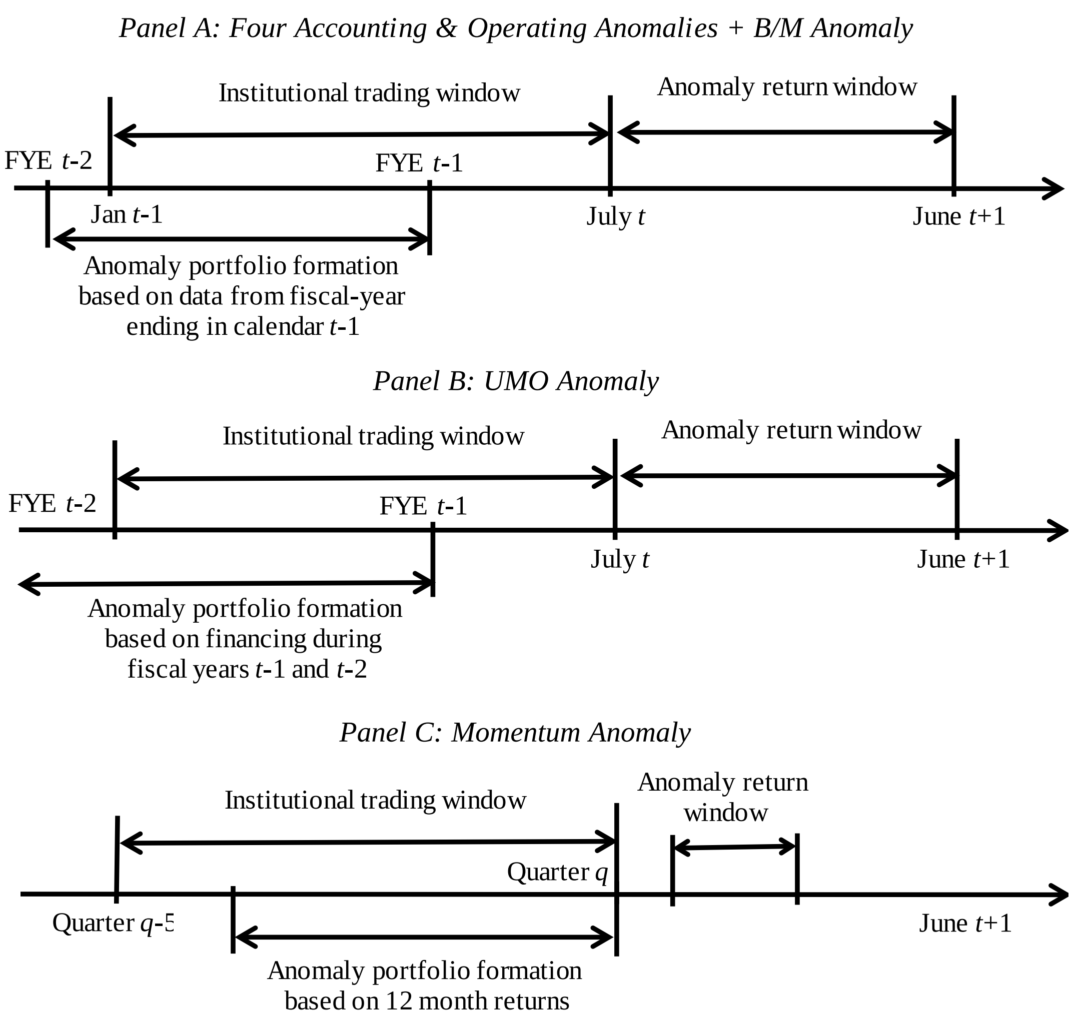
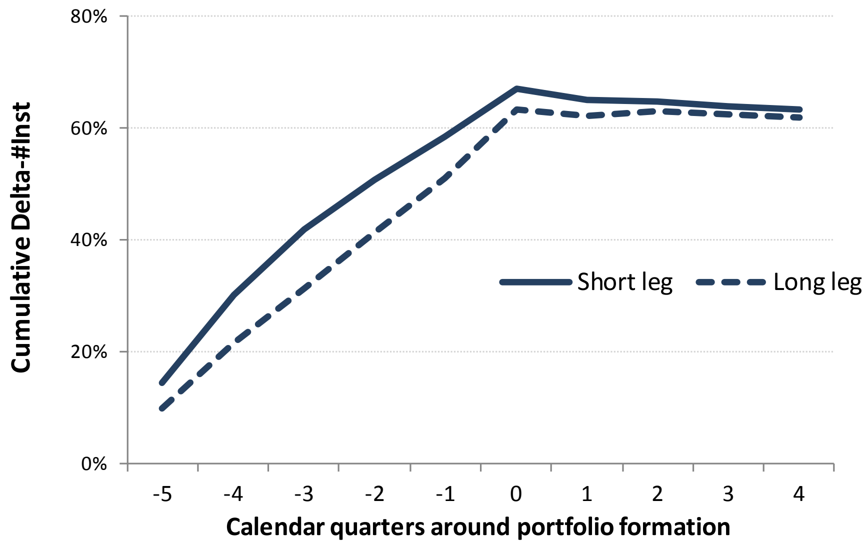


Figure 2. Cumulative changes in number of institutional investors across seven anomalies

This chart depicts the average detrended Δ#Inst across seven anomalies, cumulated over the portfolio formation window (quarters -5 to 0) through the anomaly return window (quarters 1 to 4). Δ#Inst is the change in the number of institutional investors scaled by the average number of institutions holding stocks in the same market capitalization decile at the begining of the period. Panel A ('stocks bought') depicts stocks in the highest quintile of Δ#Inst during the institutional trading window, separately for short-leg and long-leg anomaly stocks. Panel B ('stocks sold') similarly depicts stocks in the lowest Δ#Inst quintile. Δ#Inst is detrended prior to averaging across anomalies by subtracting the concurrent average cumulative Δ#Inst of stocks in the Neutral anomaly leg (middle 40%). For momentum, the three-month anomaly return window straddles quarters 0 and 1.

Panel A: Stocks bought



Panel B: Stocks sold

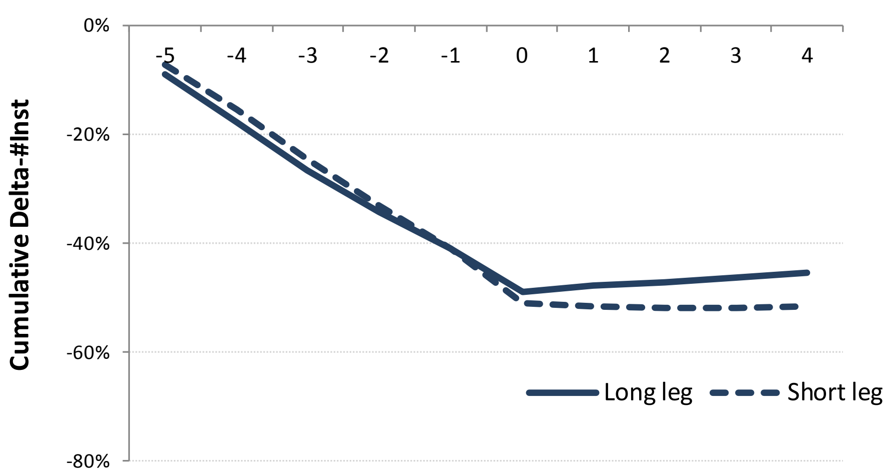


Table 1. Anomalies considered

Anomaly	Label	Description	Citation
Net Operating Assets	NOA	The sum of short-term debt (DLC), long-term debt (DLTT), minority interest (MIB), preferred stock (PSTK), and common equity (CEQ) minus cash and short-term investment (CHE), deflated by lagged total assets (AT).	Hirshleifer, Hou, Teoh, and Zhang (2004)
Gross Profitability	GP	Total revenues (REVT) minus cost of goods sold (COGS), divided by total assets (AT).	Novy-Marx (2012)
Investment to Assets	IVA	The change in gross property, plant, and equipment (PPEGT) plus the change in inventories (INVT), deflated by the lagged total assets (AT).	Lyandres, Sun, and Zhang (2008)
O-Score	OSC	The probability of bankruptcy calculated using accounting variables such as total liabilities divided by assets, working capital divided by assets, current liabilities divided by current assets, net income, and inflation-adjusted total assets applied to coefficients estimated using a logit regression of bankruptcies.	Ohlson (1980); Dichev (1998)
Book to market	B/M	Book value of common equity (SEQ or AT-LT) plus net deferred tax assets (TXDB), investment tax credit (ITCB), and postretirement benefit liabilities (PRBA), divided by market capitalization end of calendar year t.	Fama and French (1992)
Momentum	MOM	Cumulative stock return between months j-1 and j-12, where j+1 to j+3 are the months of performance evaluation.	Jegadeesh and Titman (1993)
Undervalued minus overvalued	UMO	The portfolio "U" (undervalued) contains firms with equity or debt repurchases and without any equity or debt issuances during the two most recent fiscal years. The portfolio "O" (overvalued) contains firms with equity or debt issuances and without any equity or debt repurchases during the two most recent fiscal years.	Hirshleifer and Jiang (2010)

Table 2. Anomaly returns

The table presents average monthly returns in percent for the seven anomaly portfolios in Table 1 and their equal-weighted overall average (last column), between July of 1982 and June of 2012. Anomaly portfolios are formed by ranking on the indicated variable as of June year *t* and taking a long (short) position in the highest (lowest) performing 30% tails. For all anomalies except momentum (see Table 1 for acronyms), the position is held July year *t* through June of year *t* +1. Momentum portfolios are rebalanced quarterly using prior 12 month stock returns. Excess returns (Panel A) net out the one month US Treasury bill rate; three-factor alphas (Panel B) refer to the intercept from a time-series regression of monthly value-weighted excess returns on the MKT, SMB, and HML factors, excluding HML for the B/M anomaly. Heteroskedasticity-adjusted t-statistics are in parentheses.

	NOA	GP	IVA	OSC	B/M	MOM	UMO	AVG
	Panel A: Monthly excess returns (%)							
Long leg	0.86	0.96	0.89	0.76	0.94	0.90	0.97	0.90
Short leg	0.32	0.35	0.37	0.56	0.35	0.43	0.40	0.40
Long - short	0.53	0.61	0.52	0.20	0.59	0.47	0.57	0.50
	(4.7)	(5.2)	(5.0)	(1.8)	(3.3)	(1.9)	(5.1)	(6.3)
	Panel B: Monthly three-factor alphas (%)							
Long leg	0.17	0.28	0.12	0.10	0.26	0.20	0.25	0.19
	(1.9)	(3.5)	(1.8)	(1.5)	(2.2)	(2.1)	(3.7)	(2.0)
Short leg	-0.50	-0.49	-0.41	-0.30	-0.46	-0.50	-0.38	-0.41
	(-5.2)	(-5.0)	(-4.4)	(-3.0)	(-4.3)	(-2.6)	(-3.9)	(-3.3)
Long - short	0.67	0.76	0.53	0.40	0.72	0.70	0.63	0.60
	(6.5)	(6.8)	(6.0)	(4.5)	(4.0)	(3.2)	(6.8)	(8.6)

Table 3. Summary statistics for institutional ownership

Panel A reports the means, standard deviations, and percentiles for the level of and change in the number of 13F institutional investors (*#Inst*) and the percentage of shares held by 13F institutional investors (*%Inst*) during the six calendar quarters prior to annual portfolio formation at the end of June (q-5 to q), where q refers to end of June of each year beginning in 1982. All variables are winsorized at the 1% level in both tails. Change variables are converted to annualized equivalent values. Panel B reports the means for quintiles sorted annually by Δ#Inst (q-5 to q). Data is from December 1980 through June 2011.

Panel A: Summary statistics

	Mean	**Standard deviation**	**P25**	**Median**	**P75**
#Inst (q)	84.6	118.1	13.0	40.0	108.0
%Inst (q)	42.8%	28.8%	17.8%	40.2%	65.4%
Δ#Inst (q-5 to q)	13.3%	25.9%	0.0%	10.6%	27.0%
Δ%Inst (q-5 to q)	4.7%	10.1%	-0.4%	2.5%	7.8%

Panel B: Means for portfolios sorted by Δ#Inst (q-5 to q)

	Large decrease	**2**	**3**	**4**	**Large increase**
#Inst (q)	66.4	104.8	114.4	92.2	61.9
%Inst (q)	41.8%	43.6%	45.9%	45.8%	45.3%
Δ#Inst (q-5 to q)	-19.2%	1.8%	12.3%	24.2%	50.3%
Δ%Inst (q-5 to q)	-1.3%	1.2%	2.6%	5.2%	15.1%

Table 4. Changes in institutional investor base for anomaly stocks

The table presents annualized changes in institutional ownership during the anomaly portfolio formation period, 1982 - 2012. Δ#Inst is the change in the number of institutional investors scaled by the average number of institutions holding stocks in the same market capitalization decile at the beginning of the period. Δ%Inst is the change in fraction of shares held. [See Figure 1 for timeline and Table 1 for anomaly acronoyms.] ***, **, and * indicate p-values of 1%, 5%, and 10% or less, respectively. The p-values are estimated nonparametrically and adjusted for autocorrelation using moving block bootstrapping.

		Δ#Inst	Δ%Inst			Δ#Inst	Δ%Inst
NOA	Long	12.2%	4.3%	*GP*	Long	15.0%	4.5%
	Neut	10.7%	3.3%		Neut	12.5%	3.9%
	Short	17.2%	5.3%		Short	12.0%	4.4%
	L-N	1.5%	1.0%		*L-N*	2.5%	0.6%
	S-N	6.5%***	2.0%***		*S-N*	-0.5%	0.5%
	L-S	-5.0%***	-1.0%		*L-S*	3.0%*	-0.1%
IVA	Long	9.3%	3.2%	*OSC*	Long	13.6%	4.3%
	Neut	11.6%	3.7%		Neut	12.1%	3.8%
	Short	17.3%	5.4%		Short	12.5%	4.2%
	L-N	-2.3%	-0.5%		*L-N*	1.5%	0.5%
	S-N	5.7%***	1.7%**		*S-N*	0.3%	0.4%
	L-S	-8.0%***	-2.2%***		*L-S*	1.2%	0.1%
BM	Long	5.6%	2.3%	*MOM*	Long	19.7%	5.6%
	Neut	12.6%	3.9%		Neut	9.5%	3.1%
	Short	20.9%	6.4%		Short	4.0%	2.0%
	L-N	-7.0%***	-1.6%**		*L-N*	10.2%***	2.5%***
	S-N	8.3%***	2.5%***		*S-N*	-5.4%***	-1.1%***
	L-S	-15.4%***	-4.1%***		*L-S*	15.7%***	3.6%***
UMO	Long	9.4%	2.4%	*AVG*	Long	12.1%	3.8%
	Neut	11.0%	3.6%		Neut	11.4%	3.6%
	Short	21.6%	7.5%		Short	15.1%	5.0%
	L-N	-1.6%	-1.2%*		*L-N*	0.7%	0.2%
	S-N	10.6%***	3.9%***		*S-N*	3.7%***	1.4%***
	L-S	-12.2%***	-5.1%***		*L-S*	-3.0%***	-1.2%***

Table 5. Abnormal returns of anomaly portfolios conditional on institutional demand

The table presents monthly three-factor alphas during the anomaly return window sorted independently by anomaly characteristics and change in institutional ownership during the anomaly portfolio formation period. Buy (Sell) refers to the top (bottom) quintile of change in institutional ownership. Panel A presents seven anomaly characteristics separately, using Δ#Inst to measure change in institutional ownership (change in number of institutional investors scaled by the average number of institutions holding stocks in the same market capitalization decile at the begining of the period). Panel B presents an equal weighted combination of the seven anomalies using Δ#Inst; Δ%Inst; Δ%MF; and Δ#MF to measure change in institutional ownership, where 'Δ%' refers to the change in percentage of shares held and 'MF' refers to mutual funds. Heteroskedasticity-adjusted t-statistics are in parentheses.

Panel A. Portfolio abnormal returns for seven anomalies using Δ#Inst

	NOA			*GP*			*IVA*			*OSC*		
	Buy	Sell	B-S	Buy	Sell	B-S	Buy	Sell	B-S	Buy	Sell	B-S
Long	0.23	0.20	0.03	0.16	0.35	-0.19	-0.06	0.14	-0.20	-0.14	0.23	-0.37
	(1.6)	(1.3)	(0.2)	(1.2)	(2.6)	(-1.2)	(-0.5)	(1.2)	(-1.3)	(-1.0)	(1.7)	(-2.3)
Short	-0.75	-0.15	-0.60	-0.82	-0.44	-0.38	-0.72	-0.28	-0.44	-0.65	-0.26	-0.39
	(-4.6)	(-1.0)	(-3.1)	(-4.6)	(-3.2)	(-2.0)	(-4.7)	(-1.8)	(-2.5)	(-4.1)	(-1.6)	(-2.0)
L-S	0.98	0.35	0.63	0.98	0.79	0.19	0.66	0.42	0.24	0.51	0.49	0.02
	(6.0)	(2.2)	(2.8)	(5.3)	(4.8)	(0.9)	(4.5)	(2.8)	(1.3)	(2.5)	(2.8)	(0.1)

	BM			*MOM*			*UMO*		
	Buy	Sell	B-S	Buy	Sell	B-S	Buy	Sell	B-S
Long	0.09	0.35	-0.26	0.18	0.07	0.11	0.47	0.06	0.41
	(0.5)	(2.1)	(-1.5)	(1.4)	(0.4)	(0.6)	(2.8)	(0.4)	(2.0)
Short	-0.74	-0.19	-0.55	-1.15	-0.32	-0.83	-0.61	-0.29	-0.32
	(-4.2)	(-1.1)	(-2.6)	(-4.4)	(-1.5)	(-4.2)	(-4.2)	(-1.6)	(-1.7)
L-S	0.83	0.54	0.29	1.33	0.39	0.94	1.08	0.35	0.73
	(3.1)	(3.1)	(1.2)	(4.4)	(1.8)	(3.4)	(5.7)	(1.3)	(3.0)

Panel B. Equal weighted average portfolio abnormal returns across seven anomalies

	Δ#Inst			*Δ%Inst*			*Δ#MF*			*Δ%MF*		
	Buy	Sell	B-S	Buy	Sell	B-S	Buy	Sell	B-S	Buy	Sell	B-S
Long	0.10	0.16	-0.06	0.02	0.23	-0.21	0.04	0.21	-0.17	0.07	0.19	-0.12
	(1.0)	(1.5)	(-0.5)	(0.3)	(3.0)	(-2.3)	(0.4)	(2.2)	(-1.6)	(0.9)	(2.1)	(-1.3)
Short	-0.74	-0.27	-0.47	-0.62	-0.35	-0.27	-0.58	-0.34	-0.24	-0.40	-0.42	0.02
	(-5.0)	(-1.9)	(-3.3)	(-4.7)	(-2.6)	(-2.5)	(-4.2)	(-2.6)	(-1.9)	(-3.5)	(-3.5)	(0.2)
L-S	0.84	0.43	0.41	0.64	0.58	0.06	0.62	0.55	0.07	0.47	0.61	-0.14
	(8.0)	(5.4)	(4.0)	(7.3)	(6.0)	(0.8)	(6.6)	(6.9)	(0.7)	(6.2)	(7.3)	(-1.6)

Table 6. Anomaly portfolio characteristics conditional on institutional demand

Panel A presents averages across the seven anomalies for variables observed during the six quarters preceding the anomaly return window, 1982 - 2012. '% of sample' is the count of stocks in the portfolio divided by the total count of the four portfolios. Δ#Inst is the scaled change in number of institutions; Δ%Inst (Δ%MF) is the change in percentage of shares held by institutiuons (mutual funds); and 'Δ#Inst next 4 qrts' is the change during the anomaly return window. In Panel B, #Inst, %Inst and MCap (market capitalization in million 2012 dollars) are as of the beginning of year t-1. 'Idio. volatility' is the average annualized volatility of monthly 3-factor residuals July t-3 through June t; 'Amihud illiquidity' is the average monthly Amihud's illiquidity ratio during year t-1 winsorized at 1%.

Panel A. Change in institutional ownership, averaged across the seven anomalies

	% of sample	Δ#Inst	Δ%Inst	Δ%MF	Δ#Inst next 4 qrts
Institutional Buys:					
Long Leg	21.7%	81.9%	19.9%	3.0%	9.9%
Short Leg	29.3%	85.8%	22.8%	3.6%	8.9%
[p-value for difference]	[0.000]	[0.481]	[0.060]	[0.171]	[0.721]
Institutional Sells:					
Long Leg	24.8%	-30.3%	-2.1%	0.0%	13.2%
Short Leg	24.3%	-32.4%	-2.6%	-0.1%	10.6%
[p-value for difference]	[0.577]	[0.043]	[0.148]	[0.511]	[0.038]

Panel B. Stocks characteristics, averaged across the seven anomalies

	#Inst	%Inst	Mcap (2012 $M)	Idio. volatility	Amihud illiquidity
Institutional Buys:					
Long Leg	64.4	46.1%	$1,010	47.1%	0.15
Short Leg	59.3	43.2%	$963	50.4%	0.13
[p-value for difference]	[0.587]	[0.445]	[0.701]	[0.191]	[0.641]
Institutional Sells:					
Long Leg	63.6	41.6%	$1,192	40.8%	0.25
Short Leg	71.7	42.3%	$1,428	42.9%	0.16
[p-value for difference]	[0.074]	[0.695]	[0.060]	[0.006]	[0.000]

Table 7. Quarterly abnormal returns of anomaly portfolios

The table presents quarterly three-factor alphas during each of the four quarters of the anomaly return window, averaged across seven anomalies. Portfolios are constructed by independently sorting on anomaly charactetistics and Δ#Inst, defined as the change in number of institutional investors scaled by the average number of institutions holding stocks in the same market capitalization decile at the begining of the period. Buy-minus-Sell portfolios are long (short) stocks in the top (bottom) quintile of Δ#Inst; in each case restricted to stocks that are also in the long, or short, anomaly leg as indicated in the row heading. Δ#Inst is measured during the six-quarter institutional trading window (*q* -5 to *q*) in Panel A; the five preceding quarters (*q* -5 to *q* -1) in Panel B; and the quarter prior to the anomaly return window (q) in Panel B. Heteroskedasticity-adjusted t-statistics are in parentheses.

	q+1	**q+2**	**q+3**	**q+4**	**Cumulative**
		Panel A: Buy-minus-Sell defined using Δ#Inst (q-5 to q)			
Long leg	0.27	0.11	-0.34	-0.04	-0.06
	(1.0)	(0.5)	(-1.8)	(-0.2)	(-0.5)
Short leg	-0.14	-0.43	-1.01	-0.39	-0.47
	(-0.5)	(-1.2)	(-3.8)	(-1.7)	(-3.3)
		Panel B: Buy-minus-Sell defined using Δ#Inst (q)			
Long leg	0.65	0.59	-0.13	0.12	0.25
	(3.2)	(2.5)	(-0.4)	(0.6)	(1.9)
Short leg	0.64	0.93	-0.07	0.29	0.40
	(2.5)	(2.7)	(-0.2)	(1.2)	(2.5)
		Panel C: Buy-minus-Sell defined using Δ#Inst (q-5 to q-1)			
Long leg	0.23	-0.26	-0.44	-0.15	-0.19
	(1.0)	(-1.1)	(-1.7)	(-0.7)	(-1.7)
Short leg	-0.22	-0.69	-1.27	-0.58	-0.69
	(-0.8)	(-1.9)	(-3.9)	(-2.6)	(-4.6)

Table 8. Fama-MacBeth regressions of stock returns on institutional ownership changes

The table reports average coefficient estimates from monthly cross sectional regressions, for the sample period July 1982 through June 2012. The dependent variable in columns 1-4 is the monthly stock return for months July t through June t+1. 'Δ#Inst' is the scaled change in number of institutions over the indicated window (in parentheses). Quarter q corresponds to the calendar quarter ending in June t. Δ#Inst (prior quarter) is measured during the most recent calendar quarter prior to the stock return month (dependent variable). The column 4 regression includes controls for firm size, liquidity, and seven anomaly characteristics (see Table 1), observed as of fiscal year-end of calendar t-1 (coefficients unreported). The dependent variable in column 5 ('predicted anomaly returns') is the sum of the product of the nine control characteristics used in the column 4 regression and their corresponding coefficient estimates. The dependent variable in column 6 ('residual returns') equals total returns minus the predicted anomaly returns. All independent variables are winsorized at the 1% level in both tails. T-statistics in parentheses using Newey-West correction for serial correlation (six-month lag).

Return component:	Total				Predicted anomaly returns	Residual returns
Δ#Inst (q-5:q)	-0.50					
	(-3.3)					
Δ#Inst (q-5:q-1)		-0.61	-0.60	-0.23	-0.36	-0.23
		(-3.7)	(-3.7)	(-2.5)	(-3.0)	(-2.5)
Δ#Inst (q)		0.29				
		(1.1)				
Δ#Inst (prior quarter)			0.92	0.97	-0.08	0.97
			(2.0)	(2.6)	(-0.6)	(2.6)
Characteristics	No	No	No	Yes	N/A	N/A

Table 9. Fama-MacBeth regressions using alternative proxies

The table reports average coefficient estimates from monthly cross sectional regressions for the sample period July 1982 through June 2012. The dependent variable is the monthly stock return for months July t through June t+1 (i.e., twelve regressions for each year-t institutional trading window). Δ#Inst is the scaled change in number of institutions; Δ%Inst (Δ%MF) is the change in percent of shares held by institutiuons (mutual funds); Δ%NMF is Δ%Inst - Δ%MF; Δ%MF(Flow) is the change in percent of shares held by mutual funds under in- or out-flow pressure as in Coval and Stafford (2007); and Δ%MF(Non-flow) is Δ%MF - Δ%MF(Flow). All change variables are measured over the six calendar quarters ending at the end of June t, and winsorized at the 1% level in both tails. Columns 7 and 8 exclude stocks in the top (bottom) decile of Δ%MF(Flow) and in the middle three deciles of Δ%MF(Non-flow). Column 8 includes untabulated explanatory variables including the seven anomaly characteristics the log market capitalization and Amihud's illiquidity ratio. T-statistics in parentheses using Newey-West correction for serial correlation (six-month lag).

Sample:	All						No flow pressure	
Column:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Δ#Inst	-0.50		-0.54			-0.66	-0.67	-0.29
	(-3.3)		(-3.2)			(-2.8)	(-3.1)	(-2.3)
Δ%Inst		-0.61	0.22					
		(-2.0)	(0.8)					
Δ%MF				-0.98				
				(-1.3)				
Δ%NMF				-0.56	-0.78	0.03		
				(-1.9)	(-2.2)	(0.1)		
Δ%MF (Flow-induced)					-0.09	-0.07		
					(-1.8)	(-1.5)		
Δ%MF (Non-flow)					-0.01	0.02		
					(-0.7)	(0.2)		
Characteristics	No	No	No	No	No	No	No	Yes

Table 10. Robustness checks

This table reports the average coefficient estimates from Fama-MacBeth monthly stock return regressions as in Table 7, on subsamples. In Panel A the subsamples exclude stocks with i) fewer than 20 institutional investors as of the end of June of t, ii) a market capitalization below the 20th percentile of NYSE stocks as of June of year t, or iii) a market capitalization below NYSE median as of June of year t. In Panel B the subsamples are by portfolio formation year: 1982-1996 and 1997-2011. T-statistics in parentheses are estimated using Newey-West serial correlation consistent standard errors with a six-month lag.

Panel A. Fama-MacBeth regressions excluding small stocks

Component:	Predicted anomaly returns			Residual returns		
Sample:	#Inst≥20	>NYSE 20%	>NYSE 50%	#Inst≥20	>NYSE 20%	>NYSE 50%
Δ#Inst (q-5:q-1)	-0.40	-0.38	-0.47	-0.24	0.01	-0.10
	(-3.2)	(-2.5)	(-2.5)	(-2.4)	(0.1)	(-0.5)
Δ#Inst (prior quarter)	0.02	0.09	0.18	1.18	0.72	0.09
	(0.9)	(0.6)	(0.9)	(2.7)	(1.2)	(0.1)

Panel B. Fama-MacBeth regressions in subperiods

Component:	Predicted anomaly returns		Residual returns	
Subperiod:	1982-1996	1997-2011	1982-1996	1997-2011
Δ#Inst (q-5:q-1)	-0.28	-0.43	0.04	-0.49
	(-2.9)	(-2.0)	(0.4)	(-3.3)
Δ#Inst (prior quarter)	0.06	-0.21	1.15	0.80
	(0.6)	(-0.9)	(4.2)	(1.1)