When Anomalies Are Publicized Broadly, Do Institutions Trade Accordingly?

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This draft: March 2017

Abstract

We study whether institutional investors trade on stock market anomalies. Using 14 well-documented anomalies, we observe an increase in anomaly-based trading when information about the anomalies is readily available through academic publication and the release of necessary accounting data. This finding is more pronounced among hedge funds and transient institutions, the subset of investors who likely have the ability and incentives to act on the anomalies. We directly relate the increase in trading to the observed decay in post-publication anomaly returns. Our findings support the role of institutional investors in the arbitrage process and in improving market efficiency.

JEL Classification: G12, G14, G23
Keywords: anomalies, publication impact, arbitrage, institutions, hedge funds

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1. Introduction

Finance and accounting literature has documented more than 330 variables that predict future stock returns (Green et al., 2013).[1] However, while the anomalies look great on paper, McLean and Pontiff (2016) show that once the anomalies are published, the returns associated with them decline by more than 50%. The authors discuss two potential explanations for the post-publication decline in anomaly returns: 1) anomalies are the result of statistical biases that will not persist out of sample; or 2) they are due to mispricing that is corrected by arbitrageurs.

Institutional investors are prime candidates for the role of arbitrageurs as they are generally perceived to be sophisticated, and have an increasing presence in the U.S. equity market with a 63.8% ownership stake at the end of 2013. If institutions are indeed arbitrageurs then the mispricing explanation predicts that they will trade on anomalies. However, Lewellen (2011) finds that institutions show little tendency to bet on anomalies and Edelen, Ince, and Kadlec (2016, henceforth EIK) report that institutions trade in the opposite direction of anomalies. These findings suggest that either the anomalies are the result of statistical biases, not mispricing, or that institutions do not act as arbitrageurs.

Despite recent evidence, we posit that institutions can indeed act as arbitrageurs and correct anomaly mispricing. However, to fulfill this role, they need to know about the anomaly and have the ability or incentives (or both) to act on the information. Specifically, we consider: 1) if the knowledge of the anomaly is in the public domain based on the year of academic publication; 2) if the accounting data necessary to compute the anomaly rankings is publicly available; and 3) if there is heterogeneity among institutions with respect to information processing, and the incentives to act on their information. To the best of our knowledge, this is the first paper to consider institutional trading on anomalies along these three dimensions, which will help us directly observe institutions' role as arbitrageurs.

[1] The returns associated with these variables are often called anomalies because they cannot be explained by traditional asset-pricing models (e.g., the Capital Asset Pricing Model of Sharpe (1964) and Lintner (1965), and the three-factor model of Fama and French (1993)). For a review of the literature see Subrahmanyam (2010).

Financial media and industry-oriented journals have long disseminated academic research to practitioners, which suggests that at least some practitioners condition their trading strategies on published academic findings. For example, consider the case of Dimensional Fund Advisors (DFA), which had $381 billion in assets under management (AUM) as of December 2014. DFA employs a group of 'academic leaders', including three Nobel laureates and several other top academic scholars. On its website, DFA emphasizes "bringing research to the real world" with its incorporation of stock selection screens based on academic research.[2] Additionally, Pastor et al. (2015) find that younger fund managers outperform their older peers. This finding may be related to young managers who, having just graduated, use the latest academic research they absorbed at school to beat the market.[3] However, there is scant empirical evidence of institutional investors actually trading on published research. To address this gap, we study the trading behavior of institutional investors in 14 well-documented anomalies to determine if they exploit the anomalies and help bring stock prices closer to efficient levels.[4]

Our identification strategy focuses on the period when the anomaly is first published in the academic literature. We view journal publication as a shock that increases knowledge of the existence and profitability of the strategy among arbitrageurs without directly affecting the fundamentals that drive anomaly profits. Examining the changes in both institutional trading activity and anomaly profits around publication enables us to identify the arbitrageurs and the impact of their trading on anomaly returns. In particular, we test the hypothesis that as institutions' awareness about the anomalies increases there is a rise in anomaly-based trading and a subsequent attenuation of the anomaly profits.

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[2] See DFA's "Philosophy / Research" webpage at http://us.dimensional.com/philosophy/research.aspx. DFA is not alone in their emphasis on academic credentials. Other institutional investors with strong academic ties include (but are not limited to) AQR Capital Management ($136 Billion AUM), LSV Asset Management ($89 Billion AUM), and Research Affiliates ($67 Billion AUM).

[3] See an interview of Lubos Pastor in CNN Money: "New mutual funds better than older ones?" Retrieved from http://money.cnn.com/2014/03/02/investing/young-old-mutual-funds.

[4] The 14 anomalies are net stock issues, composite equity issues, total accruals, net operating assets, gross profitability, asset growth, capital investments, investment-to-assets, book-to-market, momentum, distress, Ohlson O-score, return on assets, and post-earnings announcement drift (see Table 1 for details).

To test our hypothesis, each year we rank stocks according to each of our 14 'anomaly variables' (i.e., the variables that have been shown to predict future stock returns) and build long and short portfolios (legs) using the top and bottom quintiles.[5] We measure institutional trading by computing changes in aggregate institutional holdings in the long and short portfolios of each anomaly. We focus on the window for which the accounting information necessary to construct the anomaly rankings is publicly available. We examine trading across our full sample period (1982-2013), as well as before and after publication, to test whether institutions follow academic research. Given the relatively large number of anomalies considered in this paper, and since institutions are likely to trade on multiple signals at the same time, we also examine two aggregate portfolio strategies that combine rankings across our sample of anomalies: an 'ex-post' portfolio that ranks stocks based on anomalies that have already been published; and an 'ex-ante' portfolio that ranks stocks based on anomalies that are yet to be published. Finally, we use a vector autoregressive (VAR) model to test our prediction that anomaly-based trading by institutions leads to the post-publication decay in anomaly returns.

Throughout our analysis, in addition to examining the full set of institutions, we also consider anomaly-based trading by different institution types. There may be heterogeneity in the incentives institutions face to act on information. For example, hedge funds are the least constrained among institutional investors and have a compensation structure that can encourage risk-taking behavior (e.g., Goetzmann et al., 2003). Moreover, institutions may differ in their ability to process information (e.g., Yan and Zhang, 2009). These differences may, in turn, affect the extent to which institutions exploit anomalies. We therefore examine trading among subgroups that may be better positioned to take advantage of the anomalies: hedge funds, mutual funds, and transient institutions.[6]

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[5] Because real-world investors may update their information set about the anomaly variables on a more frequent basis than annually, we also construct a quarterly version of each anomaly using the most up-to-date data available at the end of each quarter. All our tables include results for both the annual and quarterly ranked anomalies.

[6] Transient institutions, as identified by Bushee (2001), are active investors whose portfolios exhibit high turnover. Ke and Ramalingegowda (2005) document that transient institutions are active in exploiting the post-earnings announcement drift anomaly.

Our results verify that trading with the anomaly is profitable in the original sample period, and, consistent with McLean and Pontiff (2016), we observe a decay in anomaly returns in the period after publication. When we examine anomaly-based trading in the full sample period, consistent with Lewellen (2011) and EIK, we find that, in aggregate, institutional investors do not take advantage of stock return anomalies. However, this result is driven by trading in the period before publication and it is due to the focus on aggregate institutional trading. In the four years after publication, there is a significant increase in anomaly-based trading, which suggests that institutions do try to exploit the anomalies and their timing is related to the journal publication thereof. When we focus on the hedge fund and transient institution subgroups, we find that the timing of their trading coincides with and even anticipates the journal publication of the anomalies. We observe a weaker relation between publication and anomaly-based trading for mutual funds.

We next examine institutional trading and returns in the ex-ante and ex-post portfolios. Consistent with an increase in anomaly-based trading after publication, institutional trading is larger in the ex-post portfolio, especially among hedge funds and transient institutions. We then perform Granger-causality tests to determine the causality between institutional trading and returns, and find a significant negative relation between institutional trading and future anomaly returns in the ex-post portfolio. In contrast, we find no significant relation between institutional trading and future returns in the ex-ante portfolio. These results suggest that institutional trading and anomaly publication are integral to the arbitrage process which helps bring prices to a more efficient level.

We conduct a series of tests to ensure the robustness of our results. First, to control for common determinants of institutional trading, we examine stock-level institutional trading in the ex-ante and ex-post portfolios using Fama-MacBeth cross-sectional regressions. We find consistent results for the long and short portfolios: there is a significant increase (decrease) in institutional trading in the long (short) leg of the ex-post portfolio vs. ex-ante portfolio. Second, to further understand the drivers of our results, we separately examine trading and returns in the long and short legs of the anomaly portfolios and find evidence consistent with increased trading and return decay after publication in both legs. Third, to address concerns about our anomaly selection, we confirm that our main results are similar, and in some cases stronger, for various subsets of our anomalies. Finally, we find that our main results are robust to various alternative specifications including: using SSRN posting dates instead of publication dates; including year and anomaly fixed effects in our trading regressions; controlling for the financial crisis; using different definitions to construct the ex-ante and ex-post portfolios; controlling for liquidity in the VAR analysis; and examining short sales using short-interest data.

The main contribution of our paper is to show that institutions trade on anomalies when information about the anomalies is readily available to investors through academic publication and the release of necessary accounting data. To reconcile our results with EIK, we examine institutional trading at times when the information about the anomalies may not be readily available. Specifically, we consider trading in the period prior to academic publication and in the window when the information needed to compute the anomaly rankings may not be available, and find no evidence of anomaly-based trading by institutions.[7] Further, we examine trading for a group of institutions that are neither hedge funds nor transient, and thus may not have the ability or the incentive to implement anomaly strategies. We find that these investors trade against anomalies, and may be a source of the contrarian trading documented by EIK. This result is consistent with both agency-induced preferences that are contrary to anomaly-based signals, and some institutions potentially playing a causal role in the anomalies.

This paper adds to the strand of research that investigates institutional trading and market efficiency. We assess whether institutions implement trading strategies to exploit anomalies and provide evidence that this behavior mainly occurs after anomaly publication. We relate this

[7] A key difference between EIK and our paper is that their trading window starts four quarters before our window, when the anomaly variables are being realized, whereas our window starts when most of the accounting information is publically available. Another difference is that we measure trading using the value-weighted change in holdings, while EIK use the change in number of institutions holding a stock and the equal-weighted change in holdings. In the results section, we show that when we use these alternative measures our main results hold. When we examine trading before publication and the availability of the accounting information, consistent with EIK, we find evidence that institutions trade against the anomalies.

evidence to the attenuation of the anomalies documented by McLean and Pontiff (2016) and provide evidence more consistent with the mispricing explanation than statistical biases. Our findings suggest a positive role for some institutions in contributing to more efficient markets.[8] In line with Grossmann and Stiglitz (1980), efficient security prices require market participants to actively trade on relevant information driving security prices toward the 'true' price.

This paper also contributes to the hedge fund literature. Since the collapse of Long-Term Capital Management in 1998, hedge funds have been the target of increased scrutiny by regulators and the financial press.[9] We find that our results are strongest among hedge funds and transient institutions: they actively trade on the anomalies and correct mispricing. This finding is important as it contributes to a better understanding of the role of hedge funds and transient institutions as arbitrageurs.

We also add to the debate, initiated by Fama (1976), regarding the nature of information that institutions possess. Our paper suggests that institutions learn from academic research by adopting trading strategies based on published findings. This analysis is therefore relevant for understanding the value and impact of financial academic research. Furthermore, the finding that institutions trade on the anomalies only when they have the necessary accounting data, rather than when the anomaly variables are being realized, suggests that institutions are limited in their ability to anticipate information relevant to the anomaly rankings. Finally, the documented heterogeneity in the level of anomaly-based trading across institutions indicates that institutions may differ in their incentives and abilities to process information.

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[8] Kokkonen and Suominen (2015) and Akbas et al. (2015) provide recent complementary evidence that hedge funds improve stock market efficiency. One concern is that the increase in institutional trading after publication may increase crash risk if institutions follow similar strategies and exit them at the same time. Although we cannot exclude this possibility, the fact that anomaly-based trading is highest early in the post publication period and then attenuates, helps alleviate this concern.

[9] In 2004, the Securities and Exchange Commission (SEC) tried to increase the regulation of hedge funds by issuing a rule that required all hedge funds to register with the SEC. This rule was challenged and rejected by the U.S. Court of Appeals.

2. Related Literature

Our paper is related to the literature on stock market efficiency and anomalies. The literature highlights three explanations for the existence of the anomalies. First, several papers argue that anomalies are driven by various statistical biases, such as sample selection bias (Heckman, 1979), data snooping bias (Lo and MacKinlay, 1990), simple chance (Fama, 1998), or consideration of an inappropriate significance cutoff that does not take into account multiple tests (Harvey et al., 2015). Second, some papers explain the existence of anomalies as compensation for risk consistent with asset pricing models. For example, Fama and French (1996) argue that the size and value anomalies could reflect exposure to macroeconomic risk factors. Sadka (2006) considers liquidity risk as a missing factor that could explain part of the abnormal returns associated with momentum and post-earnings-announcement drift. Finally, anomalies could be due to mispricing (e.g., Barberis and Thaler, 2003) and present investment opportunities.

If statistical biases explain anomalies we do not expect investors to react and trade on them. Cochrane (1999) discusses investor reactions to risk-based and mispricing-based anomalies. He argues that if an anomaly is based on risk, investors will not trade on it and the high average return will persist, whereas if an anomaly is driven by mispricing and is easy to trade on, then "the average investor will immediately want to invest when he hears of the opportunity. News travels quickly, investors react quickly, and such opportunities vanish quickly." However, there is a debate about whether anomaly-based trading strategies are profitable after accounting for transaction costs (e.g., Knez and Ready, 1996; Lesmond et al., 2004), and whether investors are able to exploit the mispricing given the limits of arbitrage (Shleifer and Vishny, 1997) or short-sale constraints.[10]

Another relevant strand of literature examines the role of institutional investors in the price discovery process. In particular, some studies investigate whether institutional investors contribute to market efficiency (e.g., Boehmer and Kelley, 2009). Given that there are a large number of anomalies that earn large excess returns, and some of them appear to be persistent across time

[10] Stein (2009) also points out that crowding and leverage may create negative externalities that limit the arbitrage process.

(e.g., Jegadeesh and Titman, 2001; Fama and French, 2008), institutional investors could try to trade mispriced securities. However, there is limited evidence of institutional investors trying to systematically exploit anomalies.[11] For example, few investors trade on and profit from the accruals anomaly (Ali et al., 2008). There is also evidence that investors contribute to some anomalies: institutions tend to buy growth stocks and sell value stocks contributing to the value premium (Chan et al., 2002; Frazzini and Lamont, 2008; Jiang, 2010). Institutions may also find it optimal to herd with the rest of the market, pushing asset prices away from fundamental values (e.g., Griffin et al., 2011).

Lewellen (2011) examines institutional holdings and finds that institutions as a whole do not act as arbitrageurs.[12] In contrast to Lewellen's paper, we focus on trading decisions that represent a more direct signal of institutional reaction to information than the level of institutional holdings. We also consider the time-variation in institutional trading and how it is related to the awareness of the anomalies. Moreover, in this paper we focus on the most active institutions: hedge funds and transient institutions.[13] We show that these institutions actively trade to exploit the anomalies. In contrast, we find weaker results when we examine whether mutual funds trade on the anomalies. This analysis is important for the literature that examines the investment ability and performance of hedge funds and mutual funds.[14]

Finally, some recent papers examine whether practitioners learn about potential trading opportunities from academic research, in particular in the context of return predictability. There are conflicting findings in this literature. On the one hand, Johnson and Schwartz (2000), similar to McLean and Pontiff (2016), report that the post-earnings-announcement drift was eliminated

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[11] There is evidence that some institutional investors try to exploit a specific anomaly. For example, they tend to follow momentum strategies (Grinblatt et al., 1995) and trade on the post-earnings-announcement drift (Ke and Ramalingegowda, 2005; Ali et al., 2012).

[12] See Hwang and Liu (2014) for a recent study on short-selling activity of arbitrageurs.

[13] Lewellen (2011) aggregates institutions classified as investment companies, investment advisors, and other institutions.

[14] There is a large literature on mutual funds and hedge funds. For a review of the mutual fund literature see Aragon and Ferson (2006). For a review of the hedge fund literature see Fung and Hsieh (2006).

once the anomaly was documented in academic research.[15] As mentioned previously, this observation would be consistent with both statistical biases and the possibility that academic research is attracting the attention of sophisticated investors who trade against the mispricing. Neither paper examines institutional trading. Without analyzing trading it is hard to tell which interpretation is correct. On the other hand, EIK find that institutions trade in the opposite direction of anomalies. Furthermore, Richardson et al. (2010) present survey evidence that shows practitioners read few published academic papers and pay little attention to working papers.

3. Data

We use Compustat and CRSP to obtain the accounting and financial data needed to replicate the anomalies. We consider a set of 14 well-documented anomalies (see Table 1): net stock issues, composite equity issues, total accruals, net operating assets, gross profitability, asset growth, capital investments, investment-to-assets, book-to-market, momentum, distress (failure probability), Ohlson O-score, return on assets, and post-earnings announcement drift (as measured by standardized unexpected earnings).[16] Eleven of these anomalies are studied by Stambaugh et al. (2012) and three additional anomalies (capital investments, book-to-market, and post-earnings announcement drift) are included to be consistent with recent literature (e.g., Chen et al., 2011). These anomalies are important because, with the exception of book-to-market, they are not explained by the widely used three-factor Fama-French model. Our main sample includes U.S. common stocks traded on the NYSE, AMEX, and NASDAQ from January 1982 to December 2013 (June 2014 for stock returns). We exclude utilities, financial firms, and stocks priced under $5. We compute quarterly cumulative returns using data from the CRSP monthly files.

[15] Chordia et al. (2014) find that several anomalies have attenuated significantly over time. However, they do not examine if this is due to specific trading behavior of institutional investors. Green et al. (2011) also document a significant reduction in the accrual anomaly, but they do not examine institutional trading either.

[16] The Ohlson O-score was introduced by Ohlson (1980), but the profitability of a strategy based on this measure was shown by Dichev (1998). That is why we use 1998 as the publication date.

The Thomson Reuters (TR) 13F database is used to measure institutional trading. Institutional investors that exercise investment discretion over $100 million or more in Section 13(f) securities are required to report to the SEC their end-of-quarter holdings on Form 13F within 45 days of each quarter-end. TR has provided the equity positions of such institutions since 1980. We use the list from Griffin et al. (2011) that identifies hedge funds in 13F data, and update it using the list compiled by Cella et al. (2013).[17] We identify mutual funds as non-hedge fund institutions classified as an investment company or an independent investment advisor by Brian Bushee's website.[18] We also identify transient institutions using the same source.[19] Transient institutions are characterized as having high portfolio turnover and highly diversified portfolio holdings. We thus expect them to be active in exploiting anomalies. Table 1 reports the paper that first documented each anomaly, its publication year, and the sample period used. The goal is to identify the date when a research idea is introduced to the public domain. For simplicity we do not use the publication month and assume that the papers were already public at the beginning of the year. This assumption is realistic given the lag between manuscript acceptance and eventual publication.

We replicate the anomalies using the same sample period as the original paper that identified each anomaly. Following standard conventions in the literature, on June 30th of year *t* we rank stocks into quintiles according to the anomaly variables and form long and short portfolios. The long portfolio contains underpriced securities that should be bought by arbitrageurs and the short portfolio has overpriced securities that should be sold (short). To ensure that the accounting variables necessary to construct anomaly rankings are known to investors, we use accounting data

[17] We thank Andrew Ellul for kindly sharing this list.

[18] See http://acct.wharton.upenn.edu/faculty/bushee/IIclass.html. We checked the largest mutual fund families and they were sometimes classified as an investment company and other times as an independent investment advisor.

[19] Transient institutions comprise 18.6% of institutional holdings in our sample, hedge funds comprise 15.2% of institutional holdings, and mutual funds comprise 41.4% of institutional holdings. The remainder of institutional holdings are composed of 'Other' institutions such as pension funds, endowments, insurance companies, and banks. Mutual funds and hedge funds are mutually exclusive, whereas transient investors are composed of the most active hedge funds (34.5%), mutual funds (58.4%) and Other institutions (7.1%). 73.2% of hedge funds, 35.5% of mutual funds, and 3.1% of Other institutions are transient on a value-weighted basis.

for the last fiscal year end in calendar year t – 1, most of which becomes available to market participants by the end of March of year t.[20] For each portfolio and for each anomaly, we compute value-weighted raw and risk-adjusted portfolio returns over the following twelve months (from July of year t to June of year t + 1).

Although most of the anomaly papers look at annually ranked anomalies, it is plausible that sophisticated investors update their information set about a security more frequently using the most recent available information. Presumably, this would be most relevant for anomalies that whose initial documentation in the academic literature used portfolios updated on a more frequent basis. Therefore, we also construct a quarterly version of each anomaly. Specifically, we sort stocks at the end of each calendar quarter using the most up-to-date data at the beginning of each quarter. This one-quarter gap is intended to ensure the data required to compute the anomaly variables are publicly available. We then compute value-weighted raw and risk-adjusted returns over the quarter following the sorting date. Given that we do not directly observe how often institutions update their information, throughout the paper, we present results for all the anomalies in the annually and quarterly ranked portfolios.

3.1 Summary Statistics

Table 2 Panel A presents correlations among portfolio ranks for our anomalies in addition to the first-order autocorrelation of each anomaly. Every June, we sort stocks into quintiles according to anomaly variables and compute the correlations. Consistent with Green et al. (2013), the anomalies are not strongly related to each other. Only 17 (4) out of 91 correlation coefficients have an absolute value higher than 0.25 (0.50) and the average absolute value across all anomaly pairs is 0.15, suggesting that each anomaly has its own distinct character. The low correlations between book-to-market and momentum and the other anomalies ease concerns that our results in

[20] For our annually constructed momentum ranking we use the six-month return with a three-month lag. In unreported tests we find that our results are robust to various alternate definitions of the momentum anomaly with different lengths and lags. Specifically, we also examine 12 month returns with three and four month lags as well as six-month returns with four month lags. For our quarterly constructed momentum ranking we use the six-month return with a one-month lag.

other anomalies may be driven by institutions trading in book-to-market and momentum. When we look at first-order autocorrelations for persistence, the average absolute value is 0.48.

We also examine the portfolio characteristics of the stocks in the long and short legs of all the anomalies. Table 2 Panel B summarizes the information about the size, value, momentum, and liquidity of the stocks based on the average quintile rank. We measure size, value, and momentum following the methodology of Daniel, Grinblatt, Titman, and Wermers (1997, henceforth DGTW) and illiquidity using the Amihud (2002) measure.[21] Stocks in the long leg tend to be larger and have more return momentum than stocks in the short leg. There is a statistically significant but smaller difference in average liquidity and book-to-market. Stocks in the long leg tend to be more liquid and have higher book-to-market ratios than stocks in the short leg.

Table 3 reports the difference between the performance of the long and short portfolios for the annual (Panel A) and quarterly (Panel B) rankings in the in-sample and post-publication periods. The in-sample period is defined as the sample period used in the original anomaly publication, and the post-publication period includes the period starting from the year of publication through the end of the sample. Anomaly performance is measured using average quarterly returns in excess of the risk-free rate, three-factor alphas, and the returns in excess of the DGTW benchmark. The alpha is the intercept of a regression of quarterly excess returns on the three Fama-French factors, with the exception of the book-to-market anomaly that only includes the market and size factors. Similarly, when using the DGTW benchmark for the book-to-market and momentum anomalies, we construct a benchmark without the same portfolio characteristic (e.g., excluding book-to-market when applied to the book-to-market anomaly). Consistent with the published results, when we examine the in-sample period, the average excess returns of the long-short portfolio are all positive and are significant for most of the anomalies. For the annual ranking, a long-short portfolio that takes the equally-weighted average each quarter across all the available anomalies delivers an excess return of 1.14% per quarter, which is statistically significant. When

[21] When computing the Amihud's measure we follow Anderson and Dyl (2005) and make an adjustment for the volume of NASDAQ stocks.

we consider the alphas, using the three-factor model (Fama and French, 1993), the magnitude of the outperformance of the long portfolio vs. the short portfolio is generally larger. Across all 14 anomalies, the alphas of the long-short portfolios are positive and significant. The alpha of the equally-weighted portfolio is 1.56% per quarter with a p-value of almost zero. The average DGTW-adjusted return is 0.99% per quarter and is statistically significant.[22]

The last three columns of Table 3 Panel A present the results using the post-publication period. Consistent with McLean and Pontiff (2016), we find a sizable reduction in the anomaly returns. Indeed, all the anomalies experience a reduction in average excess return. Focusing on the three-factor alphas (DGTW), nine (thirteen) of the anomalies exhibit a reduction in alpha from the original sample period used in the anomaly publication. Only four (two) anomalies still have a positive and statistically significant alpha (DGTW) at the 10% confidence level for the long-short portfolio. Considering the equally-weighted portfolio, the alpha (DGTW) of the long-short portfolio is now only 1.11% (0.64%), which represents a 29% (36%) reduction, compared to the in-sample period.[23]

When using quarterly rankings (Panel B), the performance of the long-short portfolio tends to be stronger. This suggests that it can be profitable for traders to update their portfolio more frequently. We further explore this possibility in a later analysis that examines institutional trading in quarterly-ranked anomalies. Focusing on the equally-weighted portfolio, the long-short strategy delivers a quarterly return of 1.84%, a three-factor alpha of 2.12%, and a DGTW-adjusted return of 1.47% per quarter in the in-sample period. In the post-publication period, there is again a performance decay. For instance, the three-factor alpha for the long-short strategy is 1.40% per quarter, which is a 34% reduction from the in-sample period.[24]

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[22] The DGTW-adjusted return is computed starting from 1971, which is not always the beginning of the sample used in the original papers.

[23] When we take the time-series average first, and then the cross-sectional average across anomalies (rather than a portfolio approach), the three-factor alpha (DGTW-adjusted return) in the post publication is 0.97% (0.30%), which represents a 40% (62.62%) reduction compared to the in-sample period.

[24] For the rest of the analysis the in-sample period starts in 1982, when trading data is available.

In summary, for our sample we confirm the post-publication decay documented by McLean and Pontiff (2016). In the analyses to follow, we use DGTW-adjusted returns to measure anomaly performance because they are more conducive to measuring abnormal returns over short periods than regression-based alphas, and because the post-publication reduction in the long-short portfolio is similar using both measures. For simplicity, we henceforth refer to the DGTW-adjusted return of the long-short portfolio as the anomaly return.

4. Empirical Analysis

4.1 Anomaly Level Trading Analysis for the Full Sample

In this section we examine institutional trading on the anomalies. For the annual rankings, on June 30th (t= 0) of each year we construct long and short portfolios for each anomaly. We then compute changes in aggregate institutional holdings for both portfolios. We argue that lack of information may limit institutions' ability to trade on the anomalies. Starting from (before) 2002, SEC regulations mandate that firms release their financial statements to the public within 60 (90) days of the end of their fiscal year. Thus, assuming a firm's fiscal year ends on December 31st (t= -2) they must release their accounting information by March (t= -1).[25] We therefore examine institutional trading over the three-quarter window from December 31st (t= -2) to September 30th (t= +1). During this window, the information required to construct the long and short portfolios should be available to the institutions. For the quarterly version of the anomalies, we compute institutional trading over the two quarters starting from the quarter before sorting. This approach

[25] In our sample, 71% (64%) of the firms have fiscal years that end in September (October) or later. For firms with earlier fiscal years, institutions could compute the anomaly variables earlier. However, to form anomaly rankings, institutions would need the anomaly variable for all, or at least a large number of, firms. Hence, we focus on the window that begins on December 31st. We consider the possibility that firms update rank anomalies more frequently than once per year using two approaches. First, we compute anomaly rankings on a quarterly basis using the most up to date information. Second, we consider the possibility that investors may be able to infer anomaly rankings prior to our trading window and examine trading in the year before our window begins.

is intended to capture anomaly-based trading strategies that use data obtained from quarterly financial statements (SEC form 10-Q).

If institutions attempt to exploit anomalies, we should observe significantly greater institutional buying in the long portfolio than in the short portfolio. We measure institutional trading using the changes in the percentage of shares held by institutions in the long and short portfolios (e.g., Gompers and Metrick, 2001).[26] This approach is analogous to value weighting the individual changes across all the stocks in the long and short portfolios. We prefer a value-weighted approach to an equal-weighted approach because using weighting strategies that give equal weights to stocks of different sizes can lead to results being dominated by small stocks. These stocks represent a tiny fraction of total institutional investment,[27] and, as discussed by Fama and French (2008), anomaly returns in these stocks may not be realizable due to high trading costs.

The first four columns of Table 4 Panel A present tests designed to examine whether institutions attempt to exploit the annual anomalies over the full sample period, which spans 1982 to 2013. The unit of measurement is the variable 'Long minus Short' which measures the difference between the changes in aggregate institutional holdings for the long and short legs of each anomaly-year. The observations are pooled across all the anomalies resulting in 448 observations (14 anomalies x 32 years).

The first column of Panel A presents the trading behavior of all institutions in the 13F database. The results suggest that over the full sample period, institutions, in aggregate, have not traded in a manner that exploits the anomalies: the 0.14 difference between net holdings changes in the long and short legs of the anomalies has the right sign but is not statistically different from zero. To examine if sophisticated institutional investors such as hedge funds are more active in exploiting these anomalies than less sophisticated institutions, in columns two through four, we partition the sample of institutional investors into hedge funds, mutual funds, and transient

[26] To address potential data errors, if for a given firm the total number of shares held by institutions is greater than the total number of shares outstanding, we cap the ratio at 100%. Deleting these observations deliver similar results.
[27] Indeed, in our sample we find that the bottom 80% of stocks represent only 10.81% of institutional ownership.

institutions, respectively. Over the full sample period, the results suggest that hedge funds, mutual funds, and transient institutions trade significantly with the anomalies. For instance, on average, transient institutions increase their net ownership in the anomaly stocks by 0.76% over the three-quarter window around each ranking date.

The last four columns of Panel A present results for trading in the quarterly anomalies. Consistent with the annual results, we find little evidence that, in aggregate, institutional investors trade in the direction of the anomaly. The results at the aggregate level are weaker using quarterly anomalies than annual anomalies. However, when we focus on transient institutions, consistent with exploiting the anomalies we find that these investors increase their net ownership of the anomaly stocks by 0.35% overall around each ranking date. These results suggest that only a subset of investors—i.e., transient institutions—update their anomaly-based trading strategies more frequently than annually.

4.2 Anomaly Level Trading Analysis Around the Journal Publication Date

Next, we examine whether institutional trading on the anomalies has changed over time, and, in particular, around the publication of academic research about the anomaly. We consider the three periods examined by McLean and Pontiff (2016): the in-sample and post-publication periods examined in Table 3, along with the pre-publication period. The pre-publication period is defined as the period from the end of the in-sample period to just before the publication date (for most anomalies this period is closely related to the time when the publication is a working paper). We posit that some institutions may learn about anomaly research before it is actually published, for example through conferences or the Social Science Research Network (SSRN). To the extent that the sample period in the original paper has not changed during the publication process, the pre-publication period should capture information diffusion about the anomaly before publication. Furthermore, to account for the possibility that arbitrageurs may change their post-publication trading behavior over time, we consider a fourth period, the post-publication (early) period, which is defined as the first four years of the post-publication period.

We posit that at least two channels exist through which the publication of academic research can affect institutional trading. One possibility is that a subset of institutions knows about, and trades on, the anomaly. For example, in their paper on momentum, Jegadeesh and Titman (1993) mention that a number of practitioners use relative strength rankings. If this is the case, publication may have a certification effect. Another possibility is that publication exposes the anomaly to institutions that are not aware of the strategy. For either case, we should observe that the aggregate change in institutional holdings in the anomalies increases around the journal publication date. The first four columns of Table 4 Panel B present the results of OLS regressions where the dependent variable is again long minus short trading in the annual anomalies. The independent variables are dummies that identify the in-sample, pre-publication, post-publication, and post-publication (early) periods. Because the post-publication and post-publication (early) periods overlap, we estimate their coefficients in two separate regressions. We are interested in how institutional trading relates to the publication of the anomaly, reported in the first four rows of the panel. We are also interested in the difference in trading between the post-publication (early) and in-sample periods, reported in the last row of the panel. If institutions react to publication, this difference should be positive.

The first column presents results for all institutions. The results indicate that during the in-sample, pre-publication, and post-publication periods, the long minus short trading variable is not significantly different from zero. However, during the post-publication (early) period, the change in aggregate holdings in the long leg is significantly larger than that of the short leg.[28] The average change in total net ownership during the post-publication (early) period is 0.81% over the three-quarter window around each ranking date. From the in-sample to the post-publication (early) period, there is an average increase of 0.75% of the total net ownership in the long-short portfolio over the three-quarter window. This change is economically significant. A back-of-the-envelope calculation taking the average of the total market value of the long and short portfolios, averaged across anomalies and across time, suggests that a 0.75% ownership change corresponds to

[28] Using three or five years instead of four to define the post-publication (early) period delivers similar results.

approximately \$8.55 billion change in ownership. This result suggests that institutions, in aggregate, try to exploit the annual anomalies and that the timing of their decision is related to the journal publication of the anomalies. The finding that institutions do not trade with the anomalies in the full post-publication period is consistent with institutions reducing their trading as the returns of the strategy decay.

Compared to the in-sample period, there is a similar spike in anomaly-based trading in the post-publication (early) period among hedge funds. We also observe significant trading by hedge funds in both the pre-publication and, to a lesser extent, the in-sample periods, which suggests that hedge funds may have knowledge about the anomalies prior to the journal publication of the research. This result is not surprising, as research is often made public through working papers and conference presentations, sometime before the actual publication date, and supports the perception of hedge funds being sophisticated. Furthermore, as mentioned previously, the direction of causality between trading and research is unclear. It is plausible that researchers generate their ideas from industrial practices.

Next, we examine anomaly-based trading by mutual funds and transient institutions. Although the results for mutual funds are mixed, we find that transient institutions are active in exploiting the anomalies. In fact, they even trade with the anomaly in the in-sample and pre-publication periods. Because transient institutions trade on anomalies before publication, when we compare their trading in the post-publication (early) period to the in-sample period, we observe that the difference is not statistically significant.

The last four columns of Table 4 Panel B replicates the above analysis using the portfolios sorted at the quarterly frequency. We observe increases in trading activity among hedge funds and transient institutions when we compare the post-publication (early) with the in-sample period. Again, we also see evidence that transient investors trade on anomalies before publication. For example, the average change in total net ownership is 0.44% during the pre-publication period and 0.20% during the in-sample period. The difference between the annual and quarterly frequency results indicates that only a subgroup of sophisticated traders (in particular hedge funds and transient institutions) trade on quarterly updated anomalies. However, there is a larger group of institutions that use annual data to trade on the anomalies especially after publication.

Overall, these results suggest that institutional trading is related to the journal publication of the anomaly. Institutions trade on the anomalies when they know about the anomalies through publication and have access to the necessary accounting data to compute the anomaly ranks. We also find evidence of heterogeneity among institutional investors, with hedge funds and transient institutions most actively exploiting anomalies.

Figure 1 provides the graphical representation of the annual results above for all investors. Specifically, we plot the cumulative change in ownership relative to publication date for the difference between the long and short portfolios along. Just before publication, there is a shift toward taking advantage of the anomalies.

In Internet Appendix Table 1, we replicate the results of Table 4 for each of the individual anomalies. For brevity, we present only the difference in trading between the in sample and post publication (early) periods. When we examine trading in the annually ranked anomalies for all institutions we observe an increase (decrease) in trading for 10 (4) of the anomalies, 3 (2) of which are statistically significant. The anomalies that see the biggest increase in trading after publication are momentum and total accruals. One concern is the relatively high correlation among some of the anomalies. For example, consider the 0.45 rank correlation (see Table 2, Panel A) between Net Stock Issues (NSI, published in 1995) and Composite Equity Issues (CEI, published in 2006). There may be cases where traders are only exploiting the NSI but we identify them as both NSI and CEI traders. Furthermore, because NSI was published 11 years before CEI, the correlation issue may elevate our trading measures in the in-sample and pre-publication periods for CEI and thus reduce the perceived impact of publication on trading. To address these concerns we classify anomalies as 'high-correlation' or 'low-correlation'. We create these sets by identifying all anomaly pairs with correlations above 0.40 and identify the anomaly in the pair that was published more recently as high-correlation. This process identifies five high-correlation anomalies—CEI, AG, IVA, DIS, and ROA—leaving a set of nine remaining low-correlation anomalies. Consistent with our predication, the results are stronger for the low-correlation anomalies. For example, for the all institutions, we observe an increase in trading in all but two of the low-correlation annual anomalies.

4.3 Institutional Trading and Anomaly Returns

Thus far we have provided evidence of a decay in anomaly performance and an increase in anomaly-based trading by institutions after publication. Figure 2 confirms this pattern by plotting the difference between the cumulative returns and changes in aggregate institutional ownership for the long and short portfolios, from the previous December (t= -2) to the following June (t= +4), for the in-sample and post-publication (early) periods. Institutions, in aggregate, trade more in the direction of the anomaly after publication while returns are less pronounced. This result is consistent with institutional trading reducing the anomaly returns after publication.

Given the large number of anomalies considered in this paper, and given that sophisticated institutions are likely to trade on multiple anomalies at the same time, we focus on two aggregate portfolio strategies that summarize buy and sell signals across our sample of anomalies. We use this approach to directly examine the relationship between anomaly-based trading and returns. More specifically, we construct an 'ex-ante' and an 'ex-post' portfolio. The ex-ante portfolio is based on the anomalies that are yet-to-be published, while the ex-post portfolio is constructed using the anomalies that are already published. As there are no ex-post anomalies before 1989 and no ex-ante anomalies after 2012, we focus on the common sample period, which spans from 1989 – 2012. We assign a percentile rank to each stock, based on each anomaly, and compute the equal-weighted average rank for ex-ante and ex-post anomalies. We exclude stock-quarter observations if more than half the anomaly variables are missing. Finally, we rank the stocks again based on the average rank and the top and bottom quintiles comprise the long and short portfolios, respectively. Our results are qualitatively similar if we use the annual rankings instead.

Table 5 summarizes the trading activity and returns for the ex-post and ex-ante portfolios. Panel A presents results for the annually ranked anomaly portfolios. Consistent with our earlier pooled results, we observe that trading in the ex-post portfolio is significant greater than in the ex-ante portfolio for all groups of traders except for mutual funds. Further, we again find that hedge funds and transient investors trade on the anomalies prior to publication, but in smaller magnitudes. With respect to returns, we observe a decay after publication from an annual DGTW-adjusted return of 5.25% in the ex-ante portfolio to 2.75% in the ex-post portfolio. This economically large 48% relative decrease is not statistically significant which we attribute to the low statistical power (24 annual observations) test coupled with the volition of returns. Panel B presents results for the quarterly ranked anomaly portfolios. Consistent with our earlier pooled results, we do not observe anomaly-based trading among the full universe of institutions at the quarterly level. However, among hedge funds and transient institutions, we observe both significant trading in the ex-post portfolio, and a significant difference between trading in the ex-post and ex-ante portfolios. This result implies a spike in trading among the most sophisticated investors following publication of the anomalies. We also observe a 25% relative reduction in the quarterly anomaly returns after publication, although the difference it is not statistically significant.

4.4 VAR Analysis

To provide direct evidence that anomaly-based trading following publication brings prices to efficient levels and reduces anomaly profits, we estimate a VAR model that examines quarterly trading and anomaly returns for the long-short portfolio. The VAR model requires a lead-lag relation. The interpretation of the results becomes unclear when overlapping periods of returns and trading are used. To avoid this problem, we focus on institutional trading and anomaly returns for the ex-post and ex-ante portfolios in the quarter after the ranking date. More specifically, let y_t be a vector that includes quarterly trading and returns. We estimate the following system:

$$y_t = c + Ay_{t-1} + e_t$$

The VAR on the annual (quarterly) portfolio is specified with a one-year (one-quarter) lag based upon results from the Schwarz Bayesian information criterion.[32] We perform a Granger-causality test by estimating the matrix A of coefficients. If arbitrage activity occurs, we expect to

[32] The augmented Dickey–Fuller test provides no evidence of non-stationarity in the time-series of returns and trading.

observe a negative relation between institutional trading and future anomaly returns. Moreover, due to the surge in institutional trading following publication, we expect this relation to be stronger in the ex-post portfolio than in the ex-ante portfolio.

The first four columns of Table 6 Panel A present the VAR results for the annually sorted ex-post portfolio. The first column examines the relation between aggregate institutional trading and anomaly returns. Consistent with arbitrage activity, the results suggest that institutional trading is negatively related to future anomaly returns. Columns two, three, and four report results for hedge funds, mutual funds, and transient institutions, respectively. Across all specifications, we observe that institutional trading is negatively related to future anomaly returns, although it is only statistically significant for all institutions and hedge funds. The last four columns of Panel A present results for the quarterly ranked anomaly portfolio. Analyzing the quarterly ranked portfolio allows for more statically power given the larger sample size (95 observations) compared to the annually ranked portfolio (23 observations). Consistent with arbitrage we find that trading in all four groups is negatively associated with future returns. Therefore, we identify a Granger-causal relation between trading and future anomaly returns.

Panel B columns present VAR results for the ex-ante portfolio. Our earlier findings show that institutions do not consistently trade with, or against, the anomalies prior to the anomaly publication. Consistent with these results, and inconsistent with an arbitrage process occurring prior to anomaly publication, we do not observe a significant and negative relation between institutional trading and future anomaly returns in the ex-ante portfolio for both the annual and quarterly specifications.

Overall these results support the main hypothesis of the paper. The decrease in anomaly profits following publication can at least partially be attributed to the increase in institutional arbitrage activity that occurs once published academic research brings attention to the anomaly.

4.5 Comparison with EIK

EIK report that institutions trade in the opposite direction of anomalies. In addition to focusing on publication date and different types of institutions, we differ in how we measure anomaly-based trading. Specifically, EIK measure institutional trading over a window that begins one year before the start of our trading window (in January of the previous year, t= -6), and they use the change in the number of institutions holding a stock (whereas we use a value-weighted approach). In this section, to reconcile our results with those of EIK, we examine how our results change as we adopt these two key elements of their methodology.

First, we measure anomaly-based trading using their trading window. A longer window is ideal if institutions are able to infer the anomaly rankings of stocks before the release of the firm's annual report. For example, over the course of each firm's fiscal year, while the accounting variables are being realized, institutions may be able to infer the anomaly ranking of the stock from the firm's quarterly financial statements or other publicly available information.[33]

Figure 3 presents results when we expand our trading window back an additional four quarters (t= -6 to t= -2) to mimic EIK. We present trading in all anomalies, as well as only those that are in the ex-ante and ex-post subsamples to account for the anomalies' publication status. Consistent with EIK, when we examine trading in the period before the release of information, we find some evidence of trading in the opposite direction of the anomalies, although it is not statistically significant as shown in Internet Appendix Table 2 Panel A. However, the large jump in trading around information availability (from t= -6, t= -2 to t= -6, t= -1), is consistent with the notion that institutions need the release of accounting information to trade on the anomalies. Of note, when we examine trading in the longer event window among hedge funds and transient institutions in Internet Appendix Figure 1, we find some evidence that these investors anticipate the anomaly rankings as there is positive and statistically significant trading over the period (t= -6 to t= -2). For mutual funds the results are weaker, although, as with the full sample of institutional investors, they trade with the anomalies over the longer event window (t= -6 to t= +1).

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[33] We address this concern earlier in the paper by computing anomaly rankings on a quarterly basis using the most up-to-date publicly available information.

In Internet Appendix Figure 1, we also present results for a group of investors that may not have the ability or the incentive to exploit anomalies. Specifically, we focus on investors that are neither hedge funds nor transient institutions (i.e., mutual funds, bank trusts, insurance companies, pension funds, and endowments, none of which are classified as transient institutions). We find that these investors trade significantly against the anomalies in both the ex-ante and ex-post subsamples. This evidence suggests that this group may be a source of the contrarian anomaly-based trading observed by EIK. Furthermore, as argued by EIK, the finding that these institutions trade against anomalies in both the ex-post and ex-ante subsamples is consistent with both agency-induced preferences that are contrary to anomaly-based signals, and some institutions potentially playing a causal role in the anomalies.

Next, in Internet Appendix Table 3, we examine anomaly-based trading using EIK's change in the number of institutions measure.[34] Examining the change in the number of institutions holding a stock provides an equal-weighted account of institutions' actions, whereas our value-weighted measure is representative of aggregate institutional actions. Consistent with EIK, in the four quarters before our window (t= -6 to t= -2), we observe significantly negative trading for the full, ex-post, and ex-ante sets of anomalies using this measure. However, when we examine trading in our original window (t= -2 to t= +1), we observe positive and statistically significant trading for the full, ex-post, and ex-ante sets. Furthermore, consistent with academic publication disseminating information, trading in the ex-post set of anomalies is significantly larger than trading in the ex-ante set.

Prior to the release of accounting information, there is likely ambiguity among institutions if a stock will be in the short or long leg of the anomaly. The observed negative trading during this period is consistent with the argument put forward by EIK that agency-induced preferences for certain stock characteristics may motivate trades that prove contrary to anomaly-based signals.

[34] EIK also examine trading using equal-weighted change in holdings. In Internet Appendix Table 3 we also report results using this measure. Similar to our results for the change in the number of institutions measure, we observe negative trading in the four quarters before our window (t= -6 to t= -2) and positive trading in our original window (t= -2 to t= +1).

However, the fact that we observe positive anomaly-based trading once the information is revealed suggests that institutions reverse their behavior when they realize that they are on the wrong side of the anomaly prescription. To address the concern that institutions may be trading on the year *t-1* anomaly rankings rather than the year *t* rankings, we focus on a 'persistent sample' that removes this ambiguity. We define the persistence samples as stocks that remain in the long or short legs from one year to the next.[35] In Panel B of Internet Appendix Tables 2 and 3, we show that institutions trade with the anomalies throughout the six-quarter window in the persistent sample using value-weighted and EIK trading measures (see also Internet Appendix Figure 2).

5. Robustness Checks

5.1 Fama-MacBeth Regressions

A potential concern is whether the increase in trading activity for the ex-post portfolio is robust after controlling for common determinants of institutional trading. For instance, Gompers and Metrick (2001) find that institutional ownership is systematically related to size and book-to-market. We use Fama-MacBeth cross-sectional regressions to examine the institutional trading behavior in stocks in the ex-ante and ex-post portfolios, after controlling for stock characteristics related to institutional preferences. The analysis is performed using all the stocks that have both ex-ante and ex-post portfolio rankings, even if they are not in the long or short legs. The variables of interest are four dummy variables—ex-post long, ex-post short, ex-ante long, and ex-ante short—that indicate whether the stock is in the long or short legs of the ex-post and ex-ante anomaly portfolios. Including dummy variables for the long and short legs allows us to separately examine whether institutions change their trading behavior based on positive and negative anomaly signals. The control variables are measured at the beginning of the trading window and include the log of book-to-market, the six-month cumulative stock returns, the average quarterly

[35]The persistent sample represents 40.4% of stocks in the long and short legs (i.e. anomaly stocks), 8.8% reverse year over year (i.e. long to short or short to long), 32.1% of anomaly stocks are in the neutral portfolio in the previous year, and for 18.6% the information necessary to compute the ranking is unavailable in the previous year.

Amihud's (2002) illiquidity measure, and the log of market capitalization. Institutional trading is measured by the three-quarter (two-quarter) change in the fraction of a company's stock that is owned by institutional investors, starting from two quarters (one quarter) before ranking date in the annual (quarterly) anomalies.

Table 7 presents the results using annual (first four columns) and quarterly (last four columns) rankings. All institutions trade on the anomalies in the ex-post portfolio, although the ex-post long is insignificant for mutual funds in the annual specification. When a firm is in the ex-post long portfolio, institutions buy it; when it is in the ex-post short portfolio, institutions sell it. Columns four and eight indicate that this result is especially strong for transient institutions. By contrast, the coefficients on the ex-ante dummy variables are mostly insignificant. The increase in trading from the ex-ante to the ex-post portfolio is confirmed. Indeed, in the last three rows of the table, we test whether the difference between the ex-post and ex-ante coefficients are significant. Focusing on all the institutions, we find that the ex-post long (short) coefficient is significantly higher (lower) than the ex-ante long (short) coefficient, in both the annual specification for the short leg and quarterly specification for both legs. We also test whether the difference between long and short legs is higher in the ex-post portfolio than in the ex-ante portfolio. The difference is positive and significant for all eight specifications.

The coefficients on the control variables suggest that aggregate institutional trading is increasing in growth and momentum and decreasing in illiquidity and size.[36] A similar institutional preference has been observed for growth stocks (Jiang, 2010), momentum stocks (Grinblatt et al., 1995), liquid stocks (Gompers and Metrick, 2001), and small stocks (Blume and Keim, 2014).

5.2 Long and Short Leg Results

In the previous analysis we consider trading in the long and short legs separately. It appears that after publication there has been an increase in trading in both legs characterized by more

[36] Given that momentum and book-to-market are part of our set of anomalies, we tried to run the regressions excluding these two variables from the controls. The results are comparable.

buying in the long leg and more selling in the short leg. We now examine if this finding is still present when we aggregate trading at the portfolio level. In Internet Appendix Table 4 we present results for the ex-post and ex-ante portfolios separately for the long and short leg. Overall, we find evidence that our results are driven by both sides of the anomalies. For the long leg, we do not observe greater trading after publication for the full sample of institutions. However, after publication we do observe significant increase by transient institutions in both the quarterly and annual ranked portfolios, and by hedge funds in the quarterly ranked portfolios. Furthermore, we observe a decrease in anomaly returns for both the annual and quarterly portfolios. For the annual ranked short leg portfolio, after publication we observe a significantly negative change in trading among all institutions except mutual funds and at the same there is an increase in returns. We observe a similar pattern in trading for the quarterly ranked short leg portfolio, although the returns are similarly negative in both the ex-ante and ex-post portfolios.

5.3 Other Concerns

5.3.1 Institutional Trading on Anomalies: Anomaly Set Robustness

Our set of 14 anomalies are chosen to mimic recent papers on anomalies; 11 of them are used by Stambaugh et al. (2012) while the three additional anomalies (capital investments, book-to-market, and post-earnings announcement drift) are included to be consistent with recent literature (e.g., Chen et al., 2011). Nonetheless, the selection process could be perceived as arbitrary and there is concern that our results may be sensitive to the set of anomalies that we use. As discussed earlier (Section 4.2), one element of this concern is whether our results are biased because of the relatively high correlation among some of the anomalies. Although we expect that this effect would bias us against finding results, we nevertheless address these concerns by developing a set of nine 'low-correlation' anomalies. The first row of Internet Appendix Table 5 presents the increase in institutional trading from the in-sample period to the post-publication (early) period for the low-correlation anomalies. The results for this set of anomalies are stronger. For example, the increase for all institutions is 1.27% vs. 0.75% in Table 4 Panel B.

As a further robustness test, we replicate our institutional trading result using the 11 anomalies used by Stambaugh et al. (2012) and the six anomalies that overlap with those examined by EIK.[37] These results are presented in the second and third rows of Internet Appendix Table 5, and show that our main results weaken slightly (0.73% vs. 0.75% in Table 4 Panel B) when we use the Stambaugh et al. anomalies, and strengthen when we use the EIK anomalies. Taken together, our anomaly set robustness tests give us confidence that our main results hold under alternative selections of the anomalies used.

5.3.2 Institutional Trading on Anomalies: Additional Robustness

The publication process takes several years and working papers are often made public prior to publication through conference presentations or the internet. Early dissemination draws into question whether the publication year of the anomaly research is the most appropriate one to use to highlight the publicizing and certification of the anomaly. To address this concern, we identify the first year each paper is made available on SSRN. We then rerun the institutional trading regression presented in Table 4 after replacing the publication year with the SSRN year, when available.[38] In the first row of Internet Appendix Table 6 we show that anomaly-based trading also increases following SSRN availability. Again, for brevity, we only present the results for the difference in trading between the post-publication (early) and the in-sample periods. For the full sample of institutions, the magnitude of the increase is similar to the increase when we use the journal publication year, 0.78% vs. 0.75%.

Another concern is that factors other than the anomalies may be driving our institutional trading. For example, one of these factors could be the increase in institutional trading over time. Taking the difference between long and short legs is one way to remove the impact of a trend. To further address this concern, we add year and anomaly fixed effects in the anomaly regression model presented in Table 4. Fixed effects control for unobserved heterogeneity. As our dataset is

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[37] The Stambaugh et al. (2012) sample includes the following 11 anomalies: NSI, CEI, ACC, NOA, GP, AG, IVA, MOM, DIS, OS, and ROA. The EIK sample includes the following six anomalies: NOA, GP, IVA, BM, MOM, and OS.

[38] SSRN date is not available for the following anomalies: NSI, ACC, BM, MOM, OS, and PEAD.

at the year-anomaly level, including year fixed effects effectively allows us, for any given year, to compare anomalies with different publication status (in-sample, pre-publication, etc.). Including anomaly fixed effects allows us to compare trading within the anomaly as it changes status. In Internet Appendix Table 6 we present the results of this model for the difference in trading between the post-publication (early) and the in-sample periods and find that, for the full sample of institutions, the magnitude of the increase in anomaly-based trading is greater for the fixed-effects specification: 1.13% vs. 0.75%.

The 2008 financial crisis caused a liquidity crunch that may have limited the ability of institutions to exploit anomalies. The crisis occurred during the post-publication period for all but one (gross profitability) of the anomalies. Therefore, if the financial crisis reduced the capacity of institutional investors to trade on anomalies then including this period in our sample should bias us against finding results. Nonetheless, for robustness we rerun the regressions presented in Table 4, excluding the years 2008 and 2009 from the sample. In the third row of Internet Appendix Table 6 we present the results of this model for the difference in trading between the post-publication (early) and the in-sample periods and find that, for the full sample of institutions, the magnitude of the increase in anomaly-based trading is similar after excluding the financial crisis years: 0.80% vs. 0.75%.

Another concern is that our ex-post and ex-ante portfolio trading results, presented in Table 5, are biased by the fact that in some years there are few anomalies in the ex-post and ex-ante portfolios and the regression analysis places the same weight on these years compared to years when both portfolios are well populated. For example, from 1989 to 1991 there is one anomaly (PEAD) in the ex-post portfolio, and from 2008 to 2012 there is one anomaly in the ex-post portfolio (GP). To address this concern we rerun the regressions used in Table 5, restricting the sample to observations where there is greater than one anomaly in each of the long and short portfolios, greater than two anomalies, and greater than three anomalies. For brevity, in the Internet Appendix Table 7 we show only the result for ex-post minus ex-ante. The results across all three restricted specifications are similar to the results presented in Table 5. We again find significantly greater anomaly-based trading in the ex-post portfolio among hedge funds and transient investors. The magnitude of the effect is similar. For example, among all transient institutions the ex-post minus ex-ante portfolio is 1.08% in Table 5, 1.18% when we select observations with greater than one anomaly in each portfolio, 1.23% when we select observations with greater than two anomalies in each portfolio, and 1.07% when we select observations with greater than three anomalies in each portfolio. To not lose any observations, we also estimate the regression from Table 5 using a weighted regression. We use analytic weights and our weighting variable is the minimum number of anomalies in either the ex-post or ex-ante portfolio each quarter.[39] We find similar results to those in the unweighted regressions.

Chordia et al. (2014) document that an important determinant of the attenuation of anomaly returns is the increase in liquidity. To test whether liquidity or trading Granger causes the reduction in anomaly returns, we estimate a VAR model that includes a liquidity measure in addition to trading and returns. As a liquidity measure, we use the aggregate Amihud measure for the long-short portfolio. Internet Appendix Table 8 shows that for the return equation, the coefficient on lagged trading is negative and most of the time significant for the ex-post portfolio whereas the liquidity measure coefficient is insignificant. Therefore, it seems that liquidity is not the driver of the post-publication decay in anomaly returns.

A trading strategy that fully exploits the anomalies would buy stocks in the long legs and simultaneously short-sell stocks in the short leg. A concern in our analysis is that the 13F data we use include only long institutional positions. Although we do not observe institution-level short positions, in previous analyses we examined whether institutions sell existing shares of securities that fall into the short leg of an anomaly strategy. For robustness, we also consider the change in short interest for the long and short legs around publication dates. We obtain monthly short-interest data from Compustat, starting from January 2000, because we find that many short positions

[39] For example, in 1996 there are five anomalies in the ex-post portfolio and nine anomalies in the ex-ante portfolio. We therefore assign an analytic weight of five for 1996. We cannot choose the sum (or average) of the two because there are 14 anomalies combined every year across the two portfolios.

reported by Compustat are missing before 2000, consistent with Hwang and Liu (2014). Although the short interest data is not at the institutional level, we can examine whether the stocks in the short portfolio are shorted more than the stocks in the long portfolio around anomaly publication. Every quarter, we compute the percentage of market capitalization sold short for the long and short legs and compute the change from the previous to the following quarter for both the ex-post and ex-ante portfolios. Consistent with institutions following academic research and trading on the anomalies by shorting relatively more in the short portfolio than in the long portfolio, we find that the difference in ex-post vs. ex-ante anomaly-based short-selling is equal to -0.18 with a p-value of 0.09.

6. Conclusion

Grossman and Stiglitz (1980) posit the existence of informed traders who observe that the return of a security will be high (low) and subsequently bid its price up (down). While institutional investors are often thought of as being sophisticated, there is conflicting evidence regarding their role as arbitrageurs who push market prices towards efficient levels. In this paper, we add to this debate by examining the ability of institutional investors to exploit stock anomalies when the information about the anomalies is readily available through academic publication and the release of necessary accounting data.

If institutions attempt to exploit stock anomalies, they should buy (sell) stocks that exhibit characteristics consistent with (contrary to) the anomaly. We observe an increase in anomaly-based trading among institutional investors, especially hedge funds and transient institutions, when information about the anomalies is available. If by attempting to exploit anomalies, institutions play the role of the Grossman-Stiglitz arbitrageurs, their buying activity should drive up the price of stocks exhibiting anomaly characteristics and reduce their future abnormal returns. Using a VAR model, we find a negative relation between institutional trading and future anomaly returns following academic publication of the anomaly. This result is consistent with the documented post-publication anomaly decay stemming from mispricing that is corrected by arbitrage activity.

Overall, this paper contributes to our understanding of market efficiency and potentially offers practitioners insights into how to improve their investment performance. It may also be relevant for regulators given that the findings suggest a positive role for some institutional investors, especially hedge funds and transient institutions, in contributing to more efficient markets. Finally, this result is important for the real economy because efficient prices can help firms make better-informed investment and financing decisions.

REFERENCES

Akbas, F., S. Armstrong, S. Sorescu, and A. Subrahmanyam, 2015, “Smart money, dumb money, and capital market anomalies.” Journal of Financial Economics 118, 355–382.

Ali, A., J. Chen, T. Yao, and T. Yu, 2008, “Do mutual funds profit from the accruals anomaly?” Journal of Accounting Research 46, 1–26.

Ali, A., J. Chen, T. Yao, and T. Yu, 2012, “Mutual fund competition and profiting from the post earnings announcement drift.” Working Paper.

Amihud, Y., 2002, “Illiquidity and Stock Returns: Cross-Section and Time-Series Effects.” Journal of Financial Markets 5, 31–56.

Anderson, A. and E. Dyl, 2005, “Market structure and trading volume.” Journal of Financial Research, 28, 115–131.

Aragon, G. and W. Ferson, 2006, “Portfolio performance evaluation.” Foundations and Trends in Finance 2, 83–190.

Barberis, N. and R. Thaler, 2003, “A Survey of Behavioral Finance,” in George Constantinides, Milton Harris, Rene Stulz eds., Handbook of the Economics of Finance, North-Holland.

Bernard, V., and J. Thomas, 1989, “Post-earnings-announcement drift: delayed price responses or risk premium.” Journal of Accounting Research 27, 1–36.

Blume, M.E. and Keim, D.B., 2014, “The changing nature of institutional stock investing.” Critical Finance Review, 7.

Boehmer, E., and E. Kelley, 2009, “Institutional investors and the informational efficiency of prices.” Review of Financial Studies, 22, 3563–3594.

Bushee, B., 2001, “Do institutional investors prefer near-term earnings over long-run value?” Contemporary Accounting Research 18 (2), 207–246.

Campbell, J.Y., J. Hilscher, and J. Szilagyi, 2008, “In search of distress risk.” Journal of Finance 63, 2899–2939.

Cella, C., A. Ellul, and M. Giannetti, 2013, “Investors' Horizons and the Amplification of Market Shocks.” Review of Financial Studies 26, 1607–1648.

Chan, L., H. Chen, and J. Lakonishok, 2002, "On mutual fund investment styles." Review of Financial Studies 15, 1407–1437.

Chen, L, R. Novy-Marx, and L. Zhang, 2011, "An alternative three-factor model." Working Paper.

Chordia, T., A. Subrahmanyam, and Q. Tong, 2014, "Have capital market anomalies attenuated in the recent era of high liquidity and trading activity?" Journal of Accounting and Economics 58, 41–58.

Cochrane, J. H., 1999, "Portfolio Advice for a Multifactor World," Economic Perspectives, Federal Reserve Bank of Chicago 23, 59–78.

Cooper, M.J., H. Gulen, and M.J. Schill, 2008, "Asset growth and the cross-section of stock returns." Journal of Finance 63, 1609–1652.

Daniel, K., M. Grinblatt, S. Titman, and R. Wermers, 1997, "Measuring mutual fund performance with characteristic-based benchmarks." Journal of Finance 52, 1035–1058.

Daniel, K. and S. Titman, 2006, "Market reactions to tangible and intangible information." Journal of Finance 61, 1605–1643.

Dichev, I., 1998, "Is the risk of bankruptcy a systematic risk?" Journal of Finance 53, 1131–1147.

Edelen, R., O. Ince, and G. Kadlec, 2016, "Institutional Investors and Stock Returns Anomalies", Journal of Financial Economics 119, 472-488.

Fama, E., 1976, Foundations of finance (Basic Books, New York, NY).

Fama, E., 1998, "Market efficiency, long-term returns, and behavioral finance." Journal of Financial Economics 49, 283–306.

Fama, E. and K. French, 1992, "The cross-section of expected stock returns." Journal of Finance 47, 427–465.

Fama, E. and K. French, 1993, "Common risk factors in the returns on stocks and bonds." Journal of Financial Economics 33, 3–56.

Fama, E. and K. French, 1996, "Multifactor explanations of asset pricing anomalies." Journal of Finance 51, 55–84.

Fama, E. and K. French, 2006, "Profitability, investment, and average returns." Journal of Financial Economics 82, 491–518.

Fama, E. and K. French, 2008, "Dissecting anomalies." Journal of Finance 63, 1653–1678.

Frazzini, A. and O. Lamont, 2008, "Dumb money: mutual fund flows and the cross-section of stock returns." Journal of Financial Economics 88, 299–322.

Fung, W., D. Hsieh, 2006, "Hedge funds: an industry in its adolescence." Economic Review 4, 1–34.

Goetzmann, W., J. Ingersoll, and S. Ross, 2003, "High-Water Marks and Hedge Fund Management Contracts." Journal of Finance, 58, 1685–1718.

Gompers, P., and A. Metrick, 2001, "Institutional investors and equity prices." Quarterly Journal of Economics 116, 229–259.

Green, J., J. Hand, and M. Soliman, 2011, "Going, going, gone? The demise of the accruals anomaly." Management Science 57, 797–816.

Green, J., J. Hand, and F. Zhang, 2013, "The supraview of return predictive signals." Review of Accounting Studies 18, 692–730.

Griffin, J., J. Harris, T. Shu, and S. Topaloglu, 2011, "Who drove and burst the tech bubble?" Journal of Finance 66, 1251–1290.

Grinblatt, M., S. Titman, and R. Wermers, 1995, "Momentum investment strategies portfolio performance and herding: A study of mutual fund behavior." American Economic Review 85, 1088–1105.

Grossman, S. and J. Stiglitz, 1980, "On the impossibility of informationally efficient markets", American Economic Review 70, 393–408.

Harvey, C., Y. Liu, and H. Zhu, 2015, "…And the cross-section of expected returns." Review of Financial Studies forthcoming.

Heckman, J., 1979, "Sample selection bias as a specification error." Econometrica 47, 153-161.

Hirshleifer, D., K. Hou, S.H. Teoh, and Y. Zhang, 2004, "Do investors over-value firms with bloated balance sheets." Journal of Accounting and Economics 38, 297–331.

Hwang, B. and B. Liu, 2014, "Short sellers trading on anomalies." Working Paper.

Ke, B. and S. Ramalingegowda, 2005, "Do institutional investors exploit the post-earnings announcement drift?" Journal of Accounting and Economics 39, 25–53

Knez, P. and M. Ready, 1996, "Estimating the profits from trading strategies." Review of Financial Studies 9, 1121–1163.

Kokkonen, J., and M. Suominen, 2015, "Hedge funds and stock market efficiency." Management Science 61, 2890–2904.

Jegadeesh, N. and S. Titman, 1993, "Returns to buying winners and selling losers: implications for market efficiency." Journal of Finance 48, 65–91.

Jegadeesh, N., and S. Titman, 2001, "Profitability of momentum strategies: An evaluation of alternative explanations." Journal of Finance 56, 699–720.

Jiang, H., 2010, "Institutional investors, intangible information and the book-to-market effect." Journal of Financial Economics 96, 98–126.

Johnson, B. and W. Schwartz, 2000, "Evidence that capital markets learn from academic research: earnings surprises and the persistence of post-announcement drift." Working Paper.

Lewellen, J., 2011, "Institutional investors and the limits of arbitrage." Journal of Financial Economics 102, 62–82.

Lesmond, D., M. Schill, and C. Zhou, 2004, "The illusory nature of momentum profits." Journal of Financial Economics 71, 349–380.

Lintner, J., 1965, "The valuation of risk assets and the selection of risky investments in stock portfolios and capital budgets." The Review of Economics and Statistics 47, 13–37.

Lo, A., and C. MacKinlay, 1990, "Data-snooping biases in tests of financial asset pricing models." Review of Financial Studies 3, 431–467.

Loughran, T. and J.R. Ritter, 1995, "The new issues puzzle". Journal of Finance 50, 23–51.

McLean, D. and J. Pontiff, 2016, "Does academic research destroy stock return predictability?" Journal of Finance 71, 5-32.

Novy-Marx, R., 2013, "The other side of value: Good growth and the gross profitability premium." Journal of Financial Economics 108, 1–28.

Ohlson, J.A., 1980, “Financial ratios and the probabilistic prediction of bankruptcy.” Journal of accounting research 18, 109–131.

Pástor, L., R. Stambaugh, and L. Taylor, 2015, “Scale and skill in active management.” Journal of Financial Economics 116, 23–45.

Richardson, S., I. Tuna, and P. Wysocki, 2010, “Accounting anomalies and fundamental analysis: a review of recent research advances.” Journal of Accounting and Economics 50, 410–454.

Sadka, R., 2006, “Momentum and post-earnings-announcement drift anomalies: the role of liquidity risk.” Journal of Financial Economics 80, 309–349.

Sharpe, W., 1964, “Capital asset prices: A theory of market equilibrium under conditions of risk.” Journal of Finance 19, 425-442.

Shleifer, A. and R. Vishny, 1997, “The limits of arbitrage.” Journal of Finance 52, 32–55.

Sloan, R.G., 1996, “Do stock prices fully reflect information in accruals and cash flows about future earnings?” Accounting Review 71, 289–315

Stambaugh, R., J. Yu, and Y. Yuan, 2012, “The short of it: investor sentiment and anomalies.” Journal of Financial Economics 104, 288–302.

Stein, J., 2009, “Presidential Address: sophisticated investors and market efficiency”, Journal of Finance 64, 1517–1548.

Subrahmanyam, A., 2010, “The cross-section of expected stock returns: What have we learnt from the past twenty-five years of research?” European Financial Management 14, 12–29.

Titman, S., K. Wei, and F. Xie, 2004, “Capital investments and stock returns.” Journal of Financial and Quantitative Analysis 39, 677–700.

Xing, Y., 2008, “Interpreting the value effect through the Q-theory: an empirical investigation.” Review of Financial Studies 21, 1767–1795.

Yan, X. and Z. Zhang, 2009, “Institutional investors and equity returns: Are short-term institutions better informed?” Review of Financial Studies 22, 893–924.

Figure 1

Institutional Cumulative Trading in the Long-Short Portfolios Relative to Publication Date

This figure plots the average cumulative changes in overall institutional ownership for the difference between the long and short portfolios. The long portfolio contains underpriced securities that should be bought and the short portfolio includes overpriced securities that should be sold (short). Every June, we sort stocks into quintiles according to the anomaly variables and measure the changes in percentage of shares outstanding held by all institutions in the long and short portfolios between the end of December and the end of September. We take the average across the 14 anomalies for the adjusted changes in the long and short portfolios, and the difference between the two portfolios, and we cumulate this average over time. Year 0 is the year of publication of the anomaly.

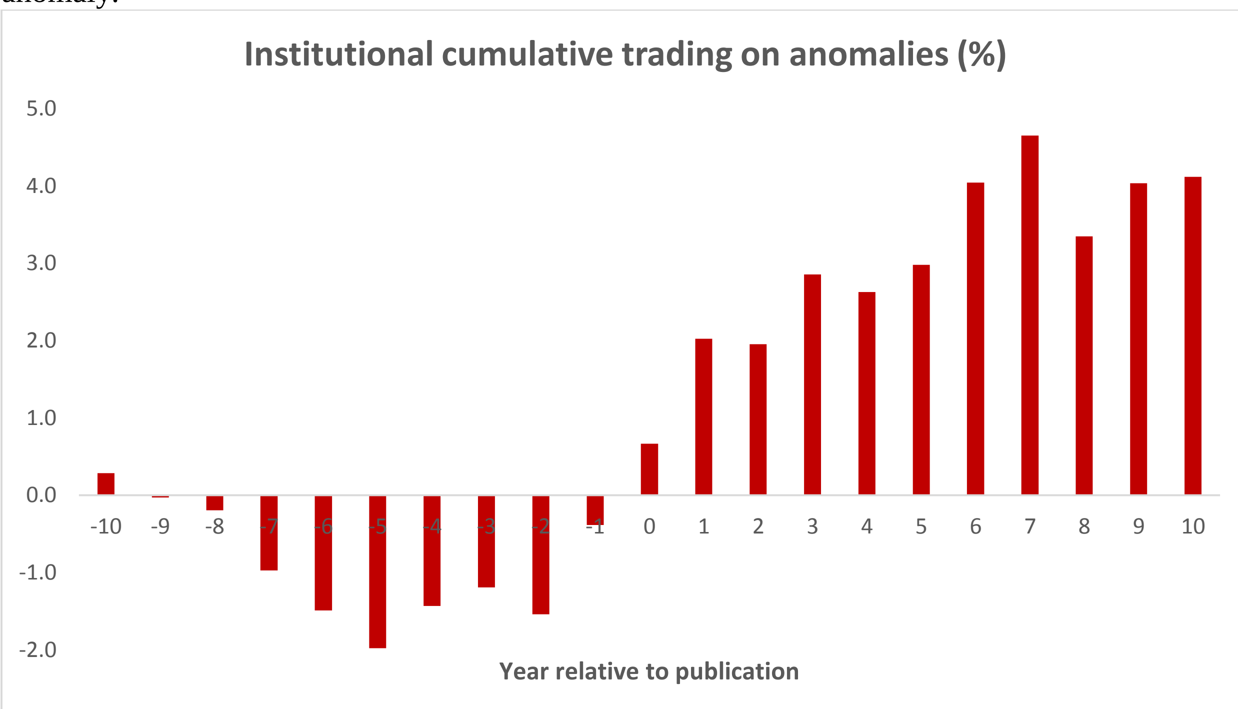


Figure 2

Cumulative Institutional Trading and Anomaly Returns by Periods

This figure plots the average difference between the cumulative returns and between changes in overall institutional ownership for the long and short portfolios. Every June, we sort stocks into quintiles according to the anomaly variables. We then compute the cumulative returns and changes in ownership for the long and short legs from the previous December to the following June for two specific periods. In-sample is the sample period of the original anomaly publication. Post-publication period (early) is composed of the four years (t= 0, t= 3) including and after the publication date of the paper. We take the average across the 14 anomalies. Returns (changes in ownership) are cumulated on a monthly (quarterly) basis. Quarter 0 is when we form the long and short portfolios.

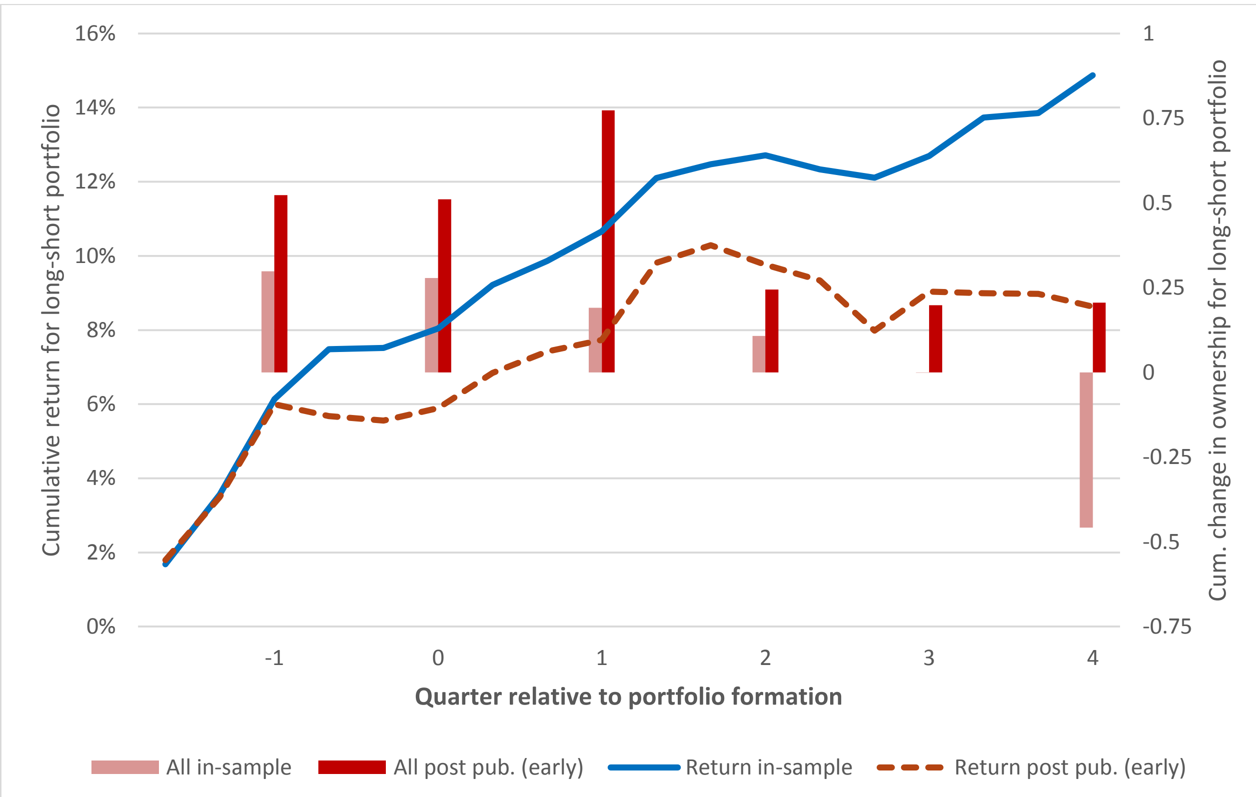


Figure 3
Institutional Trading with a Longer Window

This figure plots the average cumulative changes in overall institutional ownership for the difference between the long and the short portfolios. The long portfolio contains underpriced securities that should be bought and the short portfolio includes overpriced securities that should be sold (short). Every June we sort stocks into quintiles according to the anomaly variables and measure the changes in percentage of shares outstanding held by all institutions in the long and short portfolios. We take the average across the 14 anomalies and we cumulate this average over time. We also compute institutional trading in the ex-post and ex-ante portfolios. Ex-ante portfolio is based on the anomalies that have not been published yet. Ex-post portfolio is constructed using the anomalies that are already published. We assign a percentile rank to each stock, based on each anomaly, and compute the equal-weighted average rank for ex-ante and ex-post anomalies. We drop a stock if more than half the anomaly variables are missing. We rank the stocks again based on the average rank and the top and bottom quintiles form the long and short portfolios, respectively. We measure trading starting six quarters before ranking date ([-6, -5]) and cumulate it up to one quarter after the June sorting date ([-6, 1]).

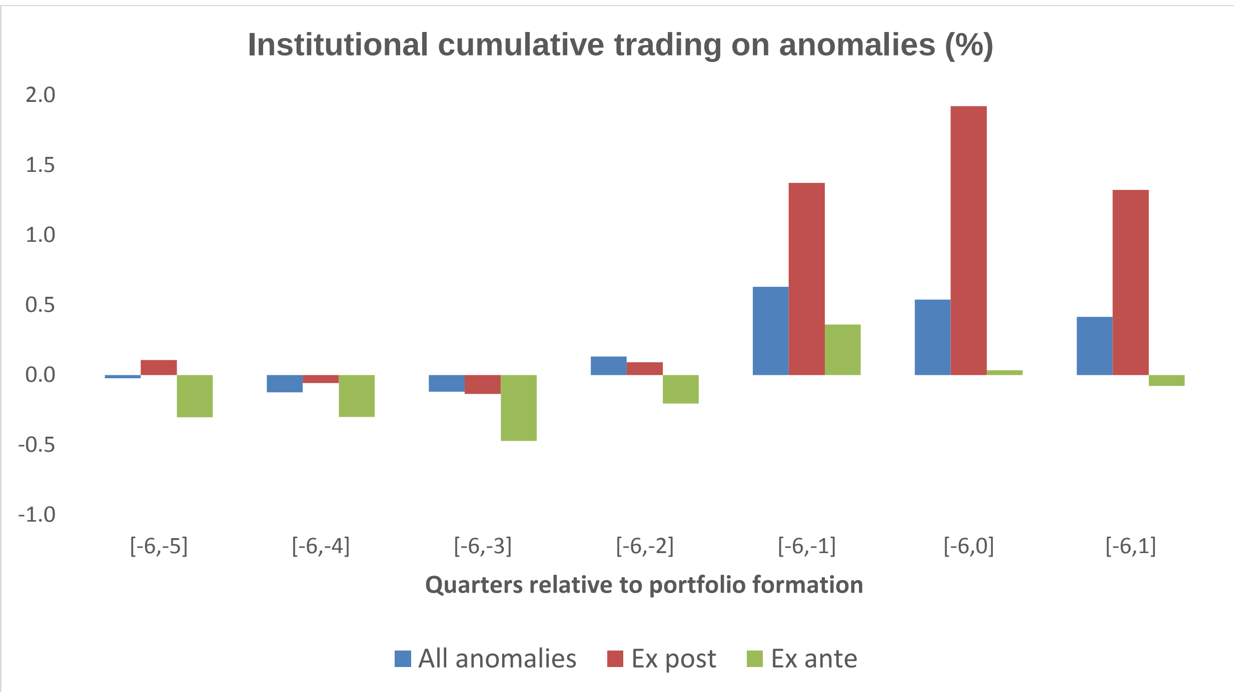


Table 1
Sample of Anomalies

This table reports the list of anomalies with information about the papers that first documented them, the publication year, and the beginning and the end year of the sample used in the anomaly publication.

Anomaly	**Label**	**Paper**	**Sample beginning year**	**Sample end year**
Net Stock Issues	NSI	Loughran and Ritter (1995)	1970	1990
Composite Equity Issues	CEI	Daniel and Titman (2006)	1968	2000
Total accruals	ACC	Sloan (1996)	1962	1991
Net Operating Assets	NOA	Hirshleifer et al. (2004)	1964	2002
Gross Profitability	GP	Novy-Marx (2013)	1963	2009
Asset Growth	AG	Cooper et al. (2008)	1963	2003
Capital Investments	CI	Titman et al. (2004)	1973	1996
Investment-to-Assets	IVA	Xing (2008)	1964	2003
Book-to-Market	BM	Fama and French (1992)	1963	1990
Momentum	MOM	Jegadeesh and Titman (1993)	1965	1989
Distress	DIS	Campbell et al. (2008)	1963	2003
Ohlson O-Score	OS	Dichev (1998)	1981	1995
Return on Assets	ROA	Fama and French (2006)	1963	2003
Post-Earnings Announcement Drift	PEAD	Bernard and Thomas (1989)	1974	1986

Table 2
Correlations and Portfolio Characteristics

This table reports correlations and characteristics for the anomalies. Panel A reports the rank correlation matrix for the 14 anomalies together with the first-order autocorrelation in the first row. Every June of year *t* we sort stocks into quintiles based on accounting data for the last fiscal year end in calendar year *t* – 1, which becomes available to market participants by the end of March. For MOM, DIS, OS, ROA, and PEAD we focus on June's ranking. The correlations are computed using the quintile ranks. Panel B reports the average size, book-to-market, momentum, and illiquidity quintile rank of stocks in the long (top quintile) and short (bottom quintile) leg of all the anomalies. Illiquidity is measured by the Amihud (2002) measure. The last column of panel B presents the p-values for the test of the difference between the long and short legs.

Panel A	**NSI**	**CEI**	**ACC**	**NOA**	**GP**	**AG**	**CI**	**IVA**	**BM**	**MOM**	**DIS**	**OS**	**ROA**	**PEAD**
First-order autocorrelation	0.38	0.87	0.26	0.69	0.89	0.29	0.28	0.37	0.79	-0.01	0.30	0.78	0.65	-0.17
NSI		0.45	0.11	0.12	0.09	0.33	0.01	0.19	0.18	0.02	0.12	0.06	0.09	0.00
CEI			0.09	0.13	0.12	0.24	-0.01	0.17	0.16	0.01	0.17	0.10	0.12	0.00
ACC				0.23	-0.08	0.30	0.07	0.25	0.10	0.05	-0.02	0.01	-0.10	0.05
NOA					0.07	0.40	0.11	0.46	-0.09	0.05	-0.02	-0.01	-0.03	0.05
GP						-0.04	-0.01	-0.02	-0.21	0.04	0.19	0.11	0.38	0.02
AG							0.17	0.60	0.29	0.02	-0.09	-0.10	-0.20	0.04
CI								0.28	0.03	0.05	-0.01	-0.06	-0.03	0.08
IVA									0.17	0.06	-0.02	-0.06	-0.12	0.07
BM										-0.08	-0.12	-0.26	-0.32	-0.07
MOM											0.59	0.10	0.16	0.25
DIS												0.43	0.55	0.33
OS													0.53	0.16
ROA														0.34

Panel B	**Long leg**	**Short leg**	**Difference**	**p-value**
Size	2.62	1.76	0.86	0.00
Book-to-market	3.13	2.76	0.37	0.00
Momentum	3.77	2.62	1.14	0.00
Illiquidity	2.25	2.73	-0.48	0.00

Table 3
Anomaly Returns

This table reports the performance of a portfolio strategy that buys the long portfolio and sells the short portfolio of stocks sorted into quintiles according to the anomaly variables. The long portfolio contains underpriced securities that should be bought and the short portfolio has overpriced securities that should be sold (short). We consider two different sample periods: the same sample period as the original anomaly publication (in-sample) and the sample period starting from the year of publication up to the end of the sample (post-publication). For the annual ranking (Panel A), every June of year t we sort stocks based on accounting data for the last fiscal year end in calendar year $t-1$, which becomes available to market participants by the end of March. For MOM, DIS, OS, ROA, and PEAD we focus on June's ranking. Next, we calculate value-weighted portfolio returns over the following four quarters. For the quarterly ranking (Panel B), at the end of each calendar quarter we sort stocks based on accounting data for the previous fiscal quarter and other financial data observed by the end of the previous quarter and construct value-weighted portfolio returns over the following quarter. The performance (expressed in percentage) is measured by the average quarterly returns in excess of the risk-free rate, the three-factor alphas, and the returns in excess of the benchmark of Daniel, Grinblatt, Titman, and Wermers (DGTW, 1997). The alpha is the intercept of a regression of quarterly excess returns on the three Fama-French factors with the exception of the book-to-market anomaly, which only includes the market and size factors. For GP, we cannot compute a post-publication alpha because there are insufficient observations. The DGTW benchmark is constructed every quarter and excludes momentum (book-to-market) when applied to the momentum (book-to-market) anomaly. The set of anomalies is described in Table 1. We also include a portfolio (EW Portfolio) that takes the equally-weighted average each quarter across all the available anomaly returns; p-values are in parentheses.

Panel A: Long-short performance with annual ranking						
	In-sample			**Post-publication**		
	Returns	**Alphas**	**DGTW**	**Returns**	**Alphas**	**DGTW**
NSI	1.41	1.09	1.03	0.96	1.62	0.96
	(0.00)	(0.00)	(0.00)	(0.21)	(0.01)	(0.04)
CEI	1.38	1.57	1.09	0.22	1.40	0.42
	(0.02)	(0.00)	(0.00)	(0.82)	(0.06)	(0.50)
ACC	0.95	1.38	0.50	0.60	0.80	0.40
	(0.15)	(0.02)	(0.23)	(0.34)	(0.22)	(0.44)
NOA	1.01	1.16	0.73	0.21	0.08	0.61
	(0.02)	(0.01)	(0.03)	(0.77)	(0.92)	(0.24)
GP	0.99	1.50	0.93	-2.88		-2.16
	(0.02)	(0.00)	(0.01)	(0.01)		(0.07)
AG	1.16	0.81	1.07	0.87	0.31	0.56
	(0.03)	(0.03)	(0.00)	(0.42)	(0.78)	(0.42)
CI	1.08	1.05	0.51	0.05	0.09	0.15
	(0.01)	(0.01)	(0.11)	(0.95)	(0.92)	(0.79)
IVA	1.21	1.06	0.92	0.72	1.26	0.89
	(0.00)	(0.00)	(0.00)	(0.52)	(0.29)	(0.19)
BM	1.77	1.65	1.25	1.27	1.14	0.81
	(0.01)	(0.01)	(0.05)	(0.13)	(0.19)	(0.24)
MOM	1.25	2.42	0.98	-0.06	0.30	-0.28
	(0.18)	(0.01)	(0.25)	(0.96)	(0.81)	(0.81)
DIS	0.90	2.50	0.10	-1.35	0.54	-0.45
	(0.36)	(0.00)	(0.85)	(0.40)	(0.67)	(0.61)
OS	1.67	2.00	1.12	0.96	3.03	1.84
	(0.09)	(0.00)	(0.00)	(0.50)	(0.00)	(0.02)
ROA	0.54	1.61	0.85	0.47	1.75	0.43
	(0.55)	(0.05)	(0.13)	(0.68)	(0.02)	(0.48)
PEAD	0.81	2.77	0.26	0.24	0.27	0.07
	(0.44)	(0.01)	(0.66)	(0.63)	(0.61)	(0.84)
EW Portfolio	1.14	1.56	0.99	0.84	1.11	0.64
	(0.00)	(0.00)	(0.00)	(0.04)	(0.01)	(0.03)

Panel B: Long-short performance with quarterly ranking						
	In-sample			Post-publication		
	Returns	Alphas	DGTW	Returns	Alphas	DGTW
NSI	1.56	1.43	1.24	0.88	1.76	1.34
	(0.00)	(0.00)	(0.00)	(0.32)	(0.01)	(0.01)
CEI	1.51	1.56	1.30	0.27	1.05	0.39
	(0.02)	(0.00)	(0.00)	(0.76)	(0.15)	(0.47)
ACC	2.32	2.17	2.12	0.54	0.49	0.38
	(0.00)	(0.00)	(0.00)	(0.49)	(0.52)	(0.52)
NOA	2.19	2.25	2.07	0.64	0.77	0.68
	(0.00)	(0.00)	(0.00)	(0.37)	(0.30)	(0.23)
GP	1.34	1.69	1.39	-1.68		-1.32
	(0.03)	(0.01)	(0.01)	(0.02)		(0.07)
AG	1.30	0.42	0.93	-0.28	-0.21	-0.18
	(0.07)	(0.39)	(0.06)	(0.79)	(0.85)	(0.79)
CI	1.78	1.85	1.14	0.48	0.66	0.24
	(0.01)	(0.01)	(0.06)	(0.57)	(0.46)	(0.70)
IVA	1.85	1.06	1.36	0.34	1.83	0.94
	(0.00)	(0.07)	(0.01)	(0.80)	(0.14)	(0.26)
BM	2.01	2.00	1.23	0.67	0.31	0.27
	(0.17)	(0.16)	(0.05)	(0.39)	(0.68)	(0.63)
MOM	2.03	2.90	1.45	2.21	2.69	1.78
	(0.04)	(0.01)	(0.12)	(0.05)	(0.01)	(0.07)
DIS	2.35	3.88	1.37	-1.16	1.23	-0.58
	(0.01)	(0.00)	(0.01)	(0.55)	(0.29)	(0.53)
OS	2.43	2.62	1.78	1.18	3.20	1.97
	(0.01)	(0.00)	(0.00)	(0.45)	(0.00)	(0.04)
ROA	0.58	1.54	0.75	0.77	1.80	0.78
	(0.47)	(0.04)	(0.15)	(0.50)	(0.01)	(0.17)
PEAD	2.25	3.47	0.81	0.44	0.62	0.49
	(0.01)	(0.00)	(0.09)	(0.38)	(0.23)	(0.25)
EW Portfolio	1.84	2.12	1.47	1.05	1.40	0.96
	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)

Table 4
Institutional Trading on the Anomaly

This table examines the trading activity of institutional investors in the 14 anomalies. The unit of measure is the variable 'Long minus Short', which measures the difference between the aggregate institutional holdings changes in the long and short legs of each anomaly. Institutional holdings (expressed in percent) are measured by the percentage of shares held by institutions in the long and short portfolios. Institutional trading is measured by the three- (two-) quarter change in institutional holdings starting from two quarters (one quarter) before ranking date in the annual (quarterly) anomalies. Observations are pooled across the anomalies. The first four columns present average trading across the full sample period in the anomalies sorted once a year and the last four columns present average trading in the anomalies sorted every quarter. Panel B presents results of a regression of trading on dummies that identify dates surrounding the publication of each anomaly. We present results for all institutions and for the subgroup of traders identified as hedge funds (HF), mutual funds (MF), and transient institutions. The last row of Panel B also reports the difference between trading in the post-publication (early) period and the in-sample period. To avoid overlap between the post-publication and post-publication (early) period we estimate two separate regressions. Robust standard errors are calculated and p-values are reported below the coefficient estimates.

Panel A: Anomaly-Based Trading in the full sample Period

	Annual				Quarterly			
	All	**HF**	**MF**	**Transient**	**All**	**HF**	**MF**	**Transient**
Full Sample	0.14	0.17	0.15	0.76	-0.11	0.01	-0.05	0.35
	(0.18)	(0.00)	(0.04)	(0.00)	(0.02)	(0.51)	(0.11)	(0.00)

Panel B: Anomaly-Based Trading in sub-sample Periods

	Annual				Quarterly			
	All	**HF**	**MF**	**Transient**	**All**	**HF**	**MF**	**Transient**
In-sample	0.07	0.11	0.31	0.67	-0.15	-0.03	0.03	0.20
	(0.64)	(0.03)	(0.00)	(0.00)	(0.02)	(0.26)	(0.46)	(0.00)
Pre-publication	0.25	0.32	-0.11	0.91	0.04	0.04	0.00	0.44
	(0.46)	(0.01)	(0.60)	(0.00)	(0.80)	(0.53)	(1.00)	(0.00)
Post-publication (Full)	0.21	0.20	0.02	0.83	-0.10	0.06	-0.16	0.51
	(0.23)	(0.00)	(0.89)	(0.00)	(0.20)	(0.07)	(0.00)	(0.00)
Post-publication (Early)	0.81	0.40	0.47	1.07	-0.08	0.10	-0.06	0.63
	(0.01)	(0.00)	(0.03)	(0.00)	(0.60)	(0.05)	(0.55)	(0.00)
Post-publication (Early)	0.75	0.29	0.16	0.39	0.07	0.13	-0.09	0.42
- In-sample	(0.04)	(0.03)	(0.49)	(0.20)	(0.69)	(0.03)	(0.42)	(0.00)

Table 5
Trading and Returns in Ex-ante and Ex-post Portfolios

This table presents the average institutional trading and risk-adjusted returns in the ex-post and ex-ante portfolios, and the difference between ex-post and ex-ante portfolios. Ex-ante portfolio is based on the anomalies that have not been published yet. Ex-post portfolio is constructed using the anomalies that are already published. Every June (for the annual ranking) or every quarter (for the quarterly ranking) we assign a percentile rank to each stock based on each anomaly and compute the equal-weighted average rank for ex-ante and ex-post anomalies. We drop a stock if more than half the anomaly variables are missing. We rank the stocks again based on the average rank and the top and bottom quintiles form the long and short portfolios, respectively. Panel A presents results based on annual rankings and Panel B presents results based on quarterly rankings. We present institutional trading in the ex-ante and ex-post portfolios for all institutions and separately for hedge funds (HF), mutual funds (MF), and transient institutions. Institutional trading is measured by the three-quarter (two-quarter) change in the fraction of a company's stock that is owned by institutional investors in the long portfolio minus the change in the short portfolio starting from the quarter before ranking date for the annual (quarterly) rankings. The portfolio returns are DGTW-adjusted returns computed over the following quarter (four quarters) after sorting date for the quarterly (annual) ranking. Newey-West standard errors are calculated and p-values are reported below the coefficient estimates.

Panel A: Annual Trading and Returns

	All	HF	MF	Transient	Return
Ex-post portfolio	1.03	0.66	0.52	2.33	2.75
	(0.04)	(0.00)	(0.31)	(0.00)	(0.18)
Ex-ante portfolio	-0.04	0.32	0.08	1.12	5.25
	(0.87)	(0.06)	(0.66)	(0.00)	(0.01)
Ex-post minus ex-ante portfolio	1.07	0.34	0.44	1.21	-2.50
	(0.08)	(0.06)	(0.33)	(0.00)	(0.25)

Panel B: Quarterly Trading and Returns

	All	HF	MF	Transient	Return
Ex-post portfolio	-0.05	0.28	-0.20	1.35	1.27
	(0.87)	(0.00)	(0.27)	(0.00)	(0.07)
Ex-ante portfolio	-0.45	-0.06	-0.24	0.27	1.69
	(0.00)	(0.43)	(0.01)	(0.02)	(0.00)
Ex-post minus ex-ante portfolio	0.40	0.34	0.04	1.08	-0.41
	(0.21)	(0.00)	(0.84)	(0.00)	(0.46)

Table 6
VAR: Trading and Returns in Ex-ante and Ex-post Portfolios

This table reports the results of the vector autoregressive (VAR) model which includes annual or quarterly institutional trading and annual or quarterly DGTW-adjusted returns for the long-short leg of the ex-post (Panel A) and ex-ante (Panel B) portfolios. Ex-ante portfolio is based on the anomalies that have not been published yet. Ex-post portfolio is constructed using the anomalies that are already published. Every June (for the annual ranking) or every quarter (for the quarterly ranking) we assign a percentile rank to each stock based on each anomaly and compute the equal-weighted average rank for ex-ante and ex-post anomalies. We drop a stock if more than half the anomaly variables are missing. We rank the stocks again based on the average rank and the top and bottom quintiles form the long and short portfolios, respectively. Institutional trading is measured by the one-year (one-quarter for the annual ranking) change in the fraction of a company's stock that is owned by institutional investors starting from the quarter of the ranking date. The VAR is specified with a one-year (one-quarter) lag based upon the Schwarz Bayesian information criterion. The first four columns present VAR results for trading and returns of the ex-post portfolio and the last four columns present VAR results for the ex-ante portfolio. We present results for all institutions and for the subgroup of traders identified as hedge funds (HF), mutual funds (MF), and transient institutions. The last four columns presents results for the subsample of traders identified as transient. p-values are reported below the coefficient estimates.

Panel A: Ex-post	**Annual**				**Quarterly**			
	All	**HF**	**MF**	**Transient**	**All**	**HF**	**MF**	**Transient**
Return								
Lag Ret	-0.18	-0.27	-0.12	-0.12	0.07	0.16	0.11	0.23
	(0.32)	(0.15)	(0.54)	(0.55)	(0.47)	(0.11)	(0.21)	(0.02)
Lag Trading	-0.02	-0.06	-0.02	-0.02	-0.01	-0.04	-0.03	-0.03
	(0.02)	(0.03)	(0.11)	(0.26)	(0.00)	(0.01)	(0.00)	(0.00)
Constant	0.21	0.26	0.19	0.22	0.01	0.01	0.00	0.02
	(0.00)	(0.00)	(0.00)	(0.00)	(0.27)	(0.05)	(0.64)	(0.01)
Trading								
Lag Ret	1.80	-1.06	-1.09	-2.54	-2.66	0.50	-1.59	-0.07
	(0.72)	(0.43)	(0.80)	(0.37)	(0.41)	(0.50)	(0.40)	(0.96)
Lag Trading	-0.09	-0.05	0.19	0.08	0.17	0.23	0.12	0.14
	(0.66)	(0.80)	(0.38)	(0.70)	(0.11)	(0.02)	(0.26)	(0.19)
Constant	0.04	0.88	0.21	2.47	-0.34	0.01	-0.30	0.21
	(0.97)	(0.01)	(0.80)	(0.00)	(0.10)	(0.79)	(0.02)	(0.03)

Panel B: Ex-Ante	Annual				Quarterly			
	All	HF	MF	Transient	All	HF	MF	Transient
Return								
Lag Ret	-0.03	-0.01	-0.08	-0.18	0.15	0.12	0.14	0.10
	(0.90)	(0.95)	(0.74)	(0.46)	(0.15)	(0.23)	(0.17)	(0.40)
Lag Trading	-0.01	0.00	0.02	0.03	0.01	0.02	0.01	0.01
	(0.56)	(0.89)	(0.30)	(0.11)	(0.34)	(0.04)	(0.44)	(0.26)
Constant	0.11	0.12	0.13	0.11	0.02	0.02	0.02	0.02
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)
Trading								
Lag Ret	4.54	-1.18	0.49	0.31	2.23	1.05	2.43	3.16
	(0.29)	(0.61)	(0.84)	(0.93)	(0.29)	(0.26)	(0.07)	(0.03)
Lag Trading	0.03	0.27	0.38	0.09	-0.07	0.09	-0.07	0.02
	(0.90)	(0.20)	(0.06)	(0.70)	(0.48)	(0.39)	(0.50)	(0.85)
Constant	-1.14	0.27	-0.23	0.81	-0.45	-0.08	-0.24	-0.08
	(0.06)	(0.42)	(0.52)	(0.05)	(0.00)	(0.11)	(0.00)	(0.27)

Table 7
Trading in Ex-ante and Ex-post Portfolios with Controls

This table reports the results of Fama-MacBeth regressions of institutional trading on dummy variables that identify stocks in the ex-ante and ex-post vs. long and short portfolios together with a test on the difference of selected coefficients. Ex-ante portfolio is based on the anomalies that have not been published yet. Ex-post portfolio is constructed using the anomalies that are already published. Every June (for the annual ranking) or every quarter (for the quarterly ranking) we assign a percentile rank to each stock based on each anomaly and compute the equal-weighted average rank for ex-ante and ex-post anomalies. We drop a stock if more than half the anomaly variables are missing. We rank the stocks again based on the average rank and the top and bottom quintiles form the long and short portfolios, respectively. Stocks from all the quintiles are used in the regressions. The dependent variable in the regressions is institutional trading for each stock in the sample. Institutional trading is measured by the three- (two-) quarter change in institutional holdings starting from two quarters (one quarter) before ranking date in the annual (quarterly) anomalies. We use the following control variables, which are measured at the beginning of the trading window: log of book-to-market, six-month cumulative stock returns, average quarterly Amihud (2002) illiquidity measure, and log of market capitalization of the specified stock. We present results for all institutions and for the subgroup of traders identified as hedge funds (HF), mutual funds (MF), and transient institutions. Newey-West standard errors are calculated and p-values are reported below the coefficient estimates.

	Annual				**Quarterly**			
	All	**HF**	**MF**	**Transient**	**All**	**HF**	**MF**	**Transient**
Constant	6.92	2.48	3.96	5.45	4.76	1.88	2.25	3.29
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Ex-post long (a)	0.73	0.37	0.10	1.21	0.60	0.22	0.14	0.97
	(0.00)	(0.00)	(0.37)	(0.00)	(0.00)	(0.00)	(0.02)	(0.00)
Ex-post short (b)	-1.91	-0.49	-1.01	-1.80	-0.95	-0.27	-0.49	-0.98
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Ex-ante long (c)	0.48	0.17	0.27	0.66	0.14	0.08	0.05	0.28
	(0.00)	(0.01)	(0.00)	(0.00)	(0.02)	(0.01)	(0.24)	(0.00)
Ex-ante short (d)	-0.53	-0.22	-0.27	-0.52	-0.02	-0.07	-0.01	-0.12
	(0.01)	(0.01)	(0.04)	(0.01)	(0.83)	(0.12)	(0.82)	(0.09)
BM	-0.32	-0.06	-0.10	0.09	-0.26	-0.05	-0.11	0.02
	(0.00)	(0.12)	(0.06)	(0.19)	(0.00)	(0.00)	(0.00)	(0.45)
Illiquidity	-0.35	-0.12	-0.18	-0.17	-0.23	-0.10	-0.09	-0.13
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Momentum	0.34	-0.02	0.12	-0.25	0.36	-0.02	0.12	-0.16
	(0.01)	(0.74)	(0.02)	(0.00)	(0.00)	(0.48)	(0.00)	(0.00)
Size	-0.68	-0.25	-0.36	-0.68	-0.51	-0.20	-0.23	-0.41
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
a-c	0.25	0.20	-0.17	0.54	0.46	0.14	0.09	0.69
	(0.20)	(0.01)	(0.16)	(0.01)	(0.00)	(0.00)	(0.16)	(0.00)
b-d	-1.38	-0.28	-0.73	-1.27	-0.93	-0.20	-0.48	-0.86
	(0.00)	(0.06)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
(a-c)-(b-d)	1.64	0.47	0.56	1.82	1.39	0.34	0.57	1.55
	(0.00)	(0.00)	(0.09)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)

Internet Appendix

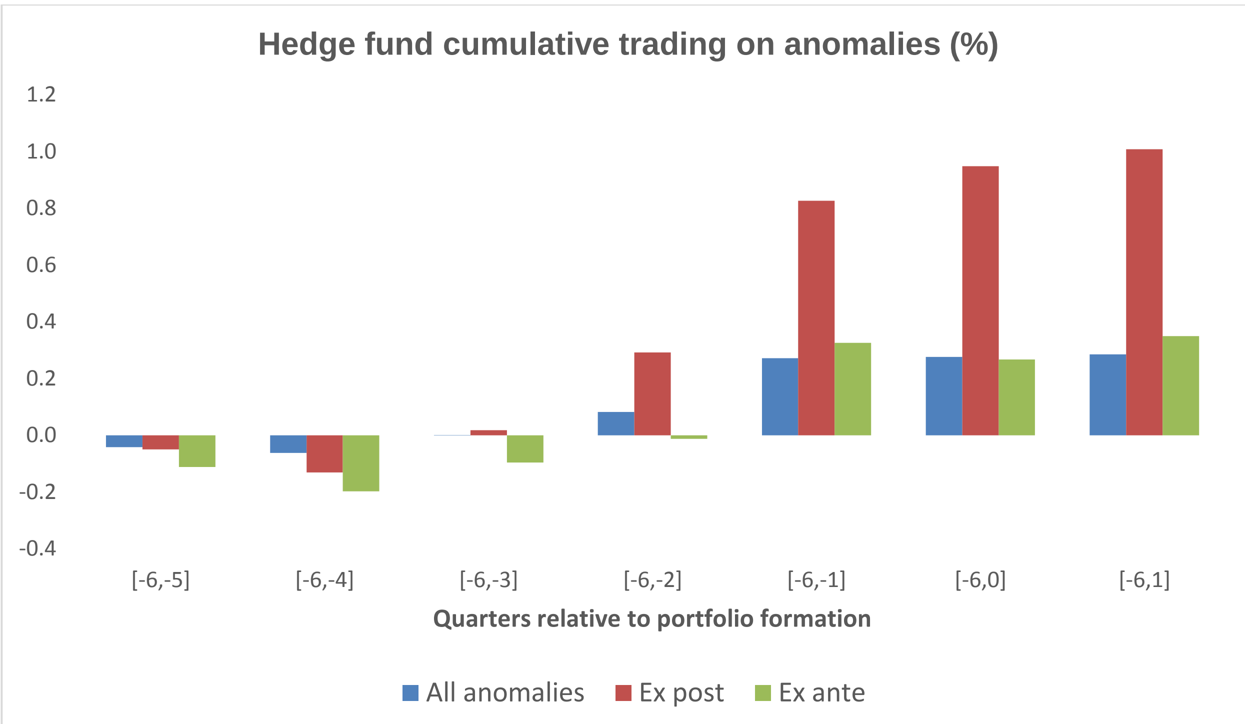
to accompany

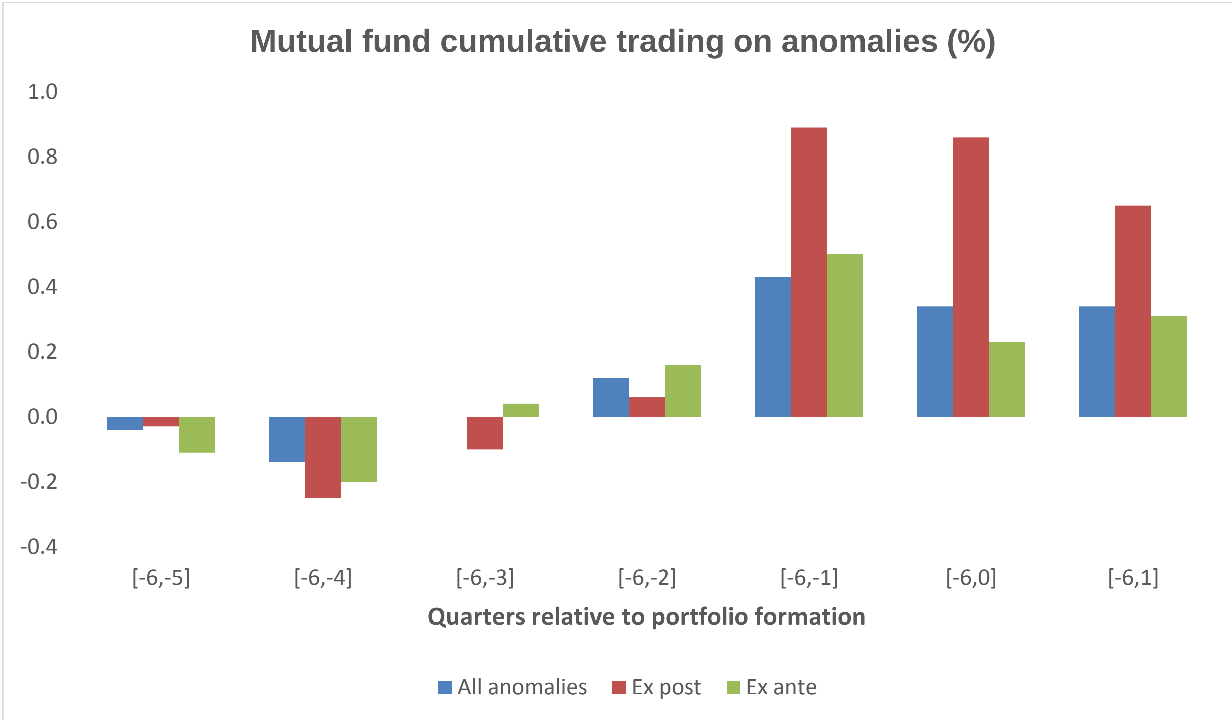
When Anomalies Are Publicized Broadly, Do Institutions Trade Accordingly?

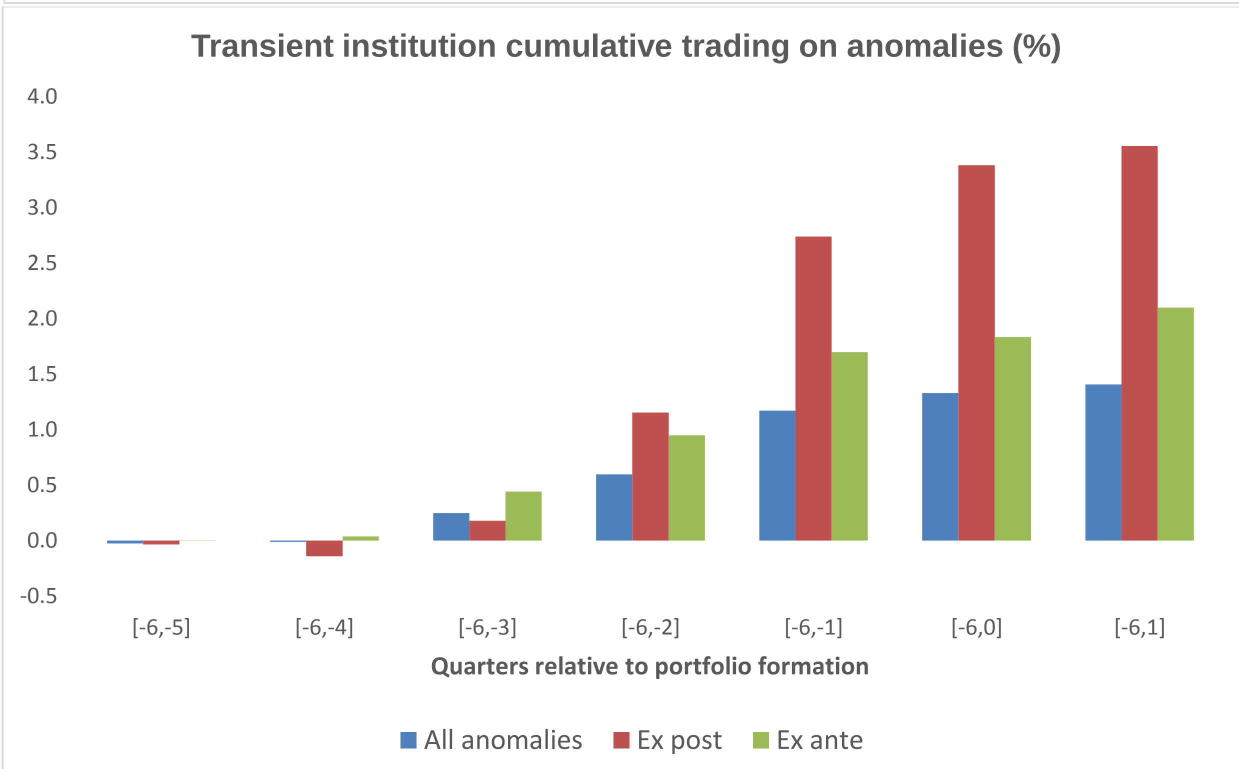
Appendix Figure 1

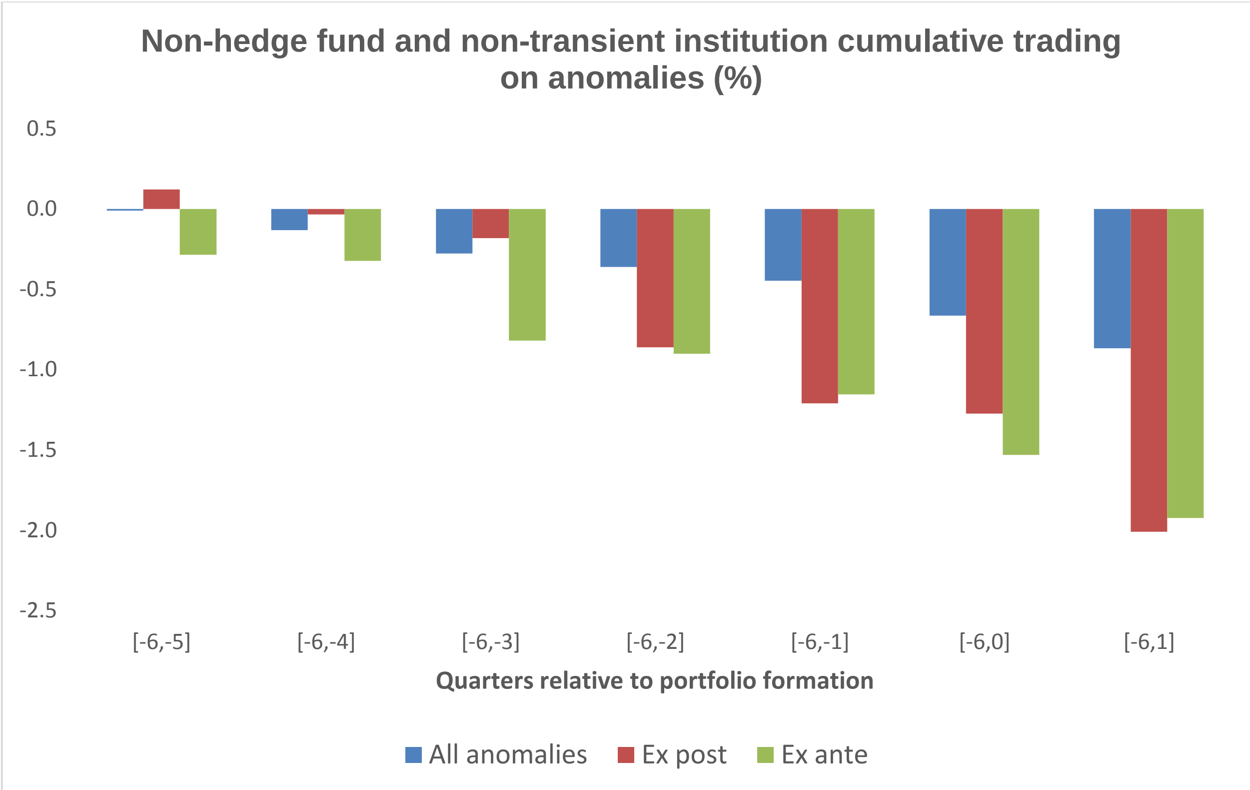
Institutional Trading with a Longer Window: Institutional Subgroups

This figure plots the average cumulative changes in ownership for hedge funds (first chart), mutual funds (second chart), transient institutions (third chart), and non-hedge fund and non-transient institutions (fourth chart) for the difference between the long and the short portfolios. The long portfolio contains underpriced securities that should be bought and the short portfolio includes overpriced securities that should be sold (short). Every June we sort stocks into quintiles according to the anomaly variables and measure the changes in percentage of shares outstanding held by all institutions, hedge funds, and transient institutions in the long and short portfolios. We take the average across the 14 anomalies and we cumulate this average over time. We also compute institutional trading in the ex-post and ex-ante portfolios. Ex-ante portfolio is based on the anomalies that have not been published yet. Ex-post portfolio is constructed using the anomalies that are already published. We assign a percentile rank to each stock based on each anomaly and compute the equal-weighted average rank for ex-ante and ex-post anomalies. We drop a stock if more than half the anomaly variables are missing. We rank the stocks again based on the average rank and the top and bottom quintiles form the long and short portfolios, respectively. We measure trading starting six quarters before ranking date ([-6, -5]) and cumulate it up to one quarter after sorting date ([-6, 1]).




Mutual fund cumulative trading on anomalies (%)
1.0
0.8
0.6
0.4
0.2
0.0
-0.2
-0.4
[-6,-5]
[-6,-4]
[-6,-3]
[-6,-2]
[-6,-1]
[-6,0]
[-6,1]
Quarters relative to portfolio formation
All anomalies
Ex post
Ex ante

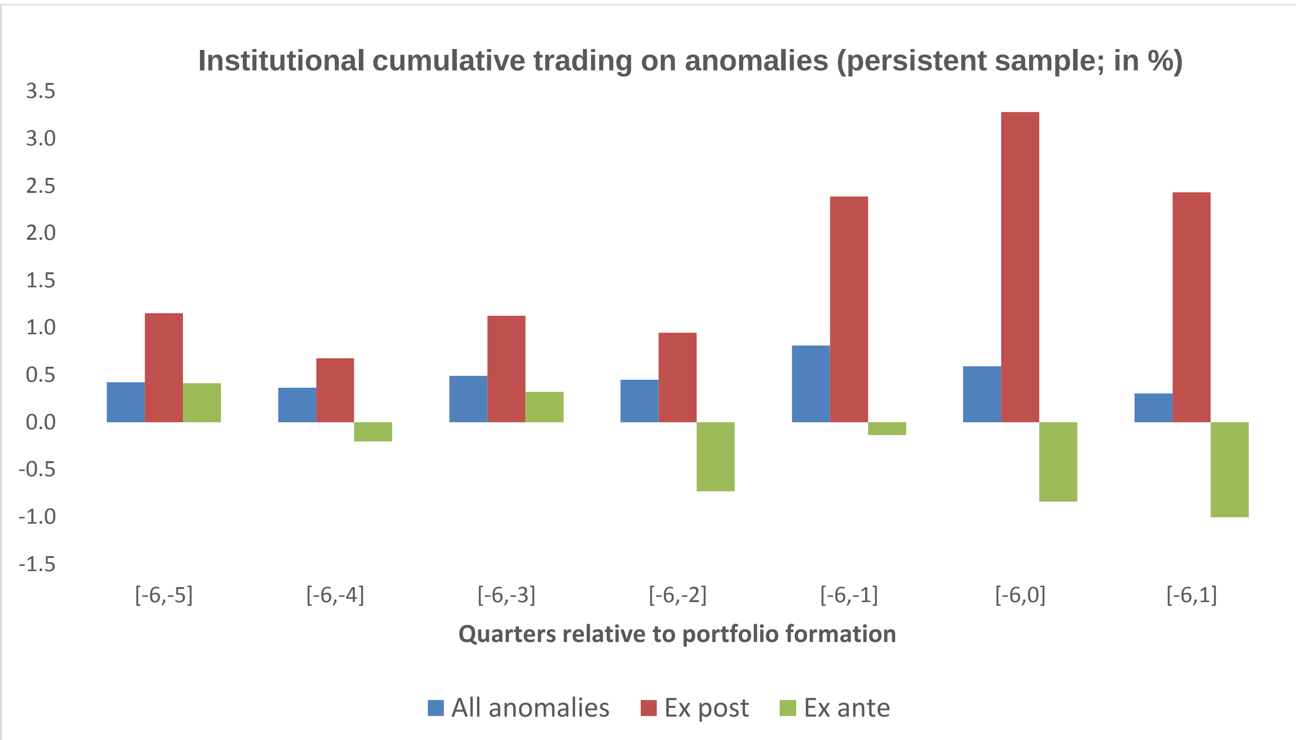

Transient institution cumulative trading on anomalies (%)
4.0
3.5
3.0
2.5
2.0
1.5
1.0
0.5
0.0
-0.5
[-6,-5]
[-6,-4]
[-6,-3]
[-6,-2]
[-6,-1]
[-6,0]
[-6,1]
Quarters relative to portfolio formation
All anomalies
Ex post
Ex ante



Non-hedge fund and non-transient institution cumulative trading on anomalies (%)
0.5
0.0
-0.5
-1.0
-1.5
-2.0
-2.5
[-6,-5]
[-6,-4]
[-6,-3]
[-6,-2]
[-6,-1]
[-6,0]
[-6,1]
Quarters relative to portfolio formation
All anomalies
Ex post
Ex ante

Appendix Figure 2
Institutional Trading: Persistent Anomaly Sample

This figure plots the average cumulative changes in institutional ownership for the difference between the long and the short portfolios for the subset of stocks—persistent sample—that are in the long or short portfolio both this year and past year. The long portfolio contains underpriced securities that should be bought and the short portfolio includes overpriced securities that should be sold (short). Every June we sort stocks into quintiles according to the anomaly variables and measure the changes in percentage of shares outstanding held by all institutions in the long and short portfolios. We take the average across the 14 anomalies and we cumulate this average over time. We also compute institutional trading in the ex-post and ex-ante portfolios. Ex-ante portfolio is based on the anomalies that have not been published yet. Ex-post portfolio is constructed using the anomalies that are already published. Every June we assign a percentile rank to each stock based on each anomaly and compute the equal-weighted average rank for ex-ante and ex-post anomalies. We drop a stock if more than half the anomaly variables are missing. We rank the stocks again based on the average rank and the top and bottom quintiles form the long and short portfolios, respectively. We measure trading starting six quarters before ranking date ([-6, -5]) and cumulate it up to one quarter after sorting date ([-6, 1]).



Appendix Table 1

This table reports the difference between trading of institutional investors in the post-publication (early) period and the in-sample period separately for all the 14 anomalies. The unit of measure is the variable 'Long minus Short', which measures the difference between the aggregate institutional holdings changes in the long and short legs of each anomaly. Institutional holdings (expressed in percent) are measured by the percentage of shares held by institutions in the long and short portfolios. Institutional trading is measured by the three- (two-) quarter change in institutional holdings starting from two quarters (one quarter) before ranking date in the annual (quarterly) anomalies. Observations are pooled across the anomalies. The first four columns present average trading across the full sample period in the anomalies sorted once a year and the last four columns present average trading in the anomalies sorted every quarter. We present results for all institutions and for the subgroup of traders identified as hedge funds (HF), mutual funds (MF), and transient institutions. Robust standard errors are calculated and p-values are reported below the coefficient estimates.

	Annual				**Quarterly**			
Anomaly	**All**	**HF**	**MF**	**Transient**	**All**	**HF**	**MF**	**Transient**
<u>Low Correlation</u>								
Net Stock Issues	0.17	0.24	0.08	0.61	-0.23	0.23	0.24	0.62
	(0.82)	(0.48)	(0.90)	(0.42)	(0.55)	(0.09)	(0.40)	(0.04)
Total accruals	3.04	0.59	1.26	1.75	0.13	0.14	0.05	1.27
	(0.07)	(0.01)	(0.04)	(0.00)	(0.83)	(0.47)	(0.89)	(0.01)
Net Operating Assets	0.82	0.30	-0.28	-0.94	-0.24	-0.15	-0.67	-0.55
	(0.24)	(0.40)	(0.60)	(0.02)	(0.44)	(0.28)	(0.00)	(0.00)
Gross Profitability	0.74	-0.25	1.18	-0.08	1.03	0.20	1.04	0.40
	(0.01)	(0.01)	(0.00)	(0.65)	(0.00)	(0.18)	(0.00)	(0.03)
Capital Investments	-0.16	0.17	-0.74	-1.25	-0.31	-0.21	-0.47	-0.61
	(0.84)	(0.38)	(0.28)	(0.03)	(0.55)	(0.16)	(0.14)	(0.01)
Book-to-Market	1.28	0.81	0.75	0.81	0.88	0.31	0.81	0.82
	(0.16)	(0.12)	(0.18)	(0.26)	(0.12)	(0.07)	(0.01)	(0.00)
Momentum	3.66	1.04	2.77	4.69	1.94	0.51	0.90	2.60
	(0.00)	(0.04)	(0.01)	(0.00)	(0.00)	(0.01)	(0.10)	(0.00)
Ohlson O-Score	-1.35	-0.68	-0.69	0.15	-2.39	-0.85	-1.51	-1.26
	(0.48)	(0.21)	(0.54)	(0.78)	(0.02)	(0.00)	(0.02)	(0.09)
Post-Earnings Announcement Drift	0.33	0.12	0.51	0.17	0.81	0.19	0.49	0.74
	(0.74)	(0.66)	(0.26)	(0.71)	(0.07)	(0.14)	(0.03)	(0.00)
<u>High Correlation</u>								
Composite Equity Issues	0.90	0.60	-0.23	0.11	0.11	0.55	-0.38	0.18
	(0.25)	(0.02)	(0.74)	(0.82)	(0.75)	(0.00)	(0.14)	(0.51)
Asset Growth	-0.63	0.29	-0.75	-0.23	-0.81	0.06	-0.82	-0.17
	(0.07)	(0.36)	(0.09)	(0.53)	(0.08)	(0.67)	(0.01)	(0.35)
Investment-to-Assets	0.80	0.82	-0.16	0.31	-0.71	0.20	-0.77	-0.01
	(0.17)	(0.02)	(0.72)	(0.50)	(0.04)	(0.22)	(0.00)	(0.97)
Distress	-2.52	-0.93	-1.74	-2.21	-0.10	-0.04	0.08	0.11
	(0.06)	(0.03)	(0.07)	(0.00)	(0.83)	(0.77)	(0.84)	(0.64)
Return on Assets	1.07	0.18	0.35	-0.18	-0.06	0.21	-0.24	0.26
	(0.19)	(0.74)	(0.70)	(0.77)	(0.92)	(0.34)	(0.50)	(0.39)

Appendix Table 2
Institutional Trading Using Different Windows

This table reports institutional trading for the difference between the long and the short portfolios for all anomaly stocks (Panel A) and for the subset of stocks—persistent sample—that are in the long or short portfolio both this year and past year (Panel B). The long portfolio contains underpriced securities that should be bought and the short portfolio includes overpriced securities that should be sold (short). Every June we sort stocks into quintiles according to the anomaly variables and measure institutional trading for all stocks in the long and short portfolios. We measure trading with the value-weighted average of the stocks in the long (short) portfolio. We take the average of long-short across the 14 anomalies and we cumulate this average over time. We also compute institutional trading in the ex-post and ex-ante portfolios. Ex-ante portfolio is based on the anomalies that have not been published yet. Ex-post portfolio is constructed using the anomalies that are already published. We assign a percentile rank to each stock based on each anomaly and compute the equal-weighted average rank for ex-ante and ex-post anomalies. We drop a stock if more than half the anomaly variables are missing. We rank the stocks again based on the average rank and the top and bottom quintiles form the long and short portfolios, respectively. We measure trading starting six quarters before ranking date ([-6, -5]) and cumulate it up to one quarter after sorting date ([-6, 1]). We also report the trading window ([-2, 1]) used in the paper. p-values are reported in parentheses.

Panel A: All stocks

Trading interval:		**[-6, -5]**	**[-6, -4]**	**[-6, -3]**	**[-6, -2]**	**[-6, -1]**	**[-6, 0]**	**[-6, 1]**	**[-2, 1]**
Value-weighted	**All anomalies**	-0.02	-0.13	-0.12	0.13	0.63	0.54	0.42	0.14
		(0.79)	(0.37)	(0.42)	(0.40)	(0.00)	(0.01)	(0.02)	(0.22)
	Ex-post	0.11	-0.06	-0.14	0.09	1.37	1.92	1.32	1.03
		(0.70)	(0.88)	(0.77)	(0.86)	(0.04)	(0.06)	(0.09)	(0.04)
	Ex-ante	-0.30	-0.30	-0.47	-0.20	0.36	0.03	-0.08	-0.04
		(0.23)	(0.31)	(0.30)	(0.58)	(0.40)	(0.94)	(0.84)	(0.88)
	Ex-post - ex-ante	0.41	0.24	0.34	0.29	1.01	1.89	1.40	1.07
		(0.25)	(0.59)	(0.62)	(0.65)	(0.19)	(0.08)	(0.10)	(0.08)

Panel B: Persistent sample

Trading interval:		**[-6, -5]**	**[-6, -4]**	**[-6, -3]**	**[-6, -2]**	**[-6, -1]**	**[-6, 0]**	**[-6, 1]**	**[-2, 1]**
Value-weighted	**All anomalies**	0.42	0.37	0.49	0.45	0.81	0.59	0.30	-0.12
		(0.00)	(0.02)	(0.01)	(0.04)	(0.00)	(0.07)	(0.28)	(0.46)
	Ex-post	1.15	0.67	1.12	0.95	2.39	3.28	2.43	1.44
		(0.03)	(0.32)	(0.19)	(0.40)	(0.06)	(0.02)	(0.07)	(0.05)
	Ex-ante	0.41	-0.21	0.32	-0.73	-0.14	-0.84	-1.01	-0.24
		(0.29)	(0.71)	(0.42)	(0.13)	(0.84)	(0.30)	(0.17)	(0.68)
	Ex-post - ex-ante	0.74	0.88	0.80	1.68	2.52	4.12	3.44	1.68
		(0.12)	(0.21)	(0.35)	(0.19)	(0.06)	(0.02)	(0.02)	(0.06)

Appendix Table 3
Institutional Trading Using Different Measures

This table reports institutional trading for the difference between the long and the short portfolios for all anomaly stocks (Panel A) and for the subset of stocks—persistent sample—that are in the long or short portfolio both this year and past year (Panel B). The long portfolio contains underpriced securities that should be bought and the short portfolio includes overpriced securities that should be sold (short). Every June we sort stocks into quintiles according to the anomaly variables and measure institutional trading for all stocks in the long and short portfolios. We use two measures of trading: the change in the number of institutions in the stocks in the long (short) portfolio and the equal-weighted average of the stocks in the long (short) portfolio. Following EIK, we scale the change in the number of institutions by the average number of institutions holding stocks in the same market capitalization decile. We take the average of long-short across the 14 anomalies and we cumulate this average over time. We also compute institutional trading in the ex-post and ex-ante portfolios. Ex-ante portfolio is based on the anomalies that have not been published yet. Ex-post portfolio is constructed using the anomalies that are already published. We assign a percentile rank to each stock based on each anomaly and compute the equal-weighted average rank for ex-ante and ex-post anomalies. We drop a stock if more than half the anomaly variables are missing. We rank the stocks again based on the average rank and the top and bottom quintiles form the long and short portfolios, respectively. We measure trading starting six quarters before ranking date ([-6, -5]) and cumulate it up to one quarter after sorting date ([-6, 1]). We also report the trading window ([-2, 1]) used in the paper. p-values are reported in parentheses.

Panel A: All stocks

Trading interval:		**[-6, -5]**	**[-6, -4]**	**[-6, -3]**	**[-6, -2]**	**[-6, -1]**	**[-6, 0]**	**[-6, 1]**	**[-2, 1]**
Number of institutions	**All anomalies**	-3.44	-6.64	-8.38	-7.76	-4.32	-0.71	1.12	6.99
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.55)	(0.42)	(0.00)
	Ex-post	-7.48	-13.76	-17.90	-16.48	-7.17	3.06	7.82	20.40
		(0.00)	(0.00)	(0.00)	(0.00)	(0.04)	(0.43)	(0.08)	(0.00)
	Ex-ante	-4.95	-8.50	-10.88	-9.39	-4.00	1.11	4.08	10.36
		(0.00)	(0.00)	(0.00)	(0.00)	(0.11)	(0.69)	(0.23)	(0.00)
	Ex-post - ex-ante	-2.53	-5.26	-7.02	-7.09	-3.17	1.95	3.75	10.04
		(0.00)	(0.00)	(0.01)	(0.03)	(0.41)	(0.67)	(0.48)	(0.00)
Equal-weighted	**All anomalies**	-0.49	-0.88	-1.01	-0.90	-0.46	-0.24	-0.11	0.76
		(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.23)	(0.59)	(0.00)
	Ex-post	-1.13	-2.11	-2.57	-2.40	-1.10	-0.24	0.04	2.28
		(0.00)	(0.00)	(0.00)	(0.00)	(0.04)	(0.71)	(0.95)	(0.00)
	Ex-ante	-0.61	-1.12	-1.30	-1.05	-0.21	0.24	0.57	1.52
		(0.00)	(0.00)	(0.00)	(0.01)	(0.60)	(0.57)	(0.23)	(0.00)
	Ex-post - ex-ante	-0.51	-0.99	-1.26	-1.35	-0.89	-0.47	-0.53	0.76
		(0.02)	(0.01)	(0.01)	(0.01)	(0.05)	(0.35)	(0.34)	(0.04)

Panel B: Persistent sample									
Trading interval:		**[-6, -5]**	**[-6, -4]**	**[-6, -3]**	**[-6, -2]**	**[-6, -1]**	**[-6, 0]**	**[-6, 1]**	**[-2, 1]**
Number of institutions	**All anomalies**	0.33	0.93	1.15	3.47	7.06	10.37	12.01	5.83
		(0.26)	(0.12)	(0.15)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
	Ex-post	1.75	5.37	6.45	10.92	19.25	26.75	29.85	14.94
		(0.19)	(0.02)	(0.03)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
	Ex-ante	-0.19	-0.82	-1.51	-0.99	1.19	2.93	3.23	4.73
		(0.81)	(0.58)	(0.47)	(0.67)	(0.66)	(0.34)	(0.28)	(0.00)
	Ex-post - ex-ante	1.95	6.19	7.97	11.91	18.06	23.82	26.62	10.21
		(0.10)	(0.01)	(0.02)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)
Equal-weighted	**All anomalies**	0.04	0.01	0.05	0.22	0.61	0.71	0.89	0.68
		(0.62)	(0.97)	(0.70)	(0.20)	(0.01)	(0.01)	(0.00)	(0.00)
	Ex-post	0.34	0.42	0.32	0.51	1.91	2.55	2.73	2.19
		(0.36)	(0.40)	(0.53)	(0.43)	(0.02)	(0.01)	(0.00)	(0.00)
	Ex-ante	0.19	-0.12	-0.29	-0.24	0.32	0.42	0.61	0.90
		(0.36)	(0.71)	(0.49)	(0.61)	(0.55)	(0.46)	(0.31)	(0.02)
	Ex-post - ex-ante	0.14	0.54	0.61	0.76	1.59	2.13	2.12	1.29
		(0.69)	(0.27)	(0.34)	(0.31)	(0.02)	(0.01)	(0.01)	(0.01)

Appendix Table 4
Trading and Returns in the Long and Short Leg of the Ex-ante and Ex-post Portfolios

This table presents the average institutional trading and risk-adjusted returns in the ex-post and ex-ante portfolios, and the difference between ex-post and ex-ante portfolios separately for the long leg (Panel A) and short leg (Panel B). Ex-ante portfolio is based on the anomalies that have not been published yet. Ex-post portfolio is constructed using the anomalies that are already published. Every June (for the annual ranking) or every quarter (for the quarterly ranking) we assign a percentile rank to each stock based on each anomaly and compute the equal-weighted average rank for ex-ante and ex-post anomalies. We drop a stock if more than half the anomaly variables are missing. We rank the stocks again based on the average rank and the top and bottom quintiles form the long and short portfolios, respectively. We present institutional trading in the ex-ante and ex-post portfolios for all institutions and separately for hedge funds (HF), mutual funds (MF), and transient institutions. Institutional trading is measured by the three-quarter (two-quarter) change in the fraction of a company's stock that is owned by institutional investors in the long and short portfolios starting from the quarter before ranking date for the annual (quarterly) rankings. The portfolio returns are DGTW-adjusted returns computed over the following quarter (four quarters) after sorting date for the quarterly (annual) ranking. Newey-West standard errors are calculated and p-values are reported below the coefficient estimates.

Panel A: Long Leg			**Annual**					**Quarterly**		
	All	**HF**	**MF**	**Transient**	**Return**	**All**	**HF**	**MF**	**Transient**	**Return**
Ex-post portfolio	1.30	0.63	1.01	1.01	0.51	0.59	0.35	0.40	0.79	0.16
	(0.03)	(0.01)	(0.00)	(0.00)	(0.49)	(0.03)	(0.00)	(0.01)	(0.00)	(0.52)
Ex-ante portfolio	1.30	0.59	0.98	0.72	1.63	0.53	0.24	0.33	0.29	0.62
	(0.02)	(0.01)	(0.00)	(0.00)	(0.09)	(0.02)	(0.01)	(0.01)	(0.00)	(0.01)
Ex-post minus ex-ante portfolio	0.00	0.04	0.03	0.28	-1.12	0.05	0.11	0.07	0.50	-0.47
	(0.99)	(0.52)	(0.79)	(0.00)	(0.27)	(0.72)	(0.01)	(0.41)	(0.00)	(0.07)

Panel B: Short Leg			**Annual**					**Quarterly**		
	All	**HF**	**MF**	**Transient**	**Return**	**All**	**HF**	**MF**	**Transient**	**Return**
Ex-post portfolio	0.27	-0.02	0.48	-1.32	-2.24	0.63	0.07	0.60	-0.56	-1.12
	(0.69)	(0.93)	(0.35)	(0.00)	(0.24)	(0.04)	(0.57)	(0.00)	(0.00)	(0.05)
Ex-ante portfolio	1.35	0.27	0.89	-0.39	-3.62	0.98	0.30	0.58	0.02	-1.07
	(0.03)	(0.31)	(0.00)	(0.16)	(0.01)	(0.00)	(0.01)	(0.00)	(0.91)	(0.01)
Ex-post minus ex-ante portfolio	-1.07	-0.30	-0.41	-0.93	1.38	-0.35	-0.23	0.03	-0.58	-0.05
	(0.06)	(0.05)	(0.33)	(0.02)	(0.47)	(0.14)	(0.00)	(0.86)	(0.00)	(0.91)

Appendix Table 5

Institutional Trading on the Anomaly: Anomaly Set Robustness

This table reports the difference between trading of institutional investors in the post-publication (early) period and the in-sample period for three different subsets of the 14 anomalies. The low-correlation sample includes the following nine anomalies: NSI, ACC, NOA, GP, CI, BM, MOM, OS, and PEAD. The Stambaugh et al. (2012) sample includes the following 11 anomalies: NSI, CEI, ACC, NOA, GP, AG, IVA, MOM, DIS, OS, and ROA. The EIK sample include the following six anomalies: NOA, GP, IVA, BM, MOM, and OS. The unit of measure is the variable 'Long minus Short', which measures the difference between the aggregate institutional holdings changes in the long and short legs of each anomaly. Institutional holdings (expressed in percent) are measured by the percentage of shares held by institutions in the long and short portfolios. Institutional trading is measured by the three- (two) quarter change in institutional holdings starting from two quarters (one quarter) before ranking date in the annual (quarterly) anomalies. Observations are pooled across the anomalies. The first four columns present results when the anomalies are sorted once a year and the last four columns present results when the anomalies are sorted every quarter. We present results for all institutions and for the subgroup of traders identified as hedge funds (HF), mutual funds (MF), and transient institutions. Robust standard errors are calculated and p-values are reported below the coefficient estimates.

	Annual				**Quarterly**			
	All	**HF**	**MF**	**Transient**	**All**	**HF**	**MF**	**Transient**
Low-correlation	1.27	0.36	0.59	0.96	0.27	0.08	0.09	0.61
	(0.01)	(0.04)	(0.06)	(0.03)	(0.25)	(0.31)	(0.56)	(0.00)
Stambaugh et al. (2012)	0.73	0.25	0.18	0.52	-0.10	0.12	-0.21	0.43
	(0.10)	(0.11)	(0.55)	(0.18)	(0.61)	(0.09)	(0.12)	(0.01)
EIK	1.46	0.48	0.72	1.27	0.11	0.06	-0.08	0.53
	(0.03)	(0.06)	(0.09)	(0.05)	(0.74)	(0.55)	(0.70)	(0.05)

Appendix Table 6

Institutional Trading on the Anomaly: Additional Robustness

This table reports the difference between trading of institutional investors in the post-publication (early) period and the in-sample period for the 14 anomalies. We consider three robustness checks. First, we use SSRN year instead of publication year when available. Second, we include year and anomaly fixed effects in the panel regression. Third, we consider the non-financial crisis sample where the years 2008 and 2009 are restricted from the sample period. The unit of measure is the variable 'Long minus Short', which measures the difference between the aggregate institutional holdings changes in the long and short legs of each anomaly. Institutional holdings (expressed in percent) are measured by the percentage of shares held by institutions in the long and short portfolios. Institutional trading is measured by the three- (two) quarter change in institutional holdings starting from two quarters (one quarter) before ranking date in the annual (quarterly) anomalies. Observations are pooled across the anomalies. The first four columns present results when the anomalies are sorted once a year and the last four columns present results when the anomalies are sorted every quarter. We present results for all institutions and for the subgroup of traders identified as hedge funds (HF), mutual funds (MF), and transient institutions. Robust standard errors are calculated and p-values are reported below the coefficient estimates.

	Annual				**Quarterly**			
	All	**HF**	**MF**	**Transient**	**All**	**HF**	**MF**	**Transient**
SSRN year	0.78	0.29	0.36	0.39	0.06	0.11	0.01	0.34
	(0.02)	(0.03)	(0.10)	(0.20)	(0.71)	(0.05)	(0.91)	(0.01)
Year & anomaly fixed effects	1.13	0.26	0.73	0.32	0.30	0.11	0.22	0.33
	(0.01)	(0.10)	(0.01)	(0.26)	(0.16)	(0.12)	(0.11)	(0.01)
Non-financial crisis sample	0.80	0.22	0.17	0.46	0.11	0.08	-0.06	0.44
	(0.06)	(0.13)	(0.54)	(0.22)	(0.58)	(0.20)	(0.64)	(0.00)

Appendix Table 7

Trading in Ex-ante and Ex-post Portfolios: Number of Anomalies Robustness

This table presents the average institutional trading in the difference between ex-post and ex-ante portfolios. Ex-ante portfolio is based on the anomalies that have not been published yet. Ex-post portfolio is constructed using the anomalies that are already published. Every June (for the annual ranking) or every quarter (for the quarterly ranking) we assign a percentile rank to each stock based on each anomaly and compute the equal-weighted average rank for ex-ante and ex-post anomalies. We impose a filter that for each date we need more than one, two, or three anomalies to be able to construct the portfolio. We drop a stock if more than half the anomaly variables are missing. We rank the stocks again based on the average rank and the top and bottom quintiles form the long and short portfolios, respectively. We present results for all institutions and for the subgroup of traders identified as hedge funds (HF), mutual funds (MF), and transient institutions. Institutional trading is measured by the three-quarter (two-quarter) change in the fraction of a company's stock that is owned by institutional investors in the long portfolio minus the change in the short portfolio starting from the quarter before ranking date for the annual (quarterly) rankings. The last row provides results of a weighted regression. We use analytic weights and our weighting variable is the minimum number of anomalies in either the ex-ante or the ex-post portfolio. Newey-West standard errors are calculated and p-values are reported below the coefficient estimates.

	Annual				Quarterly			
	All	**HF**	**MF**	**Transient**	**All**	**HF**	**MF**	**Transient**
> 1 Anomaly	1.42	0.22	0.66	1.29	0.56	0.30	0.16	1.18
	(0.09)	(0.36)	(0.32)	(0.03)	(0.21)	(0.01)	(0.57)	(0.00)
> 2 Anomaly	1.62	0.27	0.73	1.47	0.47	0.27	0.12	1.23
	(0.07)	(0.28)	(0.30)	(0.02)	(0.32)	(0.03)	(0.68)	(0.00)
> 3 Anomaly	1.58	0.34	0.78	1.41	0.25	0.27	0.03	1.07
	(0.03)	(0.11)	(0.20)	(0.01)	(0.64)	(0.06)	(0.94)	(0.00)
Weighted regression	1.58	0.34	0.78	1.41	0.36	0.30	0.07	1.09
	(0.03)	(0.11)	(0.20)	(0.01)	(0.44)	(0.01)	(0.81)	(0.00)

Appendix Table 8

VAR: Trading and Returns in the Ex-post Portfolio: Liquidity Robustness

This table reports the results of the vector autoregressive (VAR) model which includes annual or quarterly institutional trading and annual or quarterly DGTW-adjusted returns for the long-short portfolio of the ex-post portfolio, and a measure of liquidity. Ex-post portfolio is constructed using the anomalies that are already published. Every June (for the annual ranking) or every quarter (for the quarterly ranking) we assign a percentile rank to each stock based on each anomaly and compute the equal-weighted average rank for the ex-post anomalies. We drop a stock if more than half the anomaly variables are missing. We rank the stocks again based on the average rank and the top and bottom quintiles form the long and short portfolios, respectively. Institutional trading is measured by the one-year (one-quarter for the annual ranking) change in the fraction of a company's stock that is owned by institutional investors starting from the quarter of the ranking date. The VAR is specified with a one-year (one-quarter) lag based upon the Schwarz Bayesian information criterion. We present results for all institutions and for the subgroup of traders identified as hedge funds (HF), mutual funds (MF), and transient institutions. The measure of liquidity is the Amihud (2002) illiquidity measure. p-values are reported below the coefficient estimates.

	Annual				Quarterly			
	All	**HF**	**MF**	**Transient**	**All**	**HF**	**MF**	**Transient**
Return								
Lag Ret	-0.16	-0.27	-0.11	-0.15	-0.32	-0.25	-0.22	-0.12
	(0.39)	(0.16)	(0.59)	(0.49)	(0.06)	(0.12)	(0.24)	(0.52)
Lag Trading	-0.02	-0.06	-0.02	-0.02	-2.92	-11.95	-3.95	-6.01
	(0.02)	(0.04)	(0.14)	(0.31)	(0.00)	(0.00)	(0.01)	(0.02)
Lag Liquidity	7.66	-1.36	2.21	-8.45	-608.24	-648.83	-1212.80	-1938.14
	(0.71)	(0.95)	(0.92)	(0.69)	(0.71)	(0.68)	(0.51)	(0.30)
Constant	0.19	0.26	0.19	0.24	21.17	22.18	21.46	22.39
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Trading								
Lag Ret	4.12	-1.08	0.97	-2.21	-0.06	-0.02	-0.02	-0.02
	(0.40)	(0.43)	(0.83)	(0.45)	(0.13)	(0.12)	(0.39)	(0.26)
Lag Trading	-0.24	-0.05	0.05	0.06	-0.33	-0.19	-0.28	-0.19
	(0.24)	(0.82)	(0.83)	(0.77)	(0.10)	(0.34)	(0.15)	(0.35)
Lag Liquidity	936.44	-10.14	614.44	109.52	109.57	-41.11	-68.93	-284.86
	(0.08)	(0.94)	(0.19)	(0.70)	(0.79)	(0.70)	(0.76)	(0.06)
Constant	-1.60	0.90	-0.98	2.30	0.11	0.36	0.25	0.88
	(0.22)	(0.02)	(0.41)	(0.00)	(0.92)	(0.21)	(0.68)	(0.02)
Liquidity								
Lag Ret	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	(0.80)	(0.77)	(0.86)	(0.88)	(0.74)	(0.78)	(0.81)	(1.00)
Lag Trading	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	(0.89)	(0.69)	(0.90)	(0.82)	(0.55)	(0.35)	(0.78)	(0.26)
Lag Liquidity	0.72	0.70	0.70	0.71	0.70	0.70	0.71	0.74
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Constant	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	(0.50)	(0.58)	(0.48)	(0.54)	(0.45)	(0.47)	(0.46)	(0.48)