# When Anomalies Are Publicized Broadly, Do Institutions Trade Accordingly?

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Abstract

This paper studies whether institutional investors trade on 14 well-documented stock market anomalies. We show that there is 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 institutions with high turnover, the subset of investors who likely have the abilities and incentives to act on the anomalies. We directly relate the increase in trading to the observed decay in post-publication anomaly returns. Our results support the role of institutional investors in the arbitrage process and in improving market efficiency.

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## 1. Introduction

Finance and accounting literature has documented more than 300 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 decay 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.[2] There is some recent support for both statistical biases (Harvey et al., 2016, Linnainmaa and Roberts, 2016, and Hou et al. 2017) and mispricing (Engelberg et al., 2016). However, even if mispricing drives the anomalies, it is still unclear who corrects prices.

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 this recent evidence, we show 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 anomaly has been publicized through academic publication; 2) if the accounting data necessary to compute the anomaly rankings have been released; and 3) if there is heterogeneity among institutions with respect to information

[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).

[2] McLean and Pontiff (2016) compare the decay in anomaly returns out-of-sample but before publication, to the decay after publication, to distinguish between the effect of statistical biases and informed trading. Their findings provide support for both explanations.

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 determine institutions' role as arbitrageurs.

Financial media and industry-oriented journals have long disseminated academic research to practitioners and some institutions have strong academic ties, which suggests that at least some practitioners condition their trading strategies on published academic findings. For example, Dimensional Fund Advisors (DFA) employs a group of 'academic leaders', including three Nobel laureates and several other top academic scholars. On their website, they emphasize "bringing research to the real world" using stock selection screens based on academic research.[3] Another institution with academic ties is AQR Capital Management. They sponsor an annual $100,000 award "honoring unpublished papers that provide the most significant investment insights and most innovative approaches to the real-world challenges that investors face." However, given the scant empirical evidence of institutional investors actually trading on published research, it is possible that DFA and AQR are exceptions to the norm. Therefore, we study the trading behavior of institutional investors in 14 anomalies to determine if they exploit the anomalies and help bring stock prices closer to efficient levels. Our set of anomalies was chosen to be consistent with previous papers on anomaly research (Chen et al., 2011, Stambaugh et al. 2012, and EIK). These anomalies are prime candidates for institutional trading as they produce risk-adjusted alpha in the original sample, are all published in prestigious academic journals, and are highly cited.

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

[3] In Internet Appendix Figure 1 we include a snapshot from DFA's website publicizing a timeline of their effort to incorporate research into their trading strategies, including value (book-to-market) and profitability which are two of the anomalies we study.

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 that contributes to the subsequent attenuation of the anomaly profits.

To test our hypothesis, each year we rank stocks according to each of our 'anomaly variables' (i.e., the variables that have been shown to predict future stock returns) and build long and short portfolios using the top and bottom quintiles. We measure 'anomaly trading' by institutions by computing the change in the percentage of the long and short portfolios held by institutions separately and taking the difference between the two. The change is computed during a 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 and trade on the documented anomalies. Given that 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. We examine the trading activity and returns associated with these portfolios, and 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.

In addition to examining the full set of institutions, we also consider anomaly-based trading by different institution types as there may be heterogeneity in the incentives they 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. Existing literature provides some support for this prediction. Akbas et al. (2015) find that hedge fund flows attenuate anomalies and Ke and Ramalingegowda (2005) document that institutions with high portfolio turnover—*transient institutions*—are active in exploiting the post-earnings announcement drift anomaly. We therefore examine trading among hedge funds and transient institutions as they may be better positioned to take advantage of the anomalies. We also examine trading by mutual funds as they are the largest institutional subgroup. Given the mixed evidence on whether they constitute 'smart money' or 'dumb money' (e.g., Berk and Van Binsbergen, 2015, and Akbas et al., 2015), we expect their anomaly trading to be weaker than that of hedge funds and transient institutions.

Our results verify that trading on anomalies 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 anomalies. However, this result is driven by trading in the period before publication. Figure 1 provides a graphical representation of our main finding by plotting anomaly trading relative to publication date. Just before publication, there is a shift toward exploiting the anomalies that continues several years after publication. We verify the significance of this result using a regression model that includes time fixed effects to control for changes in institutional ownership over our sample period. 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 also find evidence, albeit weaker, that mutual funds trade on the anomalies, which is more consistent with them being 'smart money'.

We next examine anomaly trading and returns in the ex-post and ex-ante portfolios. Consistent with institutions trading on anomalies after publication, anomaly trading is larger in the ex-post portfolio, especially among hedge funds and transient institutions. We then perform Granger-causality tests and find a negative relation between lagged trading and returns in the ex-post portfolio. However, consistent with trading levels being too low before publication to impact returns, we do not observe a significant relation between lagged trading and returns in the ex-ante portfolio. These results provide an explanation for the post-publication decay: institutional trading and anomaly publication are part of the arbitrage process, which helps bring prices to a more efficient level.

We also examine anomaly trading at the individual stock level in the ex-ante and ex-post portfolios using Fama-MacBeth and panel regressions. This approach allows us to control for common determinants of institutional trading and provides an additional test of our prediction that anomaly trading increases after publication. We find consistent results, anomaly trading is significantly larger in stocks in the ex-post portfolio relative to stocks in the ex-ante portfolio. To provide further support for the arbitrage process and the reduction in anomaly profits after publication, we focus on the subgroup of anomaly stocks that are actually traded by institutions. We find that institutions are able to select stocks that deliver superior future performance, and this performance is reduced in the ex-post portfolio. This result also suggests that exploiting anomalies could be an important source of profits for institutional investors.

We conduct a series of tests to ensure the robustness of our results. First, we separately examine trading in the long and short legs of the anomaly portfolios, and find evidence of increased trading after publication in both legs. Second, we focus on a subset of the anomalies where we expect the increase in trading around publication to be the largest. We find that more distinct anomalies (i.e., those that have low correlations with already documented anomalies) exhibit a larger increase in trading around publication. Finally, we find that our main results are robust to various alternative specifications including: focusing on various subsets of our anomalies to address concerns about the selection process; measuring anomaly trading using quarterly rankings instead of annual rankings; using SSRN posting dates instead of publication dates; clustering standard error on time in our trading regressions; using different definitions to construct the ex-ante and ex-post portfolios; 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 and find no evidence of anomaly-based trading by institutions in these settings.[4] 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 even after academic publication, and may be a source of the contrarian trading documented by EIK.

Our 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 result 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. 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.

We also contribute 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.[5] We find that our results are strongest among hedge funds and transient institutions: they actively trade on the anomalies and correct mispricing. This finding deepens our understanding of the role of these 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

[4] 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. Other differences between EIK and our paper include the length of the trading window and how trading activity is computed. In the results section we examine the impact of these methodological differences on our results.
[5] 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.

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.

## 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 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, and Linnainmaa and Roberts, 2016), simple chance (Fama, 1998), or consideration of an inappropriate significance cutoff that does not take into account multiple tests (Harvey et al., 2016). Second, some papers explain the existence of anomalies as compensation for risk consistent with asset pricing models (e.g., Fama and French, 1996, and Sadka, 2006). Finally, anomalies could be due to mispricing (e.g., Barberis and Thaler, 2003, and Engelberg et al., 2016)) and present investment opportunities.

If statistical biases explain anomalies, we do not expect investors to 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, and 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.

Another relevant strand of literature examines the relation between institutional investors and asset prices. 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 significant excess returns, and some of them appear to be persistent across time (e.g., Jegadeesh and Titman, 2001, Fama and French, 2008), institutional investors could try to trade mispriced securities. Although there is some evidence institutional investors try to exploit individual anomalies, such as momentum (Grinblatt et al., 1995) and the post-earnings-announcement drift (Ke and Ramalingegowda, 2005, Ali et al., 2012), there is limited evidence of institutional investors trying to systematically exploit anomalies, and some evidence that investors contribute to anomalies. For example, institutions tend to buy growth stocks and sell value stocks contributing to the value premium (Chan et al., 2002, Frazzini and Lamont, 2008, and 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). Furthermore, there is evidence that analyst recommendations run contrary to anomaly prescriptions (Engelberg et al., 2017). Institutions trading on these recommendations could exacerbate mispricing.

Lewellen (2011) examines institutional holdings and finds that institutions as a whole do not act as arbitrageurs. 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, whereas Lewellen (2011) aggregates institutions classified as investment companies, investment advisors, and other institutions, we separately examine mutual funds and the most active institutions: hedge funds and transient institutions.

Our paper is also related to Akbas et al. (2015). Using mutual fund flows to proxy for 'dumb money' and hedge funds flows as a proxy for 'smart money', they find that mutual fund flows exacerbate anomaly mispricing, whereas hedge fund flows attenuate mispricing. We complement this paper by providing more direct evidence of the arbitrage activity by institutional investors using trading information rather than flows. Given EIK findings, it remains unclear whether institutions purchase underpriced securities in the long leg when facing inflows and sell overpriced securities in the short leg to meet outflows. Furthermore, we show that it is important to condition on academic publication, as academia may help 'dumb money' become smarter.

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. Johnson and Schwartz (2000) study the post-earnings announcement drift anomaly and Green et al. (2011) examine the accruals anomaly. Similar to McLean and Pontiff (2016), both papers document a decline in anomaly returns following academic publication. As previously mentioned, this observation would be consistent with both statistical biases and academic research attracting the attention of sophisticated investors who correct the mispricing. Neither paper examines institutional trading and without analyzing trading it is hard to tell which interpretation is correct. In contrast, Richardson et al. (2010) present survey evidence that shows practitioners read few published academic papers and pay little attention to working papers. Graham and Harvey (2001) find mixed evidence that executives follow corporate finance literature. They also report that "CFOs pay very little attention to risk factors based on momentum and book-to-market value", although, they find executives with MBAs are more likely to follow research than those without. Together with the findings of EIK, Lewellen (2011), and Engelberg et al. (2017), it is not a foregone conclusion that institutions follow academic research, trade on the anomalies, and contribute to the post-publication decay.

## 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).[6] 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 among the most important ones because, with the exception of book-to-market, they are not explained by the widely used three-factor Fama-French (1993) model and are published in top-tier academic journals.

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.

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.[7] 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). We identify mutual funds as non-hedge fund institutions classified as an investment company or an independent investment advisor by Brian Bushee's website.[8] We also identify transient institutions using the same source. Transient institutions are characterized as having high portfolio turnover.[9] Transient institutions comprise 18.4% of institutional holdings in our sample, hedge funds 15.0%, and mutual funds

[6] The Ohlson O-score was introduced by Ohlson (1980), but the profitability of a strategy based on this measure was shown by Dichev (1998). For this reason we use 1998 as the publication date. Following a similar logic, we choose 1992 as the publication date for book-to-market even though it was initially documented by Stattman (1980).

[7] The TR 13F database does not report short positions. In the robustness section, we examine anomaly trading using short-interest data from Compustat.

[8] 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.

[9] Bushee (2001) uses factor and cluster analysis (rather than a specific level of turnover) to classify institutions based on their expected investment horizon. We estimate the quarterly portfolio turnover of institutions in our sample and find that the average transient institution has a quarterly turnover of 66.8%, while the average quarterly turnover rate for the rest of the sample is 25.0%.

41.5%. Mutual funds and hedge funds are mutually exclusive, whereas there is overlap between transient investors and these institutions.[10]

Table 1 reports the paper that first documented each anomaly, its publication year, and the sample period used. 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. To ensure that the accounting variables necessary to construct anomaly rankings are known to investors, we use accounting data 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 $t$.[11]

### 3.1 Summary Statistics

Table 2 presents correlations among portfolio ranks for our anomalies in addition to the first-order autocorrelation of each anomaly. Consistent with Green et al. (2013), the anomalies are not strongly related to each other. Indeed, the average absolute value across all anomaly pairs is 0.15 with a standard deviation of 0.14, 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 other anomalies may be

[10] Transient institutions are composed of the most active hedge funds (34.1%), mutual funds (58.6%), and other institutions—bank trusts, insurance companies, pension funds, and endowments (7.3%). 41.6% of hedge funds, and 25.9% of mutual funds are transient.

[11] In the original publications, DIS, OS, ROA, and PEAD are constructed on quarterly frequency. For these anomalies we compute annual rankings using accounting data for the fiscal quarter ending in January, February, or March. Further, MOM is constructed each June 30th using 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 a four-month lag. In the robustness section we examine trading on quarterly-ranked anomalies.

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 next compute the performance of each of our 14 anomalies to ensure that we are able to replicate the original profitability of each anomaly and confirm that the post-publication decay documented by McLean and Pontiff (2016) is also present in our sample. Table 3 reports the difference between the performance of the long and short portfolios 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 our sample. Anomaly performance is measured in the four quarters following the ranking date using three-factor alphas and value-weighted portfolio returns in excess of the benchmark of Daniel, Grinblatt, Titman, and Wermers (DGTW, 1997). The alpha is the intercept of a regression of quarterly value-weighted portfolio 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 anomaly three-factor alphas (DGTW-adjusted returns) are all positive and are significant for all (most of) the anomalies.[12] The alpha (DGTW-adjusted return) of a portfolio equally invested in each of the anomalies, is 1.56% (0.95%) per quarter. When we examine anomaly returns in the post-publication period, consistent with McLean and Pontiff (2016), we find a sizable reduction in the anomaly returns. The return of the equally-weighted portfolio decreases by 0.45% (0.31%) per quarter using three-factor alphas (DGTW-adjusted returns).

[12] DGTW benchmarks are available starting from 1971, which prevents us from computing DGTW-adjusted returns for the original in-sample period for many of the anomalies. 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 following analyses, 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

In this section, we examine institutional trading on anomalies. On June 30th of each year (t= 0) we construct long and short portfolios for each anomaly. 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).[13] 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 institutions.

We measure anomaly trading by institutions by computing the change in the percentage of the long and short portfolios held by institutions separately and taking the difference between the two.[14] Specifically, for a given anomaly we calculate the change in the percentage of the long portfolio held by institution type $j$ for the [-2, 1] window as follows:

$$\frac{\sum_i P_{i,1} \times Shares_{i,j,1}}{\sum_i P_{i,1} \times Shrout_{i,1}} - \frac{\sum_i P_{i,-2} \times Shares_{i,j,-2}}{\sum_i P_{i,-2} \times Shrout_{i,-2}} \tag{1}$$

[13] 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 the anomaly rankings, institutions would need the anomaly variable for all, or at least a large number of firms.
[14] To address potential errors in 13F data, if for a given firm the total number of shares held by institutions is greater than the number of shares outstanding, we cap the ratio at 100%. Omitting these observations delivers similar results.

where subscript $i$ refers to any stock in the long portfolio, $P_{i,t}$ is the price for stock $i$ at time $t$, $Shares_{i,j,t}$ is the number of shares of stock $i$ held by institution type $j$ at time $t$ and $Shrout_{i,t}$ is the number of shares outstanding for stock $i$ at time $t$. We calculate the change for the short portfolio in a similar manner. 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. In our sample we find that the bottom 80% of stocks according to market capitalization represents only 10.81% of institutional ownership, and, as discussed by Fama and French (2008), anomaly returns in these stocks may not be realizable due to high trading costs.

*4.1.1 Anomaly Trading in the Full Sample Period*

Table 4 Panel A presents results for tests that examine whether institutions attempt to exploit the anomalies over the full sample period, which spans 1982 to 2013. The first column presents anomaly trading for the full set of institutions. The results suggest that over the full sample period, institutions, in aggregate, do not trade in a manner that exploits the anomalies: the 0.14% anomaly trading has the right sign but is not statistically different from zero. To examine if there is heterogeneity in exploiting anomalies, we focus on the hedge fund, mutual fund, and transient institution subgroups (see columns 2-4). Over the full sample period, the results suggest that hedge funds, mutual funds, and transient institutions trade significantly on the anomalies. For instance, anomaly trading by transient institutions is 0.76%.[15] At first glance it is surprising that each subgroup exhibits significant anomaly trading while the full set of institutions does not. This discrepancy is driven by institutions that are not classified as hedge funds, mutual funds, or transient

[15] The change in ownership for each institutional group is computed as a percentage of market capitalization of the long and short portfolio rather than as a percentage of each group's relative ownership. Our approach biases us against observing large trading magnitudes among the smaller institutional subgroups such as transient institutions and hedge funds, and makes the large magnitudes we observe among these groups more striking.

institutions, trading against the anomalies. In section 4.3, we explore anomaly trading by these other institutions, which are generally perceived as being less sophisticated.

### *4.1.2 Anomaly Level Trading Around the Journal Publication Date*

Next, we examine whether institutional trading on anomalies has changed 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, and it should capture information diffusion about the anomaly before publication, for example through conferences or the Social Science Research Network (SSRN). As a result, some institutions may trade on anomalies during this period. We also consider that arbitrageurs may change their post-publication trading behavior over time. For example, the post-publication return decay may discourage anomaly trading. Therefore, we also examine trading in the first four years of the post-publication period, which we call the post-publication (early) period.[16]

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, anomaly trading should increase around the journal publication date. Table 4 Panel B presents the results of OLS regressions where the dependent variable is again anomaly trading. The independent variables are dummies that identify the in-sample, pre-publication, post-publication (full), and

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

post-publication (early) periods. Because the post-publication (full) and post-publication (early) periods overlap, we estimate their coefficients in two separate regressions as follows:

$$y_{k,t} = B_1 in\text{-}sample_{k,t} + B_2 pre\text{-}publication_{k,t} + B_3 post\text{-}publication(full)_{k,t} + e_{k,t} \quad (2)$$

$$y_{k,t} = B_1 in\text{-}sample_{k,t} + B_2 pre\text{-}publication_{k,t} + B_4 post\text{-}publication(early)_{k,t} + e_{k,t} \quad (3)$$

In both regressions the coefficient estimates are equivalent to computing the mean of trading in each subperiod. Therefore, $B_1$ and $B_2$ are identical in the two equations. Furthermore, we compute heteroscedasticity robust standard errors.

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 the full set of institutions. The results indicate that during the in-sample, pre-publication, and post-publication (full) periods, anomaly trading is not significantly different from zero. However, during the post-publication (early) period, anomaly trading is 0.81% and statistically significant, and from the in-sample to the post-publication (early) period, there is an economically significant increase of 0.74% in anomaly trading. 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 the 0.74% change corresponds to approximately $8.4 billion. This result suggests that institutions, in aggregate, try to exploit the anomalies and that the timing of their trades is related to the journal publication of the anomalies. The finding that institutions trade on the anomalies in the post-publication (early) period, but not in the full post-publication period, is consistent with institutions reducing their trading as the returns of the strategy decay.

Next, we examine anomaly trading by hedge funds, mutual funds, and transient institutions. Compared to the in-sample period, there is a similar spike in anomaly 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, some time before the actual publication date, and supports the perception of hedge funds being sophisticated.

We find that mutual funds trade significantly on the anomalies in the post-publication (early) period but not in the post-publication (full) period. This finding is consistent with mutual fund anomaly trading decreasing as the returns to the anomaly strategies decay. We find more consistent evidence that transient institutions are active in exploiting the anomalies. In fact, they even trade on the anomalies in the in-sample and pre-publication periods. Because mutual funds and transient institutions both trade on anomalies in the in-sample period, 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 for either group.

We are concerned that the increase in institutional trading in anomalies after publication is driven by a general time trend effect rather than publication. For example, the increase in institutional ownership over our sample period could drive our findings. To address this concern, we re-estimate the model with time fixed effects and report the results of this analysis in Table 4 Panel C.[17] We find that after controlling for time fixed effects, the estimate for the change in trading from the in-sample to the post-publication (early) period increases for the full-set of institutions (1.26%), mutual funds (0.67%), and transient institutions (0.73%). The estimates are statistically significant across all four institution groups.

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

[17] Taking the difference between the long and short legs implicitly, although imperfectly, controls for time trends. Because time fixed effects prevent us from estimating the coefficients in each individual sample period, but better control for time trends, we include them in this, and subsequent analyses, where we are only concerned with the difference between the coefficients on the post-publication (early) period and the in-sample period.

heterogeneity among institutional investors, with hedge funds and transient institutions most actively exploiting anomalies.

We have so far 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 cumulative anomaly returns and trading, 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.

**4.2 Portfolio Level Trading and Returns**

Given that sophisticated institutions are likely to trade on multiple anomalies at the same time, we next 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 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 to 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, excluding stock-quarter observations for the ex-post or ex-ante portfolio if more than half the anomaly variables are missing. Then, we rank the stocks again based on the average rank and the top and bottom quintiles comprise the long and short portfolios, respectively.

Table 5 summarizes the trading activity for the ex-post and ex-ante portfolios. Consistent with our earlier pooled results, we observe that trading in the ex-post portfolio is greater than in the ex-ante portfolio for all groups, although the difference is insignificant for mutual funds. This finding implies a spike in trading following publication of the anomalies. Further, we find that hedge funds and transient institutions trade significantly in the ex-ante anomaly portfolio. This result suggests that some sophisticated investors take advantage of the anomalies before publication.

In untabulated analysis we examine the anomaly returns on the two portfolios. We observe a decay from 1.43% per quarter in the ex-ante portfolio to 0.73% in the ex-post portfolio. Although economically large, the 49% relative decrease is not statistically significant which we attribute to the low statistical power of the test (24 observations) coupled with the noisiness of the return process.

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 trading and anomaly returns for the long-short portfolio. We examine trading and returns in the (t= -2 to t= 2) window, where t= 0 is the sorting quarter. Using this window avoids overlaps and gaps between consecutive periods of trading and returns. More specifically, let $y_t$ be a vector that includes trading and returns. We estimate the following system:

$$y_t = c + Ay_{t-1} + e_t \tag{4}$$

The VAR is specified with a one-year lag based on the Schwarz Bayesian information criterion. We also check for non-stationarity with the augmented Dickey-Fuller test and find no evidence. We perform a Granger-causality test by estimating the matrix $A$ of coefficients. If the documented increase in anomaly trading following publication is the result of arbitrage activity, we expect to observe a negative relation between lagged institutional trading and anomaly returns in the ex-post portfolio.[18]

The first four columns of Table 6 present the VAR results for the ex-post portfolio. The coefficients of interest are presented in the second row of the table. Consistent with arbitrage, lagged institutional trading is negatively related to anomaly returns. Despite the relatively short time-series, the coefficients are

[18] To address the concern that an increase in liquidity drives the attenuation of anomaly returns (Chordia et al., 2014), in Internet Appendix Table 1 we estimate a VAR model that includes a liquidity measure in addition to trading and returns. The results suggest that liquidity is not the driver of the post-publication decay in anomaly returns.

significant for the full set of institutions and hedge funds. This result implies a Granger-causal relation between lagged trading and anomaly returns.

The last four columns present VAR results for the ex-ante portfolio. Our earlier findings show that the full set of institutions do not trade on the anomalies prior to publication, suggesting that there is limited arbitrage occurring during this period. Consistent with this result, across all institution types, we do not observe a negative relation between institutional lagged trading and anomaly returns in the ex-ante portfolio. This result suggests that, even though hedge funds and transient institutions trade on the anomalies in the ex-ante portfolio, their activity is not large enough to correct anomaly mispricing.

Overall, these results support our hypothesis that 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.

### 4.3 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 change in holdings with 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 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.

Figure 3 presents results for 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 2, we find some evidence that these investors anticipate the anomaly rankings as there is positive (which we verify as statistically significant) trading over the period (t= -6 to t= -2). For mutual funds the results are weaker, although, as with the full set of institutional investors, they trade on the anomalies over the longer event window (t= -6 to t= 1).

In Internet Appendix Figure 2, 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 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 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. 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 their measure. However, when we examine trading in our 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 arbitrage activity after academic publication, trading in the ex-post set of anomalies is significantly larger than trading in the ex-ante set.[19]

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 window is consistent with the findings of EIK. 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 persistent sample as stocks that remain in the same leg from one year to the next.[20] We show that institutions trade on the anomalies throughout the six-quarter window in the persistent sample using our (Internet Appendix Table 2 Panel B) and EIK's trading measures (Internet Appendix Table 3 Panel B).

### 4.4 Stock-Level Anomaly Trading

Next, we use Fama-MacBeth regressions to test our hypothesis—that anomaly trading increases after publication—at the individual stock level. This approach allows us to control for common determinants of institutional trading (e.g., Gompers and Metrick, 2001, and Blume and Keim, 2017). 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-

[19] EIK also examine trading using equal-weighted change in holdings. In Internet Appendix Table 3, we also report results using this measure. Similar to 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).

[20] 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.

post and ex-ante anomaly portfolios. 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 Amihud's (2002) illiquidity measure, and the log of market capitalization.[21] Institutional trading is the dependent variable and is again measured by the three-quarter change in the fraction of a company's stock that is owned by institutional investors, starting from two quarters before ranking date.

Table 7 presents the results of this analysis. All institution groups trade on the anomalies in the ex-post portfolio, although the coefficient on ex-post long is insignificant for mutual funds. As prescribed by the anomalies, when a stock is in the ex-post long portfolio, institutions buy it; when it is in the ex-post short portfolio, institutions sell it. This result is especially strong for transient institutions. By contrast, the coefficients on the ex-ante dummy variables indicate weaker anomaly trading. To gauge the impact of publication on trading, we test whether the difference between the ex-post and ex-ante coefficients is significant. We find that the ex-post long coefficient is significantly larger than the ex-ante long coefficient for hedge funds and transient institutions, whereas the ex-post short coefficient is significantly smaller than the ex-ante short coefficient for all four institutional groups. In the last row, we also test whether the difference between long and short legs is higher in the ex-post portfolio than in the ex-ante portfolio, and find that it is positive and significant for all four specifications.

For robustness, Internet Appendix Table 4 replicates the above analysis as a panel regression with time fixed effects and standard errors clustered on firm and time. The firm-level clustering is included to control for the fact that institutional trading might be persistent at the stock level. As in the Fama-Macbeth regressions, we find evidence consistent with institutions trading on anomalies after academic publication.

### 4.5 Anomaly Stock Performance Conditional on Institutional Trading

The empirical findings so far provide evidence of arbitrage activity by institutional investors. A related question is whether institutional trading to exploit anomalies is profitable. This question is relevant

[21] Given that momentum and book-to-market are part of our set of anomalies, in untabulated results we run the regressions excluding these two variables from the controls and find that our results are robust.

both because the profitability of the trading strategy is the driver of the arbitrage activity, and because exploiting anomalies could be an important source of profits for institutional investors. To answer it, we examine the individual stocks in the long and short portfolios of each anomaly that are actually traded by institutional investors. This test addresses the concern that institutions could select the worst performing stocks among all the securities in the two portfolios.

We sort stocks into two portfolios conditional on institutional trading: the 'with-anomaly' portfolio, which is long the long-leg stocks institutions buy and short the short-leg stocks institutions sell; and the 'other' portfolio, which is long the non-long-leg stocks institutions buy and short the non-short-leg stocks institutions sell. We do this for both the ex-post and ex-ante anomaly rankings. We then compute the DGTW-adjusted returns for each portfolio over the following year. To avoid overlap between trading and returns, we measure trading from two quarters before ranking date to the ranking date (end of June) and returns during the next four quarters (July to the following June). To mimic the actual returns earned by each group as closely as possible, we weight stocks in each portfolio according to the absolute value of the change in the dollar value of institutional holdings.[22] This approach allows us to determine if the anomaly stocks institutions trade produce abnormal returns. The other portfolio provides a benchmark against which to compare these trades.

The first four columns of Table 8 Panel A presents the risk-adjusted returns of the ex-ante portfolio stocks. The first column shows results for anomaly trading by the full set of institutions, and reports a significantly positive 2.07% abnormal return per quarter for the with-anomaly portfolio. In contrast, trades in the other portfolio earn returns close to zero, and the difference between the two portfolios is statistically significant. These results provide support for the importance of trading in the same direction as the anomalies. Columns two through four present results for trading by hedge funds, mutual funds, and transient institutions. Across all groups we find consistent outperformance of the anomaly stocks institutions trade.

[22] More specifically, for a given stock we compute the change in the fraction of shares held by institutions and multiply this change by the market capitalization of the stock at the beginning of the period. This approach avoids mechanically giving more weight to better performing stocks.

Furthermore, if we compare these results to the returns of the entire ex-ante anomaly portfolio (1.43%), it appears that institutions are able to select high-performing anomaly stocks.

When we examine the ex-post portfolio in the last four columns, consistent with the post-publication decay in anomaly returns, we find that returns are lower than those earned on the ex-ante portfolio. Nonetheless, the same pattern persists, trading in the with-anomaly portfolio is more profitable than trading in the other portfolio. Taken together, these results provide evidence that institutional investors profit when they trade to exploit the anomalies and these profits decay after publication.

Given that some institutions, especially hedge funds and transient institutions, are not likely to hold the portfolio for the whole year, in Table 8 Panel B we examine the performance of the different portfolios using a shorter two-quarter window. We find that the portfolio risk-adjusted returns tend to be higher, in particular for hedge funds and transient institutions. Hedge funds deliver the highest performance (4.02% per quarter) by trading on the anomalies. This result suggests that anomaly trading may play a part in the outperformance of hedge funds documented by past research (e.g., Jagannathan et al., 2010, and Kokkonen and Suominen, 2015).

## 5. Robustness Checks

In this section we present a series of tests to ensure the robustness of our main results. To save space all the results are reported in the Internet Appendix.

### 5.1 Long and Short Leg Results

In the Fama-MacBeth stock-level analysis we consider trading in the long and short legs separately. It appears that after publication there is an increase in trading in both legs characterized by more buying in the long leg and more selling in the short leg. For further robustness, we examine if this finding is still present when we aggregate trading at the anomaly level. We estimate the change in trading from the in-sample to post-publication (early) period using pooled regressions. We present these results in Internet Appendix Table 5, and find evidence that our results are driven by both the long and short legs. For example, for the full set of institutions trading, we find that there is a significant increase (decrease) in trading in the long (short) leg stocks.

**5.2 Anomaly Selection**

Our set of anomalies are chosen to mimic previous papers on anomaly research. 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. To address this concern we replicate our institutional trading result using the 11 anomalies (NSI, CEI, ACC, NOA, GP, AG, IVA, MOM, DIS, OS, and ROA) used by Stambaugh et al. (2012) and the six anomalies (NOA, GP, IVA, BM, MOM, and OS) that overlap with those examined by EIK. For brevity, we focus on the change in trading between the in-sample and post-publication (early) periods. These results are presented in Internet Appendix Table 5. We observe that results for the full set of institutions strengthen both when we use the Stambaugh et al. anomalies (1.52% vs. 1.26% in Table 4 Panel C), and the EIK anomalies (2.34%). These findings give us confidence that our main results hold under alternative selections of the anomalies used.

Another concern is the relatively high cross correlation among some of the anomalies. For example, consider the 0.45 correlation (see Table 2) between NSI (published in 1995) and CEI (published in 2006). There may be cases where traders are trying to exploit 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 this concern we classify anomalies as ‘high-correlation’ or ‘low-correlation’. We create these sets by identifying all anomaly pairs with correlations above 0.40 (where a discontinuity exists in the correlation matrix) 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). We present these results in Internet Appendix Table 5 and find that trading in the low-correlation anomalies is stronger than in the high-correlation anomalies. For example, the increase for the full set of institutions is 1.54% for low-correlation anomalies vs. 0.64% for high-correlation anomalies.

In Internet Appendix Table 6, we report the increase in trading around publication for each of the individual anomalies. It is important to recognize that, at the individual level, the statistical power is greatly reduced. When we examine trading for the full set of institutions we observe an increase in trading around publication for 11 of the 14 anomalies. In this setting, we also observe more consistent results for the low-correlation anomalies. For example, eight out of the nine low-correlation anomalies experience an increase in trading and the two that see the greatest increase in trading after publication, MOM and ACC, are both in this group.

### 5.3 Trading in quarterly-ranked anomalies

Although most of the anomaly papers in our sample construct portfolios annually, it is possible that some investors trade more frequently using the most recent available information. Therefore, we also construct a quarterly version of each anomaly using the most up-to-date data available at the end of each quarter.[23] To account for more frequent trading, we measure anomaly trading by institutions over a shorter two-quarter window that starts one quarter before the ranking date.[24] The results, presented in Internet Appendix Table 5, show that the change in trading from the in-sample to post-publication (early) period is positive and statically significant across all institution groups when we use the quarterly rankings. Although the magnitudes of trading estimates for the annual and quarterly anomalies are not directly comparable because they are based on different window lengths and frequencies, when we compare the different institution groups we find that the results are strongest among transient institutions. This finding is consistent with our prior, as transient institutions exhibit the high levels of turnover required to trade on the quarterly-ranked anomalies.

[23] Specifically, we sort stocks at the end of each calendar quarter using the most up-to-date data at the beginning of each quarter from CRSP and the quarterly Compustat file. This one-quarter gap is intended to ensure the data required to compute the anomaly variables are publicly available. This approach is intended to capture anomaly-based trading strategies that use data obtained from quarterly financial statements (SEC form 10-Q) and more frequent market data. For our quarterly constructed momentum ranking we use the six-month return with a one-month lag.

[24] One concern is that our window may not capture anomaly trading if institutions move in and out of the anomaly stocks within our trading window. In untabulated results we replicate this analysis using a one-quarter window that starts one quarter before the ranking date. We find similar results that mitigates this concern.

As our earlier results suggest that institutions follow academic research in selecting stocks, we next consider that the information transmitted through publication also includes how often the stocks are ranked. Specially, some anomalies are documented as a profitable strategy using annual data, while other anomalies use quarterly or monthly data (MOM, DIS, OS, ROA, and PEAD), and we posit that the frequency at which the anomaly variables are sorted in their initial documentation in the academic literature drives differences in trading in the quarterly-ranked anomalies. We split our sample of anomalies into the nine anomalies originally constructed annually and the five originally constructed more frequently. Consistent with our prediction, we find that the increase in trading around publication in the quarterly-ranked anomalies is larger for the quarterly/monthly documented anomalies compared to the annually documented anomalies across all institution groups.[25]

### 5.4 Additional Concerns

The publication process takes several years and working papers are often made public prior to publication through conferences, seminars, or the internet. Early dissemination draws into question whether the publication year of the anomaly research is the most appropriate date for identifying when the anomaly is first publicized. To address this concern, In Internet Appendix Table 5 we estimate the increase in trading around the SSRN, rather than publication, year when available. We show that anomaly-based trading also increases following SSRN availability. For example, for the full set of institutions, the magnitude of the increase is similar to the increase for when we use the journal publication year, 1.22% vs. 1.26%.

We are also concerned that cross-correlations may bias our standard error estimates. Specifically, institutional trading in different anomalies in a given time period may be correlated. To address this concern,

[25] As the annually-documented anomalies are ranked in June, we expect the difference in trading between the annually- and quarterly-documented anomalies to be driven by trading on the March, September, and December rankings. In an untabulated analysis we find that this is indeed the case. Institutions trade significantly on the annually-documented anomalies in June but not in the other quarters. Conversely, they trade significantly on the quarterly-documented anomalies across all four quarters.

we cluster standard errors on time. In Internet Appendix Table 5 we present the results and find that across all institution types anomaly trading remains statistically significant.

Another concern is that our ex-post and ex-ante portfolio trading results, presented in Table 5, may be biased by the fact that in some years there are only a few anomalies in the ex-post or 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 only one anomaly (PEAD) in the ex-post portfolio and from 2008 to 2012 there is only one anomaly (GP) in the ex-ante portfolio. To address this concern, in Internet Appendix Table 7 we re-estimate the regressions in Table 5, restricting the sample to periods where there are more than one, two, and three anomalies in each of the ex-ante and ex-post portfolios. We also estimate a specification where we weight the regression by the minimum number of anomalies in either the ex-post or ex-ante portfolio each period. For the full set of institutions, the coefficient on the ex-post minus ex-ante portfolio is between 1.42% and 1.62% and statistically significant across the four specifications. These estimates are higher than the 1.07% estimate from Table 5.

A trading strategy that fully exploits the anomalies would buy stocks in the long leg and simultaneously short-sell stocks in the short leg. A concern in our analysis is that the 13F data include only long institutional positions. Although we do not observe institution-level short positions, in previous analyses we examined whether institutions sell existing shares, or do not buy new 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. Similar to Hwang and Liu (2014), we obtain monthly short-interest data from Compustat, starting from January 2000, because many short positions reported by Compustat are missing before 2000. Because the short interest data is at the stock level, we examine whether the stocks in the short portfolio are shorted more than the stocks in the long portfolio around anomaly publication. Every year, we compute the percentage of market capitalization sold short for the long and short legs and compute the change from the previous two quarters to the following quarter for both the ex-post and ex-ante portfolios. Consistent with institutions following academic research and trading on anomalies by shorting relatively more in the short leg than in the long leg, we find that anomaly shorting in the ex-post portfolio is -0.50 (p=0.09). Furthermore, we find that the difference between ex-post and ex-ante portfolios is negative (-0.39) although not significant (p=0.17). These findings suggest that the exclusion of short positions in the TR 13F dataset may lead to an underestimation, rather than overestimation, of the magnitude of anomaly trading.

## 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. Our paper adds 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 anomalies. 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 lagged institutional trading and anomaly returns following academic publication of the anomaly. This result is consistent with the post-publication anomaly decay, documented by McLean and Pontiff (2016), stemming from mispricing that is corrected by arbitrage activity. Our support for the mispricing explanation is relevant to the ongoing replication crisis debate in the anomaly literature (Harvey, 2017, and Hou et al., 2017). Specifically, our paper suggests that there may be limits to replication in the sense that if institutions correct mispricing, one cannot necessarily infer that non-robust results are due to statistical biases.

Our paper has implications for the extent to which academics engage with practitioners and suggest that both parties may gain from more connections. To the extent that academics are concerned with societal benefits, our results show that information transmission from academia to industry can help correct mispricing and contribute to more efficient markets. This result has possible implications for the real economy because efficient prices can help firms make better informed investment and financing decisions (Van Binsbergen and Opp, 2016). From the practitioner's perspective, more engagement with academia has the potential to improve investment performance.

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**Figure 1**

**Cumulative Institutional 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. Every June 30th, we sort stocks into quintiles according to the anomaly variables and measure the change, between the end of December and the end of September, in the percentage of the long and short portfolios held by institutions separately and take the difference between the two. We take the average across the 14 anomalies. Year 0 is the year of publication of the anomaly.

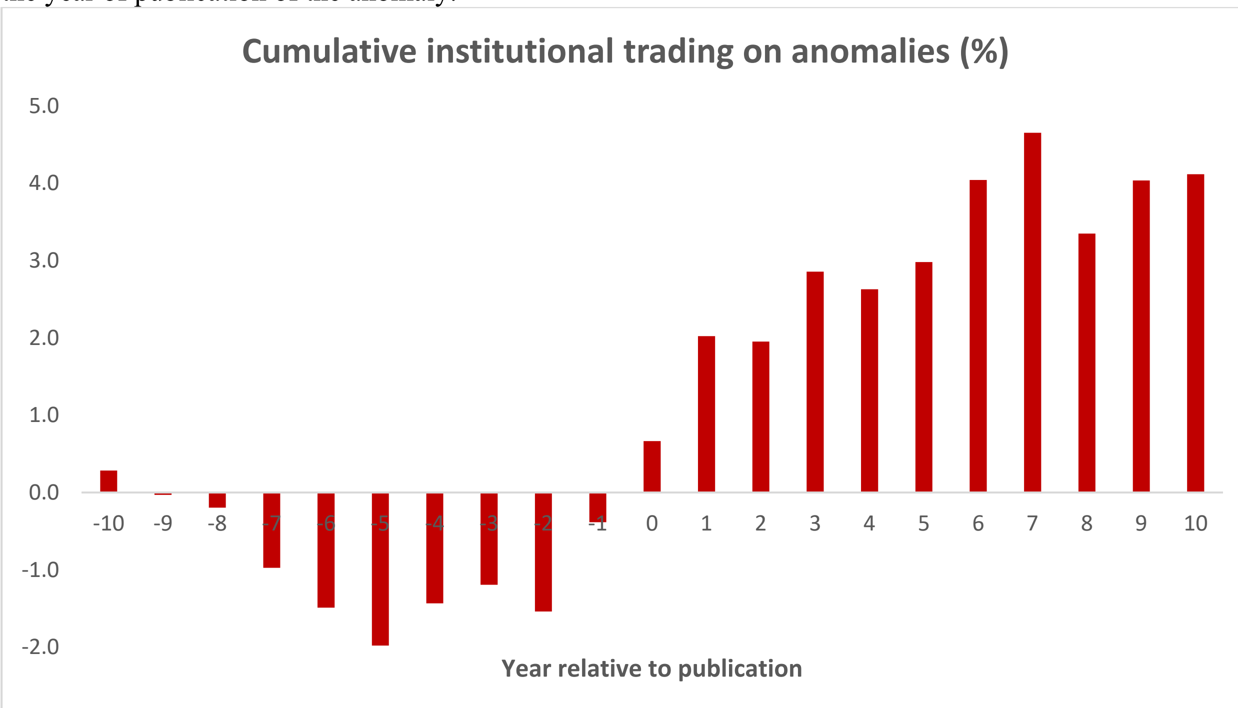


**Figure 2**
**Cumulative Institutional Trading and Anomaly Returns by Periods**

This figure plots the average difference between the cumulative returns and between changes in overall institutional ownership for the long and short portfolios. The long portfolio contains underpriced securities that should be bought and the short portfolio includes overpriced securities that should be sold. Every June 30th, we sort stocks into quintiles according to the anomaly variables. We then compute the cumulative returns and changes in ownership for the difference in 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 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.

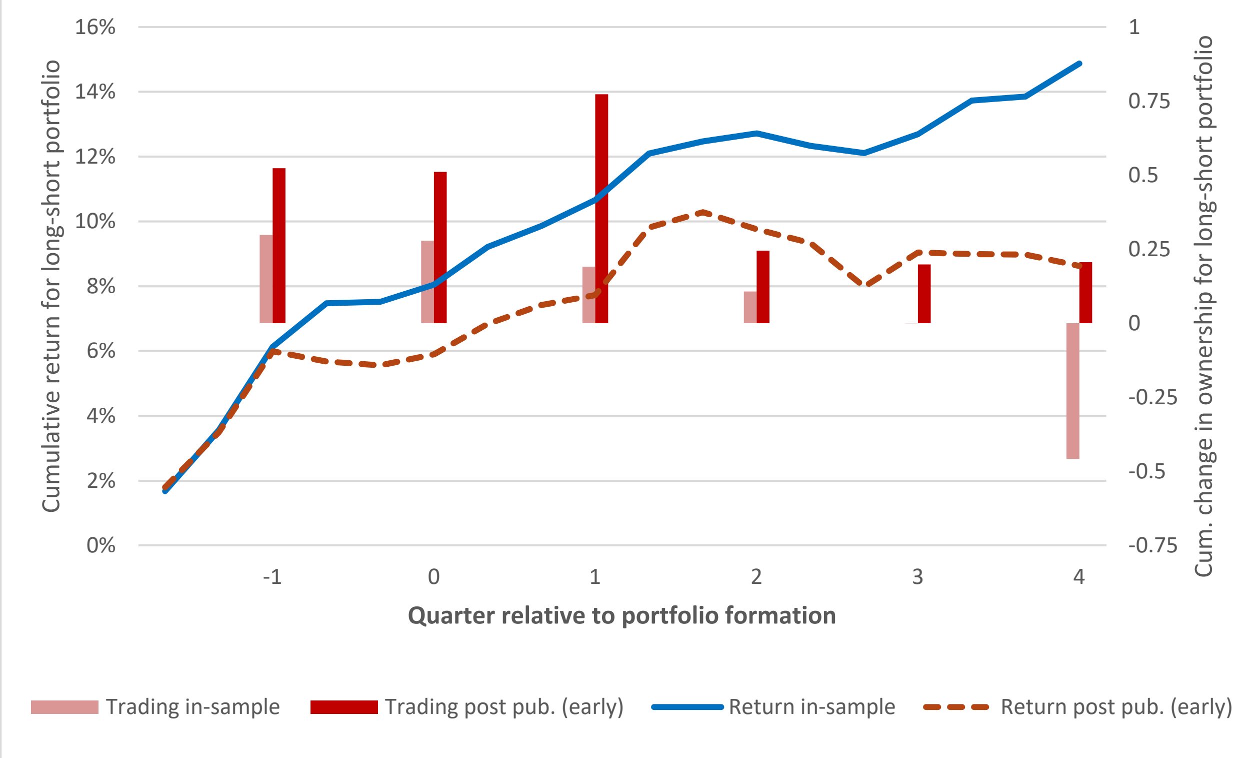


**Figure 3**

**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. Every June 30th, we sort stocks into quintiles according to the anomaly variables and measure the change in the percentage of the long and short portfolios held by institutions separately and take the difference between the two. We take the average across the 14 anomalies for each cross-section and then calculate the time-series average. 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]). For example, [-6, -1] refers to cumulative institutional trading that occurs in the window that starts six quarters before the June 30th portfolio formation date and ends one quarter before.

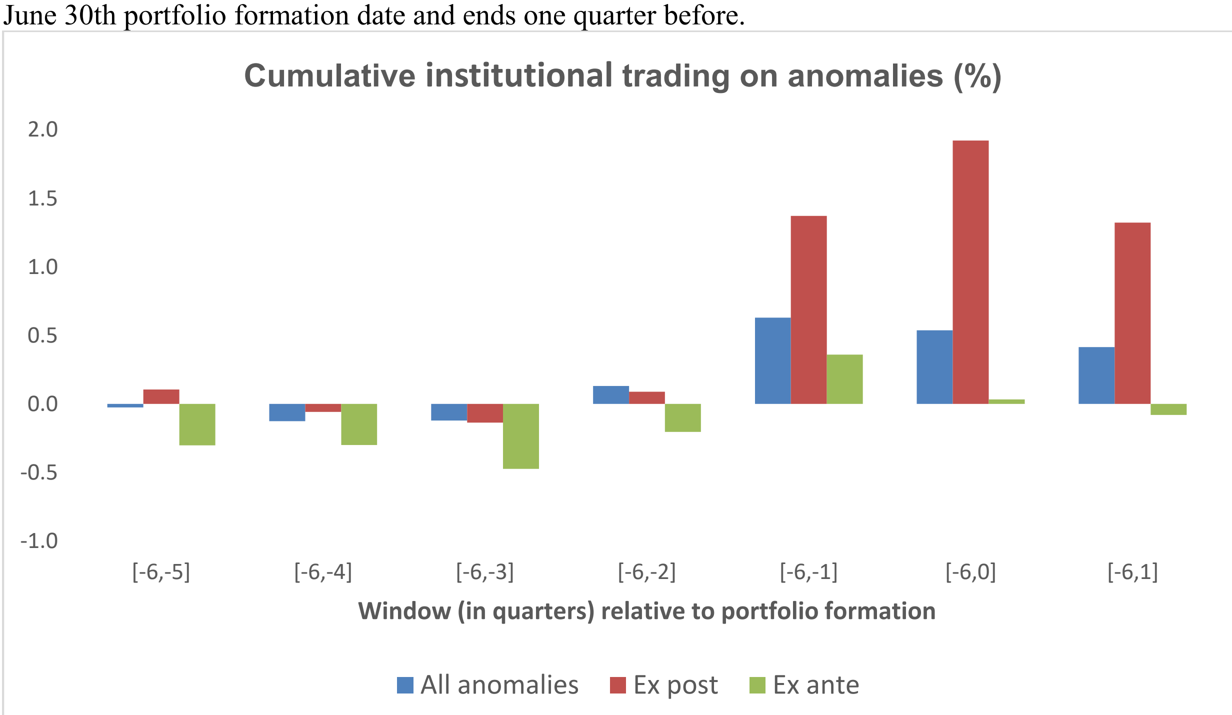


**Table 1**
**Sample of Anomalies**

This table reports the list of anomalies with information about the papers that first documented them, the publication year and journal, the beginning and the end year of the sample used in the anomaly publication, and the year when the paper was first posted on SSRN when available. The journals are abbreviated as follows: Journal of Finance (JF), The Accounting Review (TAR), Journal of Accounting and Economics (JAE), Journal of Financial Economics (JFE), Journal of Financial and Quantitative Analysis (JFQA), Review of Financial Studies (RFS), Journal of Accounting Research (JAR).

| Anomaly | Label | Paper | Journal | Sample beginning year | Sample end year | SSRN year |
|---|---|---|---|---|---|---|
| Net Stock Issues | NSI | Loughran and Ritter (1995) | JF | 1970 | 1990 | |
| Composite Equity Issues | CEI | Daniel and Titman (2006) | JF | 1968 | 2003 | 2001 |
| Total accruals | ACC | Sloan (1996) | TAR | 1962 | 1991 | |
| Net Operating Assets | NOA | Hirshleifer et al. (2004) | JAE | 1964 | 2002 | 2003 |
| Gross Profitability | GP | Novy-Marx (2013) | JFE | 1963 | 2010 | 2010 |
| Asset Growth | AG | Cooper et al. (2008) | JF | 1968 | 2003 | 2005 |
| Capital Investments | CI | Titman et al. (2004) | JFQA | 1973 | 1996 | 2001 |
| Investment-to-Assets | IVA | Xing (2008) | RFS | 1964 | 2003 | 2008 |
| Book-to-Market | BM | Fama and French (1992) | JF | 1963 | 1990 | |
| Momentum | MOM | Jegadeesh and Titman (1993) | JF | 1965 | 1989 | |
| Distress | DIS | Campbell et al. (2008) | JF | 1963 | 2003 | 2005 |
| Ohlson O-Score | OS | Dichev (1998) | JF | 1981 | 1995 | |
| Return on Assets | ROA | Fama and French (2006) | JFE | 1963 | 2003 | 2001 |
| Post-Earnings Announcement Drift | PEAD | Bernard and Thomas (1989) | JAR | 1974 | 1986 | |

**Table 2**
**Rank Correlations**

This table reports correlations for the anomalies. It reports the rank correlation matrix for the 14 anomalies together with the first-order autocorrelation in the first row. Every June 30th 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. The correlations are computed using the quintile ranks each year and then averaged across the sample period. The set of anomalies is described in Table 1.

| | **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 |

**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. 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). Every June 30$^{th}$ 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. Next, we calculate value-weighted portfolio returns over the following four quarters. The performance (expressed in percentage) is measured by the three-factor alphas and the average quarterly value-weighted portfolio returns in excess of the benchmark of Daniel, Grinblatt, Titman, and Wermers (DGTW, 1997). The alpha is the intercept of a regression of quarterly value-weighted portfolio 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.

| | **Three-factor alphas** | | **DGTW-adjusted returns** | |
|---|---|---|---|---|
| | **In-sample** | **Post-publication** | **In-sample** | **Post-publication** |
| NSI | 1.09 | 1.62 | 1.03 | 0.96 |
| | (0.00) | (0.01) | (0.00) | (0.04) |
| CEI | 1.68 | 1.40 | 1.25 | 0.42 |
| | (0.00) | (0.06) | (0.00) | (0.50) |
| ACC | 1.38 | 0.80 | 0.50 | 0.40 |
| | (0.02) | (0.22) | (0.23) | (0.44) |
| NOA | 1.16 | 0.08 | 0.73 | 0.61 |
| | (0.01) | (0.92) | (0.03) | (0.24) |
| GP | 1.46 | | 0.89 | -2.16 |
| | (0.00) | | (0.01) | (0.07) |
| AG | 1.11 | 0.31 | 1.07 | 0.56 |
| | (0.01) | (0.78) | (0.00) | (0.42) |
| CI | 1.05 | 0.09 | 0.51 | 0.15 |
| | (0.01) | (0.92) | (0.11) | (0.79) |
| IVA | 1.06 | 1.26 | 0.92 | 0.89 |
| | (0.00) | (0.29) | (0.00) | (0.19) |
| BM | 1.65 | 1.14 | 1.25 | 0.81 |
| | (0.01) | (0.19) | (0.05) | (0.24) |
| MOM | 2.42 | 0.30 | 0.98 | -0.28 |
| | (0.01) | (0.81) | (0.25) | (0.81) |
| DIS | 2.50 | 0.54 | 0.10 | -0.45 |
| | (0.00) | (0.67) | (0.85) | (0.61) |
| OS | 2.00 | 3.03 | 1.12 | 1.84 |
| | (0.00) | (0.00) | (0.00) | (0.02) |
| ROA | 1.61 | 1.75 | 0.85 | 0.43 |
| | (0.05) | (0.02) | (0.13) | (0.48) |
| PEAD | 2.77 | 0.27 | 0.26 | 0.07 |
| | (0.01) | (0.61) | (0.66) | (0.84) |
| EW portfolio | 1.56 | 1.11 | 0.95 | 0.64 |
| | (0.00) | (0.01) | (0.00) | (0.01) |

**Table 4**
**Institutional Trading on the Anomaly**

This table examines the trading activity of institutional investors in the 14 anomalies. We measure anomaly trading by institutions by computing the three-quarter change (starting from two quarters before ranking date) in the percentage of the long and short portfolios held by institutions separately and taking the difference between the two. Observations are pooled across the anomalies. Panel A presents average anomaly trading across the full sample period. Panel B presents results of a regression of trading on dummies that identify dates surrounding the publication of each anomaly. The in-sample period is defined as the sample period used in the original anomaly publication. The pre-publication period is defined as the period from the end of the in-sample period to just before the publication year. The post-publication period (full) includes the period starting from the year of publication through the end of the sample. The post-publication (early) period is defined as the first four years of the post-publication period. We present results for the full set of institutions (All) 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. Panel C reports the difference between trading in the post-publication (early) period and the in-sample period when the model is estimated with time fixed effects. Robust standard errors are calculated and p-values are reported below the coefficient estimates.

**Panel A: Anomaly-based trading in the full sample period**

| | All | HF | MF | Transient |
|---|---|---|---|---|
| Full Sample | 0.14 | 0.17 | 0.15 | 0.76 |
| | (0.18) | (0.00) | (0.04) | (0.00) |

**Panel B: Anomaly-based trading in the sub-sample period**

| | All | HF | MF | Transient |
|---|---|---|---|---|
| In-sample | 0.07 | 0.11 | 0.31 | 0.68 |
| | (0.62) | (0.02) | (0.00) | (0.00) |
| Pre-publication | 0.25 | 0.33 | -0.14 | 0.89 |
| | (0.49) | (0.01) | (0.50) | (0.00) |
| Post-publication (Early) | 0.81 | 0.40 | 0.47 | 1.07 |
| | (0.01) | (0.00) | (0.03) | (0.00) |
| Post-publication (Full) | 0.21 | 0.20 | 0.02 | 0.83 |
| | (0.23) | (0.00) | (0.89) | (0.00) |
| Post-publication (Early) - In-sample | 0.74 | 0.29 | 0.16 | 0.39 |
| | (0.04) | (0.03) | (0.49) | (0.21) |

**Panel C: Time fixed effects**

| | All | HF | MF | Transient |
|---|---|---|---|---|
| Post-publication (Early) - In-sample | 1.26 | 0.29 | 0.67 | 0.73 |
| | (0.00) | (0.07) | (0.02) | (0.04) |

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

This table presents the average institutional trading 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 30th, 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 the full set of institutions (All) and separately for hedge funds (HF), mutual funds (MF), and transient institutions. We measure anomaly trading by institutions by computing the three-quarter change (starting from two quarters before ranking date) in the percentage of the long and short portfolios held by institutions separately and taking the difference between the two. Newey-West standard errors are calculated and p-values are reported below the coefficient estimates.

| | **All** | **HF** | **MF** | **Transient** |
|---|---|---|---|---|
| Ex-post portfolio | 1.03 | 0.66 | 0.52 | 2.33 |
| | (0.04) | (0.00) | (0.31) | (0.00) |
| Ex-ante portfolio | -0.04 | 0.32 | 0.08 | 1.12 |
| | (0.87) | (0.06) | (0.66) | (0.00) |
| Ex-post minus ex-ante portfolio | 1.07 | 0.34 | 0.44 | 1.21 |
| | (0.08) | (0.06) | (0.33) | (0.00) |

**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 anomaly institutional trading and annual DGTW-adjusted returns for the long-short leg of the ex-post and ex-ante portfolios. Ex-post portfolio is constructed using the anomalies that are already published. Ex-ante portfolio is based on the anomalies that have not been published yet. Every June 30th, 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 computing the one-year change (starting from two quarters before ranking date) in the percentage of the long and short portfolios held by institutions separately and taking the difference between the two. DGTW-adjusted returns are computed from value-weighted portfolio returns during the same windows used for trading. The VAR is specified with a one-year lag based upon the Schwarz Bayesian information criterion. We present results for the full set of institutions (All) and for the subgroup of traders identified as hedge funds (HF), mutual funds (MF), and transient institutions. p-values are reported below the coefficient estimates.

| | **Ex-post portfolio** | | | | **Ex-ante portfolio** | | | |
|---|---|---|---|---|---|---|---|---|
| | **All** | **HF** | **MF** | **Transient** | **All** | **HF** | **MF** | **Transient** |
| **Dependent variable: Return** | | | | | | | | |
| Lag Ret | -0.18 | -0.27 | -0.12 | -0.12 | -0.03 | -0.01 | -0.08 | -0.18 |
| | (0.32) | (0.15) | (0.54) | (0.55) | (0.90) | (0.95) | (0.74) | (0.46) |
| Lag Trading | -0.02 | -0.06 | -0.02 | -0.02 | -0.01 | 0.00 | 0.02 | 0.03 |
| | (0.02) | (0.03) | (0.11) | (0.26) | (0.56) | (0.89) | (0.30) | (0.11) |
| Constant | 0.21 | 0.26 | 0.19 | 0.22 | 0.11 | 0.12 | 0.13 | 0.11 |
| | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) |
| **Dependent variable: Trading** | | | | | | | | |
| Lag Ret | 1.80 | -1.06 | -1.09 | -2.54 | 4.54 | -1.18 | 0.49 | 0.31 |
| | (0.72) | (0.43) | (0.80) | (0.37) | (0.29) | (0.61) | (0.84) | (0.93) |
| Lag Trading | -0.09 | -0.05 | 0.19 | 0.08 | 0.03 | 0.27 | 0.38 | 0.09 |
| | (0.66) | (0.80) | (0.38) | (0.70) | (0.90) | (0.20) | (0.06) | (0.70) |
| Constant | 0.04 | 0.88 | 0.21 | 2.47 | -1.14 | 0.27 | -0.23 | 0.81 |
| | (0.97) | (0.01) | (0.80) | (0.00) | (0.06) | (0.42) | (0.52) | (0.05) |

**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 30th, 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 for a given stock is measured by the three-quarter change in institutional holdings starting from two quarters before ranking date. 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 follow Anderson and Dyl (2005) and make an adjustment in the liquidity measure for the volume of NASDAQ stocks. We present results for the full set of institutions (All) and for the subgroup of traders identified as hedge funds (HF), mutual funds (MF), and transient institutions. The last three rows present tests of the difference between the coefficients indicated by the letters a, b, c and d. Newey-West standard errors are calculated and p-values are reported below the coefficient estimates.

| | **All** | **HF** | **MF** | **Transient** |
|---|---|---|---|---|
| Constant | 6.92 | 2.48 | 3.96 | 5.45 |
| | (0.00) | (0.00) | (0.00) | (0.00) |
| Ex-post long (a) | 0.73 | 0.37 | 0.10 | 1.21 |
| | (0.00) | (0.00) | (0.37) | (0.00) |
| Ex-post short (b) | -1.91 | -0.49 | -1.01 | -1.80 |
| | (0.00) | (0.00) | (0.00) | (0.00) |
| Ex-ante long (c) | 0.48 | 0.17 | 0.27 | 0.66 |
| | (0.00) | (0.01) | (0.00) | (0.00) |
| Ex-ante short (d) | -0.53 | -0.22 | -0.27 | -0.52 |
| | (0.01) | (0.01) | (0.04) | (0.01) |
| BM | -0.32 | -0.06 | -0.10 | 0.09 |
| | (0.00) | (0.12) | (0.06) | (0.19) |
| Illiquidity | -0.35 | -0.12 | -0.18 | -0.17 |
| | (0.00) | (0.00) | (0.00) | (0.00) |
| Momentum | 0.34 | -0.02 | 0.12 | -0.25 |
| | (0.01) | (0.74) | (0.02) | (0.00) |
| Size | -0.68 | -0.25 | -0.36 | -0.68 |
| | (0.00) | (0.00) | (0.00) | (0.00) |
| a-c | 0.25 | 0.20 | -0.17 | 0.54 |
| | (0.20) | (0.01) | (0.16) | (0.01) |
| b-d | -1.38 | -0.28 | -0.73 | -1.27 |
| | (0.00) | (0.06) | (0.01) | (0.00) |
| (a-c)-(b-d) | 1.64 | 0.47 | 0.56 | 1.82 |
| | (0.00) | (0.00) | (0.09) | (0.00) |

**Table 8**

**Anomaly Stock Performance Conditional on Institutional Trading**

This table reports quarterly value-weighted DGTW-adjusted returns of stocks selected conditional on institutional trading. Every June 30th, we measure aggregate institutional holdings changes in stocks in the long and short legs of the ex-ante and ex-post portfolios. Institutional trading for a given stock is measured by the two-quarter change in institutional holdings starting from two quarters before ranking date. We then sort stocks conditional on institutional trading into two portfolios: the 'with-anomaly' portfolio, which is long the long-leg stocks institutions buy and short the short-leg stocks institutions sell; the 'other' portfolio, which is long the non-long-leg stocks institutions buy and short the non-short-leg stocks institutions sell. We then compute in Panel A (Panel B) the next year (next two-quarter) value-weighted DGTW-adjusted returns for each portfolio using as weights the absolute value of the dollar amount traded by institutions. We also compute the DGTW-adjusted returns of the difference of the two portfolios. We present results for the full set of institutions (All) and for the subgroup of traders identified as hedge funds (HF), mutual funds (MF), and transient institutions. p-values are presented below each risk-adjusted return.

| **Panel A: Next year returns** | **Ex-ante portfolio** | | | | **Ex-post portfolio** | | | |
|---|---|---|---|---|---|---|---|---|
| | **All** | **HF** | **MF** | **Transient** | **All** | **HF** | **MF** | **Transient** |
| With-anomaly portfolio | 2.07 | 2.64 | 1.62 | 1.90 | 0.88 | 0.85 | 0.94 | 0.49 |
| | (0.02) | (0.00) | (0.05) | (0.03) | (0.30) | (0.22) | (0.27) | (0.52) |
| Other | -0.13 | 0.21 | -0.10 | 0.00 | -0.14 | 0.56 | -0.17 | 0.07 |
| | (0.70) | (0.52) | (0.70) | (0.99) | (0.67) | (0.05) | (0.57) | (0.79) |
| Difference | 2.20 | 2.44 | 1.72 | 1.91 | 1.02 | 0.29 | 1.11 | 0.42 |
| | (0.03) | (0.01) | (0.05) | (0.04) | (0.30) | (0.70) | (0.22) | (0.59) |

| **Panel B: Next two-quarter returns** | **Ex-ante portfolio** | | | | **Ex-post portfolio** | | | |
|---|---|---|---|---|---|---|---|---|
| | **All** | **HF** | **MF** | **Transient** | **All** | **HF** | **MF** | **Transient** |
| With-anomaly portfolio | 2.33 | 4.02 | 1.57 | 2.29 | 0.66 | 1.91 | 0.85 | 0.66 |
| | (0.09) | (0.00) | (0.24) | (0.07) | (0.64) | (0.09) | (0.56) | (0.60) |
| Other | -0.45 | 0.16 | -0.38 | -0.02 | -0.40 | 0.55 | -0.49 | -0.06 |
| | (0.31) | (0.70) | (0.35) | (0.95) | (0.41) | (0.17) | (0.29) | (0.87) |
| Difference | 2.78 | 3.86 | 1.95 | 2.31 | 1.06 | 1.36 | 1.33 | 0.72 |
| | (0.07) | (0.00) | (0.17) | (0.08) | (0.51) | (0.24) | (0.39) | (0.58) |

# Internet Appendix

to accompany

**When Anomalies Are Publicized Broadly, Do Institutions Trade Accordingly?**

**Internet Appendix Figure 1**
**Dimensional Fund Advisors “Bringing Research to the Real World”**

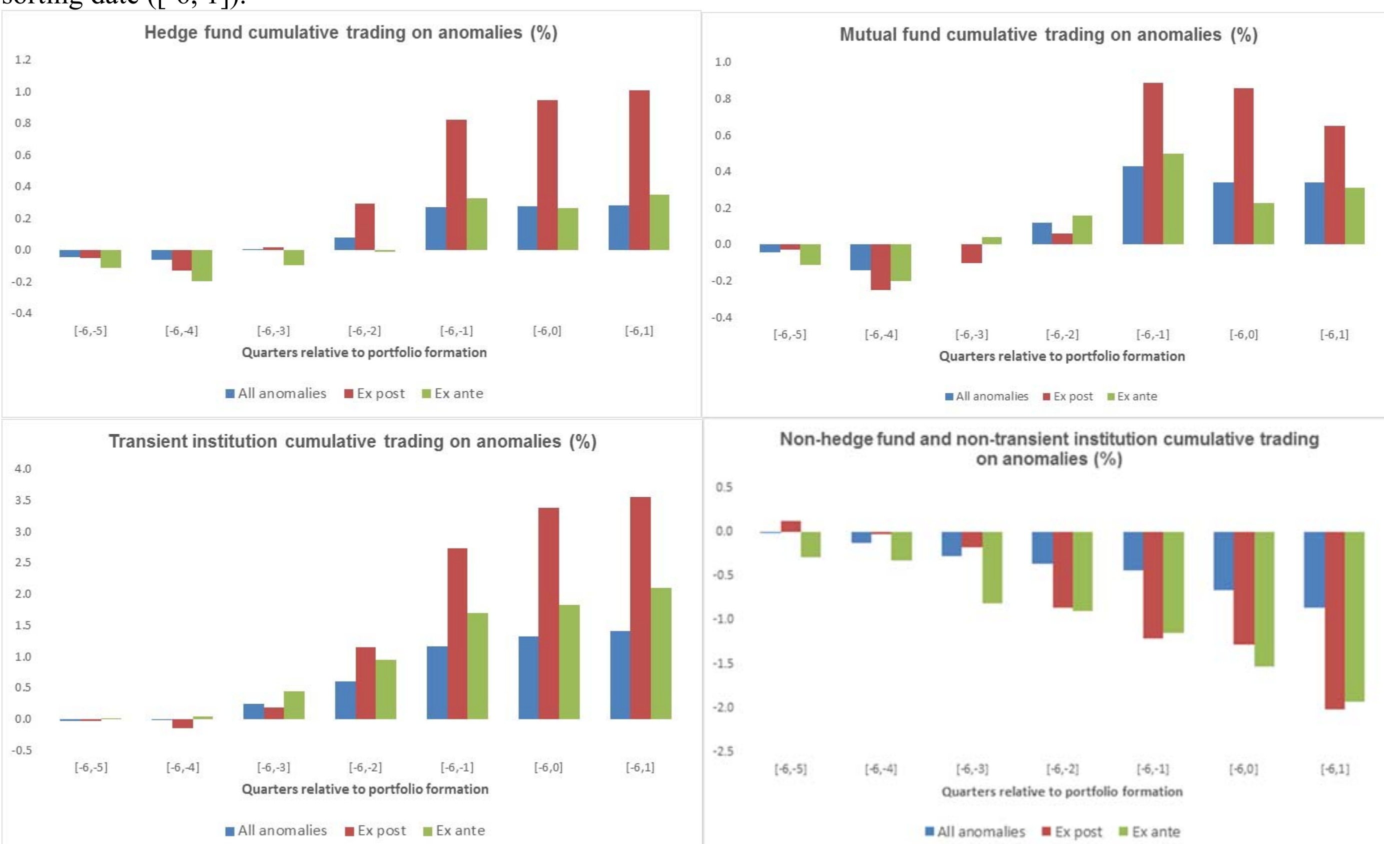
This figure presents a snapshot from DFA’s “Philosophy / Research” webpage available at http://us.dimensional.com/philosophy/research.aspx. They provide a timeline that describes when academic research is incorporated into their trading strategies.

## BRINGING RESEARCH TO THE REAL WORLD

| | | |
|---|---|---|
| **Small Cap Breakthrough** | 1981 | Dimensional pioneers diversified, cost-efficient trading in small cap stocks. |
| **Variable Maturity** | 1983 | Dimensional develops a term-aware approach designed to maximize expected returns within a short-term, high-quality, low-volatility range. |
| **Global Bond Diversification** | 1990 | Dimensional designs global bond strategies that pursue reduced volatility and increased expected returns. |
| **Value Strategies** | 1992 | Dimensional designs multifactor approach to expand flexibility across stock market dimensions. |
| **Tax Management** | 1999 | Dimensional engineers portfolios tailored to client goals and tax costs. |
| **Applied Core Equity** | 2005 | Dimensional develops integrated portfolios designed to deliver broad diversification and low-friction factor exposures. |
| **Inflation Protection** | 2006 | Dimensional builds strategies designed to provide protection against unexpected inflation. |
| **Variable Credit** | 2009 | In response to improved bond market trading data, Dimensional develops diversified, risk-aware portfolios that seek higher expected returns and access to the entire range of non-securitized investment-grade credit. |
| **Profitability** | 2012 | Research identifies a new dimension of expected returns in equity markets. |

**Internet Appendix Figure 2**
**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. Every June 30th, we sort stocks into quintiles according to the anomaly variables and measure the change in the percentage of the long and short portfolios held by institutions separately and take the difference between the two. We take the average across the 14 anomalies for each cross-section and then calculate the time-series average. 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]).



**Internet Appendix Table 1**
**VAR: Trading and Returns in the Ex-post and Ex-ante Portfolio, Liquidity Robustness**

This table reports the results of the vector autoregressive (VAR) model which includes anomaly institutional trading and annual DGTW-adjusted returns for the long-short portfolio of the ex-post and ex-ante portfolio, and a measure of liquidity. Ex-post portfolio is constructed using the anomalies that are already published. Ex-ante portfolio is based on the anomalies that have not been published yet. Every June 30th, we assign a percentile rank to each stock based on each anomaly and compute the equal-weighted average rank for the ex-post and ex-ante 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 computing the one-year change (starting from two quarters before ranking date) in the percentage of the long and short portfolios held by institutions separately and taking the difference between the two. DGTW-adjusted returns are computed from value-weighted portfolio returns during the same windows used for trading. The VAR is specified with a one-year lag based upon the Schwarz Bayesian information criterion. We present results for the full set of institutions (All) 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. We follow Anderson and Dyl (2005) and make an adjustment in the liquidity measure for the volume of NASDAQ stocks. p-values are reported below the coefficient estimates.

| | Ex-Post Portfolio | | | | Ex-Ante Portfolio | | | |
|---|---|---|---|---|---|---|---|---|
| | **All** | **HF** | **MF** | **Transient** | **All** | **HF** | **MF** | **Transient** |
| **Dependent variable: Return** | | | | | | | | |
| Lag Ret | -0.16 | -0.27 | -0.11 | -0.15 | 0.05 | 0.08 | 0.03 | -0.11 |
| | (0.39) | (0.16) | (0.59) | (0.49) | (0.83) | (0.75) | (0.89) | (0.69) |
| Lag Trading | -0.02 | -0.06 | -0.02 | -0.02 | 0.00 | -0.01 | 0.03 | 0.03 |
| | (0.02) | (0.04) | (0.14) | (0.31) | (0.71) | (0.81) | (0.17) | (0.15) |
| Lag Liquidity | 0.08 | -0.01 | 0.02 | -0.08 | -0.17 | -0.20 | -0.28 | -0.12 |
| | (0.71) | (0.95) | (0.92) | (0.69) | (0.47) | (0.38) | (0.22) | (0.58) |
| Constant | 0.19 | 0.26 | 0.19 | 0.24 | 0.13 | 0.13 | 0.15 | 0.12 |
| | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) |
| **Dependent variable: Trading** | | | | | | | | |
| Lag Ret | 4.12 | -1.08 | 0.97 | -2.21 | 3.68 | -0.53 | -0.83 | 1.80 |
| | (0.40) | (0.43) | (0.83) | (0.45) | (0.44) | (0.84) | (0.74) | (0.62) |
| Lag Trading | -0.24 | -0.05 | 0.05 | 0.06 | 0.00 | 0.25 | 0.30 | 0.05 |
| | (0.24) | (0.82) | (0.83) | (0.77) | (0.99) | (0.22) | (0.13) | (0.85) |
| Lag Liquidity | 9.36 | -0.10 | 6.14 | 1.10 | 1.67 | -1.36 | 3.29 | -2.56 |
| | (0.08) | (0.94) | (0.19) | (0.70) | (0.70) | (0.56) | (0.15) | (0.38) |
| Constant | -1.60 | 0.90 | -0.98 | 2.30 | -1.25 | 0.36 | -0.49 | 0.98 |
| | (0.22) | (0.02) | (0.41) | (0.00) | (0.06) | (0.32) | (0.21) | (0.03) |
| **Dependent variable: Liquidity** | | | | | | | | |
| Lag Ret | 0.04 | 0.04 | 0.03 | 0.02 | -0.28 | -0.25 | -0.20 | -0.22 |
| | (0.80) | (0.77) | (0.86) | (0.88) | (0.24) | (0.29) | (0.38) | (0.41) |
| Lag Trading | 0.00 | 0.01 | 0.00 | 0.00 | -0.01 | 0.01 | -0.02 | 0.00 |
| | (0.89) | (0.69) | (0.90) | (0.82) | (0.44) | (0.54) | (0.20) | (0.89) |
| Lag Liquidity | 0.72 | 0.70 | 0.70 | 0.71 | 0.61 | 0.58 | 0.64 | 0.56 |
| | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.01) | (0.00) | (0.01) |
| Constant | 0.03 | 0.02 | 0.03 | 0.03 | 0.08 | 0.08 | 0.06 | 0.09 |
| | (0.50) | (0.58) | (0.48) | (0.54) | (0.02) | (0.01) | (0.07) | (0.01) |

**Internet 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. Every June 30th, we sort stocks into quintiles according to the anomaly variables and measure institutional trading by computing the change in the percentage of the long and short portfolios held by institutions separately and taking the difference between the two. We take the average of long-short across the 14 anomalies for each cross-section and then calculate the time-series average. 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]** |
|---|---|---|---|---|---|---|---|---|---|
| | **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 -** | 0.41 | 0.24 | 0.34 | 0.29 | 1.01 | 1.89 | 1.40 | 1.07 |
| | **ex-ante** | (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]** |
|---|---|---|---|---|---|---|---|---|---|
| | **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 -** | 0.74 | 0.88 | 0.80 | 1.68 | 2.52 | 4.12 | 3.44 | 1.68 |
| | **ex-ante** | (0.12) | (0.21) | (0.35) | (0.19) | (0.06) | (0.02) | (0.02) | (0.06) |

**Internet 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. Every June 30th, 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 for each cross-section and then calculate the time-series average. 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) |

**Internet Appendix Table 4**
**Trading in Ex-ante and Ex-post Portfolios with Controls: Panel Regressions**

This table reports the results of panel 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 30th, 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 for a given stock is measured by the three-quarter change in institutional holdings starting from two quarters before ranking date. 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 follow Anderson and Dyl (2005) and make an adjustment in the liquidity measure for the volume of NASDAQ stocks. We present results for the full set of institutions (All) and for the subgroup of traders identified as hedge funds (HF), mutual funds (MF), and transient institutions. The regressions include time fixed effects and standard errors are clustered on firm and time. p-values are reported below the coefficient estimates.

| | All | HF | MF | Transient |
|---|---|---|---|---|
| Ex-post long (a) | 0.74 | 0.40 | 0.11 | 1.17 |
| | (0.00) | (0.00) | (0.37) | (0.00) |
| Ex-post short (b) | -2.02 | -0.54 | -1.06 | -1.87 |
| | (0.00) | (0.00) | (0.00) | (0.00) |
| Ex-ante long (c) | 0.49 | 0.17 | 0.30 | 0.71 |
| | (0.00) | (0.01) | (0.00) | (0.00) |
| Ex-ante short (d) | -0.52 | -0.21 | -0.28 | -0.51 |
| | (0.00) | (0.03) | (0.02) | (0.00) |
| BM | -0.36 | -0.06 | -0.09 | 0.17 |
| | (0.00) | (0.16) | (0.14) | (0.03) |
| Illiquidity | -0.26 | -0.10 | -0.12 | -0.15 |
| | (0.02) | (0.02) | (0.07) | (0.03) |
| Momentum | 0.29 | -0.10 | 0.11 | -0.31 |
| | (0.05) | (0.18) | (0.13) | (0.00) |
| Size | -0.37 | -0.15 | -0.20 | -0.37 |
| | (0.00) | (0.00) | (0.00) | (0.00) |
| a-c | 0.25 | 0.23 | -0.20 | 0.46 |
| | (0.27) | (0.02) | (0.14) | (0.02) |
| b-d | -1.50 | -0.34 | -0.78 | -1.36 |
| | (0.00) | (0.04) | (0.01) | (0.00) |
| (a-c)-(b-d) | 1.76 | 0.57 | 0.58 | 1.82 |
| | (0.00) | (0.00) | (0.06) | (0.00) |

**Internet Appendix Table 5**
**Institutional Trading on the Anomalies: Robustness**

This table reports the difference between trading of institutional investors in the post-publication (early) period and the in-sample period for long and short legs separately and for different specifications and subsets of the 14 anomalies. 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 low-correlation sample includes the following nine anomalies: NSI, ACC, NOA, GP, CI, BM, MOM, OS, and PEAD. The quarterly/monthly documented anomalies sample includes the following five anomalies: MOM, DIS, OS, ROA, and PEAD. We also present anomaly trading results when we sort anomaly every quarter, a specification where we use SSRN year instead of publication year when available, and when we cluster standard errors in the panel regressions. We measure anomaly trading by institutions by computing the three-quarter/two-quarter change (starting from two quarters/one quarter before ranking date in the annual/quarterly anomalies) in the percentage of the long and short portfolios held by institutions separately and taking the difference between the two. Observations are pooled across the anomalies and the regressions include time fixed effects. We present results for the full set of institutions (All) 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.

| | **All** | **HF** | **MF** | **Transient** |
|---|---|---|---|---|
| Long leg | 0.56 | 0.17 | 0.31 | 0.30 |
| | (0.00) | (0.02) | (0.01) | (0.06) |
| Short leg | -0.70 | -0.11 | -0.36 | -0.43 |
| | (0.05) | (0.33) | (0.10) | (0.07) |
| Anomaly Selection | | | | |
| Stambaugh et al. (2012) sample | 1.52 | 0.23 | 0.82 | 1.14 |
| | (0.01) | (0.24) | (0.03) | (0.02) |
| EIK sample | 2.34 | 0.52 | 1.31 | 1.86 |
| | (0.00) | (0.07) | (0.01) | (0.01) |
| Low correlation sample | 1.54 | 0.32 | 0.82 | 1.01 |
| | (0.00) | (0.08) | (0.01) | (0.02) |
| High correlation sample | 0.64 | 0.23 | 0.34 | 0.19 |
| | (0.23) | (0.33) | (0.41) | (0.65) |
| Trading in the quarterly-ranked anomalies | | | | |
| Quarterly trading in all anomalies | 0.47 | 0.19 | 0.30 | 0.68 |
| | (0.02) | (0.01) | (0.02) | (0.00) |
| Quarterly trading in quarterly/monthly documented anomalies | 1.38 | 0.51 | 0.79 | 1.53 |
| | (0.00) | (0.00) | (0.00) | (0.00) |
| Quarterly trading in annually documented anomalies | 0.12 | 0.13 | 0.13 | 0.32 |
| | (0.51) | (0.05) | (0.25) | (0.01) |
| Additional Concerns | | | | |
| SSRN year | 1.22 | 0.27 | 0.66 | 0.70 |
| | (0.00) | (0.09) | (0.01) | (0.05) |
| Time clustering of standard errors | 1.26 | 0.29 | 0.67 | 0.73 |
| | (0.00) | (0.06) | (0.00) | (0.04) |

**Internet Appendix Table 6**
**Institutional Trading on each Anomaly**

This table reports the difference between trading of institutional investors in the post-publication (early) period and the in-sample period for all the 14 anomalies. We categorize the anomalies as belonging to the low-correlation or high-correlation groups. We measure anomaly trading by institutions by computing the three-quarter change (starting from two quarters before ranking date) in the percentage of the long and short portfolios held by institutions separately and taking the difference between the two. Observations are pooled across the anomalies and the regressions include time fixed effects. We present results for the full set of institutions (All) 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.

| | All | HF | MF | Transient |
|---|---|---|---|---|
| Low-Correlation | | | | |
| NSI | 0.10 | 0.04 | -0.27 | -0.19 |
| | (0.90) | (0.86) | (0.61) | (0.74) |
| ACC | 3.01 | 0.30 | 1.05 | 0.90 |
| | (0.08) | (0.33) | (0.14) | (0.28) |
| NOA | 1.27 | 0.55 | 0.74 | -0.28 |
| | (0.16) | (0.11) | (0.10) | (0.57) |
| GP | 1.26 | 0.02 | 1.59 | 0.56 |
| | (0.08) | (0.93) | (0.00) | (0.20) |
| CI | 0.37 | 0.41 | 0.24 | -0.75 |
| | (0.62) | (0.13) | (0.73) | (0.23) |
| BM | 1.15 | 0.59 | 0.70 | 0.68 |
| | (0.29) | (0.18) | (0.23) | (0.37) |
| MOM | 3.66 | 0.87 | 2.84 | 4.50 |
| | (0.00) | (0.06) | (0.00) | (0.00) |
| OS | -0.82 | -0.93 | -0.66 | -0.47 |
| | (0.64) | (0.05) | (0.47) | (0.36) |
| PEAD | 0.37 | 0.08 | 0.84 | 0.20 |
| | (0.70) | (0.84) | (0.09) | (0.73) |
| High-Correlation | | | | |
| CEI | 1.25 | 0.57 | 0.60 | 0.21 |
| | (0.14) | (0.05) | (0.35) | (0.66) |
| AG | -0.07 | 0.37 | -0.09 | 0.17 |
| | (0.91) | (0.28) | (0.85) | (0.68) |
| IVA | 1.36 | 0.90 | 0.49 | 0.71 |
| | (0.04) | (0.00) | (0.41) | (0.17) |
| DIS | -1.96 | -0.85 | -1.09 | -1.81 |
| | (0.09) | (0.01) | (0.21) | (0.00) |
| ROA | 1.58 | 0.20 | 1.29 | 0.13 |
| | (0.04) | (0.69) | (0.08) | (0.84) |

**Internet 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 30th, 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 the full set of institutions (All) and for the subgroup of traders identified as hedge funds (HF), mutual funds (MF), and transient institutions. We measure anomaly trading by institutions by computing the three-quarter change (starting from two quarters before ranking date) in the percentage of the long and short portfolios held by institutions separately and taking the difference between the two. 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.

| | **All** | **HF** | **MF** | **Transient** |
|---|---|---|---|---|
| > 1 Anomaly | 1.42 | 0.22 | 0.66 | 1.29 |
| | (0.09) | (0.36) | (0.32) | (0.03) |
| > 2 Anomaly | 1.62 | 0.27 | 0.73 | 1.47 |
| | (0.07) | (0.28) | (0.30) | (0.02) |
| > 3 Anomaly | 1.58 | 0.34 | 0.78 | 1.41 |
| | (0.03) | (0.11) | (0.20) | (0.01) |
| Weighted regression | 1.58 | 0.34 | 0.78 | 1.41 |
| | (0.03) | (0.11) | (0.20) | (0.01) |