Anomalies are Publicized Broadly, Institutions Trade Accordingly, and Returns Decay Correspondingly

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Abstract

We study whether institutional investors trade on stock market anomalies. We condition our analysis on whether information about the anomalies is readily available to investors through academic publication and the release of necessary accounting data. Using 14 well-documented anomalies, we observe an increase in anomaly-based trading among institutional investors, especially hedge funds and transient institutions, following the publication of research on anomalies. We directly relate this increase in trading to the observed decay in post-publication anomaly returns. In contrast to recent evidence, our findings support the role of institutional investors in the arbitrage process and in improving market efficiency.

JEL Classification: G12, G14, G23
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1. Introduction

Finance and accounting literature has documented more than 330 variables that predict future stock returns (Green et al., 2013).[1] However, limited evidence exists in the literature to support the notion that investors are able to systematically exploit these anomalies. McLean and Pontiff (2015) examine 97 anomalies and provide an explanation: while anomalies look great on paper, once the anomaly is published the returns associated with the anomaly decline by more than 50%. They discuss two potential explanations for the post-publication decline in anomaly returns: 1) anomalies are the result of statistical biases that will not persist out of sample; or 2) they are due to mispricing which is corrected by arbitrageurs.

Institutional investors are a prime candidate 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 65.8% ownership stake at the end of 2012. 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 et al. (2015) report that institutions actually 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. In fact, as suggested by Edelen et al. (2015), institutions could be playing a causal role with respect to the anomalies.

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

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

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

Our identification strategy focuses on the period when the anomaly is first published in the academic literature. We view journal publication as a shock that increases knowledge of the existence and profitability of the strategy among arbitrageurs without directly affecting the fundamentals that drive anomaly profits. Examining the changes in both institutional trading activity and anomaly profits around publication enable 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 arbitrage activity and a subsequent attenuation of the anomaly profits.

To examine the role of institutional investors in the arbitrage process, we first replicate our set of 14 anomalies. Following standard conventions in the literature, on June 30th of each year we rank stocks according to the "anomaly variables" (i.e., the variables that have been

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

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

[4] The anomalies we study are net stock issues, composite equity issues, total accruals, net operating assets, gross profitability, asset growth, capital investments, investment-to-assets, book-to-market, momentum, distress, Ohlson O-score, return on assets and post-earnings announcement drift. More details about these anomalies are provided in Table 1.

shown to predict future stock returns) and build long and short portfolios using the top and bottom quintiles. The long leg contains underpriced securities that should be bought by arbitrageurs and the short leg consists of overpriced securities that should be sold (short). Because real-world investors may update their information set about the anomaly variables on a more frequent basis than annually, we also construct a quarterly version of each anomaly using the most up-to-date data available at the end of each quarter. For both the annual and quarterly versions of the anomalies we verify that trading with the anomaly is profitable in the original sample period, and consistent with McLean and Pontiff (2015), there is a decay in anomaly returns in the period after publication.

We measure institutional trading by computing changes in aggregate institutional holdings in the long and short portfolio of each anomaly. We focus on the period for which the accounting information necessary to construct the anomaly rankings is publicly available (e.g., annual accounting variables are available by the end of March) and test if there is significantly greater institutional buying in the long portfolio than in the short portfolio. Observing this behavior would indicate that institutions trade to exploit the anomaly. We repeat these tests before and after the publication date and examine whether trading behavior changes around the publication date. In particular, similar to McLean and Pontiff (2015), we consider three main periods: 1) the *in-sample* period is the sample period used in the original anomaly publication; 2) the *pre-publication* period is the period from the end of the in-sample period to just before the publication date; and 3) the *post-publication* period includes the period starting from the publication year through 2013. If institutional investors trade on anomaly research, we expect to observe an increase in trading activity as the research becomes publicly available in the post-publication period. In fact, institutions could start trading during the pre-publication period if there is information spillover from avenues other than journal publication, i.e. working papers and conference presentations. We also consider a shorter post-publication period, i.e., *post-publication (early)*, to account for the possibility that, after the period immediately following publication, arbitrageurs may change their trading behavior given the reduction in anomaly profits after publication.

In our full 1982-2013 sample period, consistent with Lewellen (2011) and Edelen et al. (2015), we find that in aggregate, institutional investors do not take advantage of stock return anomalies. However, this result is driven by the in-sample period and by the focus on aggregate institutional trading. Considering the annual anomalies (i.e., anomalies based on rankings computed once a year), in the post-publication (early) period, the change in aggregate holdings for the long leg is significantly larger than the change in holdings for the short leg of anomalies. On average, from the in-sample to the post-publication (early) period, there is an increase of 0.87% of the total net ownership in the long-short portfolio over a two-quarter window. This result suggests that institutions, in aggregate, try to exploit the anomalies and their timing is related to the journal publication of the anomalies.

It is important to distinguish among different institution types as they may have different incentives 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), which may affect the extent to which they exploit anomalies. We partition institutional investors into hedge funds, mutual funds, and others and find that our results are strongest among hedge funds. We also identify *transient* institutional investors as classified by Bushee (2001). These are active investors whose portfolios exhibit high turnover. We expect that they would be more involved in anomaly trading and in particular they may attempt to take advantage of anomalies at frequencies greater than once a year. Indeed, we find that for the quarterly anomalies (i.e., anomalies based on rankings computed every quarter), transient institutions are the most active institutions to exploit anomalies and that their timing coincides with and even anticipates the journal publication of the anomalies.

Given the relatively large number of anomalies considered in this paper and since sophisticated institutions such as hedge funds are likely to trade on multiple anomalies at the same time, we focus on two aggregate portfolio strategies that combine rankings across our sample of anomalies. Each quarter, we assign each stock an "ex-post" ranking based on its aggregate ranking in all published anomalies, and an "ex-ante" ranking based on its aggregate ranking in all yet-to-be-published anomalies. The aggregate ranking is computed by taking the equal-weighted average of the percentile ranks for the ex-post and ex-ante anomalies. We then assign the top (bottom) quintile of stocks to the long (short) leg of the ex-post and ex-ante portfolios and examine returns and institutional trading in these portfolios. The results are qualitatively similar to our previous analyses. Consistent with the post-publication performance decline, the ex-ante portfolio earns larger returns than the ex-post portfolio. Consistent with the increase in anomaly-based trading after publication, institutional trading is larger in the ex-post portfolio, especially among hedge funds and transient institutions.

We posit that the observed increase in institutional trading after anomaly publication is related to the post-publication decay in anomaly returns. Using a vector autoregressive model we examine the relation between institutional trading and anomaly returns using the ex-post and ex-ante portfolios. We perform Granger-causality tests to determine the causality between institutional trading and returns, and find a significant negative relation between institutional trading and future anomaly returns in the ex-post portfolio. This relation persists among the whole institutional sample, as well as in the hedge fund, mutual fund, and transient institution subgroups. We find no significant relation between institutional trading and future returns in the ex-ante portfolio. These results suggest that institutional trading and anomaly publication are integral to the arbitrage process which helps bring prices to a more efficient level.

Edelen et al. (2015) examine institutional trading before the anomaly sorting starting from January of the previous year. In contrast, we use a much narrower window spanning the two quarters surrounding the anomaly ranking date to ensure that institutions have access to the financial and accounting data necessary to compute rankings and trade on them. Thus, our results highlight the responsive, rather than anticipatory, behavior of institutions with respect to publicly available information. However, it is a puzzle why institutions trade in the opposite direction of the anomalies in the longer event window used by Edelen et al. (2015). If institutions want to trade on the anomalies, but do not have the appropriate information, one would expect their trading behavior in the pre-information period to be neutral.[5] To address this puzzle we study the year-over-year change in anomaly rankings and separately examine institutional trading among stocks that reverse rankings and stocks with persistent rankings. We find that the results of Edelen et al. (2015) are partially explained by institutions reacting to past year's rankings rather than anticipating the anomaly signal in the current year. In stocks with persistent anomaly signals, we find evidence that institutions actually trade in the same direction as the anomalies.

To further support the evidence of arbitrage activity around publication date and connect this result to the reduction in anomaly profits, we focus on the subgroup of stocks in the long and

[5] Indeed, we look at the one-year autocorrelation of the anomaly rankings and find that there is little persistence in rankings, possibly making it difficult for institutions to predict future rankings. However, this finding does not explain why institutions trade in the opposite direction of the anomalies.

short legs that are actually traded by institutions. We find that institutions are able to select stocks that deliver superior future performance. Hedge funds, in particular, appear to select some of the best performing stocks in the long portfolio and sell stocks in the short portfolio that deliver future poor performance. On average, a strategy that purchases stocks in the long leg of the ex-post portfolio that are bought by institutions (hedge funds) and sells stocks in the short leg that are sold by institutions (hedge funds) generates a quarterly abnormal return of 1.67% (1.88%). This amount is greater than the 1.29% abnormal return obtained by simply buying the long leg and selling the short leg of the ex-post portfolio. Consistent with the post-publication return decay, these returns are lower than those earned by trading on the anomalies in the ex-ante portfolio, which is 1.90% (2.56%) for institutional (hedge fund) trades.

We also use Fama-MacBeth cross-sectional regressions to examine institutional trading in the ex-ante and ex-post portfolios. We separately examine the long and short legs of the portfolios and control for stock characteristics related to institutional preferences. Overall, we find consistent results: there is a significant increase (decrease) in institutional trading in the long (short) leg of the ex-post portfolio vs. ex-ante portfolio. We also examine short interest data. Although this data is not at the institutional level, we examine whether the stocks in the short portfolio are shorted more than the stocks in the long portfolio around anomaly publication. Consistent with investors following academic research and trading on them, the difference in differences is negative, i.e., stocks in the short portfolio are shorted more for the first four years following publication for March-to-June trading. In contrast, the average for the five years preceding publication is almost zero.

This paper contributes to the strand of research that investigates whether institutional trading facilitates market efficiency. We assess whether institutions implement trading strategies to exploit anomalies and provide evidence that this behavior occurs after anomaly publication. We relate this evidence to the attenuation of the anomalies documented by McLean and Pontiff (2015) and provide support for the mispricing explanation. As pointed out by Edelen et al. (2015), if institutions trade against anomalies they may play a causal role in the anomalies. This implication highlights concerns expressed by regulators that institutions may destabilize markets.[6] Our findings suggest a positive role for some institutions in contributing to more efficient markets.[7] In line with Grossmann and Stiglitz (1980), efficient security prices require market participants to actively trade on relevant information driving security prices toward the "true" price.

This paper also contributes to the hedge fund literature. Since the collapse of Long-Term Capital Management in 1998, hedge funds have been the target of increased scrutiny by regulators and the financial press.[8] We find that our results are strongest among hedge funds and transient institutions: they actively trade on the anomalies and correct mispricing. This finding is important to better understand their role as arbitrageurs.

We also add to the debate regarding the sophistication or skill level of institutional investors.[9] Our paper gauges investor sophistication by their ability to react to recently published anomalies and suggest heterogeneity in sophistication levels across different institution types. Finally, to the best of our knowledge, this paper is the first analysis of whether institutional investors learn from academic research by adopting trading strategies based on published findings. This analysis is relevant for understanding the value and impact of financial academic research.

2. Related Literature

Our paper is related to the literature on stock market efficiency, in particular, studies that attribute the existence of the anomalies to 1) statistical biases; 2) compensation for risk consistent with an asset pricing model; or 3) mispricing. First, several papers raise concerns about the existence of anomalies that are motivated by various biases such as sample selection

[6] For example, see the *Economist* article "Fund managers: Assets or liabilities?" Retrieved from http://www.economist.com/news/finance-and-economics/21610297-regulators-worry-asset-management-industry-may-spawn-next-financial.
[7] Kokkonen and Suominen (2015) and Akbas et al. (2015) provide recent complementary evidence of the role of hedge funds in improving stock market efficiency.
[8] 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.
[9] Papers that support the skillfulness of institutional investors include, among others, Coval and Moskowitz (2001), Cohen et al. (2002), Gibson et al. (2004), Jagannathan et al. (2010), Hendershott et al. (2015). Papers on the other side of the debate include, inter alia, Griffin and Xu (2009), Fama and French (2010), DeVault et al. (2014), and Edelen et al. (2015).

bias (Heckman, 1979), data snooping bias (Lo and MacKinlay, 1990), simple chance (Fama, 1998), or consideration of an inappropriate significance cutoff that does not take into account multiple tests (Harvey et al., 2015). Second, some papers explore a risk-based story. For example, Fama and French (1996) argue that the size and value anomalies could reflect exposure to macroeconomic risk factors. Sadka (2006) considers liquidity risk as a missing factor that could explain part of the abnormal returns associated with momentum and post-earnings-announcement drift. Finally, anomalies could be due to mispricing and present investment opportunities.

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

Another relevant strand of literature examines the role of institutional investors in the price discovery process. In particular, some studies investigate whether institutional investors contribute to market efficiency (e.g., Boehmer and Kelley, 2009). Given that there are a large number of anomalies that earn large excess returns, and some of them appear to be persistent across time (e.g., Jegadeesh and Titman, 2001, and Fama and French, 2008), institutional investors could try to trade mispriced securities. However, there is limited evidence of institutional investors trying to systematically exploit anomalies.[11] Few investors trade on and profit from the accruals anomaly (Ali et al., 2008). Institutional investors preferred large stocks in the 1980s and 1990s (Gompers and Metrick, 2001) although they later shifted toward smaller

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

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

stocks to seek "greener pastures" (Bennett et al., 2003). There is also evidence that investors contribute to some anomalies: institutions tend to buy growth stocks and sell value stocks contributing to the value premium (Chan et al., 2002; Frazzini and Lamont, 2008; Jiang, 2010). Institutions may also find it optimal to herd with the rest of the market pushing asset prices away from fundamental values (for example, Griffin et al., 2011 find that institutional investors contributed to the high-tech bubble).

Lewellen (2011) examines institutional holdings and finds that institutions as a whole do not act as arbitrageurs.[12] In contrast to Lewellen's paper, we focus on trading decisions that represent a more direct signal of institutional reaction to information than the level of institutional holdings. We also consider the time-variation in institutional trading and how it is related to the awareness of the anomalies. Moreover, in this paper we focus on the most active institutions: hedge funds, mutual funds, and especially the subset of transient institutions as defined by Bushee (2001).[13] We show that these institutions actively trade to exploit the anomalies. This analysis is important for the literature that examines the investment ability and performance of hedge funds and mutual funds.[14]

Finally, some recent papers examine whether practitioners learn about potential trading opportunities from academic research in particular in the context of return predictability. There are conflicting findings in this literature. On the one hand, Johnson and Schwartz (2000), similar to McLean and Pontiff (2015), report that the post-earnings-announcement drift was eliminated once the anomaly was documented in academic research.[15] As mentioned previously, this observation would be consistent with both statistical biases and the possibility that academic research is attracting the attention of sophisticated investors who trade against the mispricing. Neither paper examines institutional trading. Without analyzing trading it is hard to tell which interpretation is correct. On the other hand, Edelen et al. (2015) find that institutions trade in the opposite direction of anomalies. Furthermore, Richardson et al. (2010) present survey evidence

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

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

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

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

that shows practitioners read few published academic papers and pay little attention to working papers.

3. Data

We use Compustat and CRSP to obtain the accounting and financial data needed to replicate the anomalies. We consider a set of 14 well-documented anomalies (see Table 1): net stock issues, composite equity issues, total accruals, net operating assets, gross profitability, asset growth, capital investments, investment-to-assets, book-to-market, momentum, distress (failure probability), Ohlson O-score, return on assets, and post-earnings announcement drift (as measured by standardized unexpected earnings).[16] Eleven of these anomalies are studied by Stambaugh et al. (2012) and three additional anomalies (capital investments, book-to-market, and post-earnings announcement drift) are included to be consistent with recent literature (for example see Chen et al., 2011). These anomalies are important because, with the exception of book-to-market, they are not explained by the widely used three-factor Fama-French model. Our main sample includes US 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.

INSERT TABLE 1 HERE

The Thomson Reuters (TR) 13F database is used to measure institutional trading. Institutional investors that exercise investment discretion over $100 million or more in Section 13(f) securities are required to report to the SEC their end-of-quarter holdings on Form 13F within 45 days of each quarter-end. TR has provided the equity positions of such institutions since 1980. We use the list from Griffin et al. (2011) that identifies hedge funds in 13F data, and update it using the list compiled by Cella et al. (2013).[17] We identify mutual funds as non-hedge fund institutions classified as an investment company or an independent investment advisor by

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

Brian Bushee's web site.[18] We also identify transient institutional investors using the same source. Transient institutions are characterized as having high portfolio turnover and highly diversified portfolio holdings. We thus expect them to be active in exploiting anomalies.[19] Table 1 reports the paper that first documented each anomaly, its publication year and the sample period used. The goal is to identify the date when a research idea is introduced to the public domain. For simplicity we do not use the publication month and assume that the papers were already public at the beginning of the year. This assumption is realistic given the publication lag between manuscript submission and its final publication.

Table 2 Panel A presents correlations among portfolio ranks for our anomalies in addition to the first-order autocorrelation of each anomaly. Every June, we sort stocks into quintiles according to anomaly variables and compute the correlations. Consistent with Green et al. (2013), the anomalies are not strongly related to each other. Only 15 (3) out of 91 correlation coefficients are higher than 0.25 (0.50) and the average correlation coefficient across all anomaly pairs is 0.10, suggesting that each anomaly has its own distinct character. The low correlation between book-to-market and momentum and the other anomalies eases concerns that our results in other anomalies may be driven by institutions trading in book-to-market and momentum. When we look at first-order autocorrelations for persistence, the average is 0.45 among the anomalies and only 6 out of 14 are greater than 0.50.

We also examine the portfolio characteristics of the stocks in the long and short legs of all the anomalies. Table 2 Panel B summarizes the information about the size, value, momentum, and liquidity of the stocks based on the average quintile rank. We measure size, value, and momentum following the methodology of Daniel, Grinblatt, Titman, and Wermers (1997; DGTW) and illiquidity using the Amihud (2002) measure.[20] Stocks in the long leg tend to be larger and have more return momentum than stocks in the short leg. There is a statistically significant but smaller difference in average liquidity and book-to-market. Stocks in the long leg tend to be more liquid and have higher book-to-market ratios than stocks in the short leg.

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

[19] For instance, Ke and Ramalingegowda (2005) document that transient institutions are the most active in exploiting the post-earnings announcement drift anomaly.

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

INSERT TABLE 2 HERE

3.1 Summary Statistics

We first replicate the anomalies using the same sample period as in the original papers. Nine of these anomalies are based on annual accounting data. Following standard conventions in the literature, on June 30th of year *t* we rank stocks into quintiles according to the "anomaly variables" and form long and short portfolios. The long portfolio contains underpriced securities that should be bought by arbitrageurs and the short portfolio has overpriced securities that should be sold (short). To ensure that the accounting variables necessary to construct anomaly rankings are known to investors, we use accounting data for the last fiscal year end in calendar year $t - 1$, which becomes available to market participants by the end of March.[21] For each portfolio and for each anomaly, we compute value-weighted raw and risk-adjusted portfolio returns over the following twelve months (from July of the formation year to June of the next year).

We posit that sophisticated investors are likely to update their information set about a security using the most recent available information as opposed to updating annually. Therefore we also construct a quarterly version of each anomaly using the most up-to-date data at the beginning of each quarter. For balance sheet items, we use the figure from the previous quarter. For income statement items, we aggregate the figures for the four quarters up to and including the previous quarter. This one-quarter gap is intended to ensure the data required to compute the anomaly variables are publicly available. We then compute value-weighted raw and risk-adjusted returns over the quarter following sorting date.

Table 3 reports the difference between the performance of the long and short portfolios for the annual (Panel A) and quarterly (Panel B) rankings in the in-sample and post-publication periods. The in-sample period is defined as the sample period used in the original anomaly publication, and the post-publication includes the period starting from the year of publication through June 2013 in Panel A and December 2013 in Panel B. Anomaly performance is measured using average quarterly returns, the returns in excess of the DGTW benchmark, and 3-factor alphas. The alpha is the intercept of a regression of quarterly excess returns on the three

[21] In our sample, 59.9% of firms have fiscal years that end on December 31st. Before 2002, the deadline for financial reporting was 90 days after fiscal year-end. Starting from 2002, the reporting deadline is 60 days after fiscal year-end. For the anomalies that are constructed quarterly (DIS, OS, ROA, and PEAD) or monthly (MOM) in the original papers, we focus on June's ranking for the annual results.

Fama-French factors with the exception of the book-to-market anomaly that only includes the market and size factors. Similarly, when using the DGTW benchmark for the book-to-market and momentum anomalies we construct a benchmark without the same portfolio characteristic (e.g., excluding book-to-market when applied to the book-to-market anomaly). Consistent with the published results, when we examine the in-sample period, the average raw excess returns of the long-short portfolio are all positive and are significant for most of the anomalies. For the annual ranking, a long-short portfolio that takes the equally-weighted average each quarter across all the available anomalies delivers an excess return of 1.12% per quarter, which is statistically significant. When we consider the alphas using the 3-factor model (Fama and French, 1993) the magnitude of the outperformance of the long portfolio vs. the short portfolio is generally larger. Across all 14 anomalies, the alphas of the long-short portfolios are positive and significant. The alpha of the equally-weighted portfolio is 1.54% per quarter with a p-value of almost zero. The average DGTW-adjusted return is 0.97% per quarter and is statistically significant.[22]

The last three columns of Table 3 Panel A present the results using the post-publication period. Consistent with McLean and Pontiff (2015), we find a sizable reduction in the anomaly returns. Indeed, all the anomalies experience a reduction in average raw return. Focusing on the 3-factor alphas (DGTW), nine (thirteen) of the anomalies exhibit a reduction in alpha from the original sample period used in the anomaly publication. Only four (two) anomalies still have a positive and statistically significant alpha (DGTW) at the 10% confidence level for the long-short portfolio. Considering the equally-weighted portfolio, the alpha (DGTW) of the long-short portfolio is now only 1.05% (0.61%), which represents a 32% (36%) reduction compared to the in-sample period, which measures returns in the period used in the paper.[23]

When using quarterly rankings (Panel B), the performance of the long-short portfolio tends to be stronger. This suggests that it can be profitable for traders to update their portfolio more frequently. Focusing on the equally-weighted portfolio, the long-short strategy delivers a quarterly return of 1.84%, a 3-factor alpha of 2.12%, and a DGTW-adjusted return of 1.47% per

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

[23] When we take the time-series average first, and then the cross-sectional average across anomalies (rather than a portfolio approach), the 3-factor alpha (DGTW-adjusted return) in the post publication is 0.96% (0.32%), which represents a 40% (60%) reduction compared to the in-sample period.

quarter in the in-sample period. In the post-publication period, there is again a performance decay. For instance, the 3-factor alpha for the long-short strategy is 1.40% per quarter, which is a 34% reduction from the in-sample period.[24]

In summary, for our sample we confirm the post-publication decay documented by Mclean and Pontiff (2015). Given that the post-publication reduction in the long-short portfolio is similar if we use the 3-factor alpha or the DGTW-adjusted return, we use the latter measure of performance throughout this paper. For simplicity, we hereafter refer to the DGTW-adjusted return of the long-short portfolio as the anomaly return.

INSERT TABLE 3 HERE

Next we examine anomaly returns in each of the four quarters following the June 30th ranking and analyze how these returns vary with respect to the anomaly publication date.[25] In addition to the in-sample and post-publication period, we also consider the pre-publication period, which is the period from the end of the in-sample period to just before journal publication (for most anomalies this period is closely related to the time when the publication is a working paper). In the post-publication period we also distinguish a sub-period, post-publication (early), which includes the four years starting from the publication date. Examining these additional periods provides further granularity. We posit that sophisticated institutions may find out about anomaly research before it is actually published, for example through conferences or SSRN. To the extent that the sample period in the original paper has not changed during the publication process, the pre-publication period should capture information diffusion about the anomaly before publication. Additionally, by using both the post-publication (early) and the full post-publication period we can examine whether the increase in anomaly-based trading is stronger immediately after publication.

Table 4 presents OLS regressions that empirically examine the anomaly returns across these periods. The unit of observation is anomaly-year and the sample spans 1982 to 2013. The observations are pooled resulting in 448 observations (14 anomalies x 32 years). The dependent variable is the quarterly mean DGTW-adjusted return on the anomaly (the return of the long-short portfolio) in the first, second, third, or fourth quarter after the anomaly sorting as specified

[24] For the rest of the analysis the in-sample period starts in 1982, when trading data is available.
[25] To conserve space, we only present the results for the annual rankings.

in columns 1 through 4, respectively. The independent variables are dummies that identify in-sample, pre-publication, and post-publication periods indicating how the returns relate to the publication of the anomaly. We suppress the constant term so that the coefficients on the dummy variables represent the average return in the specified period. We run an additional specification which replaces the post-publication dummy with a dummy for the post-publication (early) period, and report the coefficient on the post-publication (early) period in the last row of the table. Robust standard errors are calculated and p-values are reported below the coefficient estimates.

INSERT TABLE 4 HERE

Consistent with McLean and Pontiff (2015) the results again suggest that the anomaly returns are the strongest in the in-sample period and decay after the publication of the anomaly. The decay from the in-sample to the post-publication period is 45% for the first quarter. We also find that the anomaly returns are stronger closer to the anomaly ranking date. While there is evidence that anomaly profits persistent beyond the first quarter during the in-sample period, albeit at smaller magnitudes, returns are statistically indistinguishable from zero after the first quarter during the pre-publication and post-publication periods. This finding suggests that investors may profit more from the anomaly by ranking at frequencies greater than once per year. We further explore this possibility in a later analysis that examines institutional trading in quarterly-ranked anomalies.

4. Empirical Analysis

4.1 Anomaly Level Trading Analysis for the Full Sample

In this section we examine the trading behavior of institutional investors in the anomalies. For the annual anomalies, on June 30th of each year we construct long and short portfolios for each anomaly. We then compute changes in aggregate institutional holdings for the two portfolios from March 31st to September 30th.[26] By the end of March, the information required to construct the long and short portfolios should be available to the institutions. If institutions act as

[26] For the quarterly version of the anomalies, we sort at the end of each calendar quarter based on accounting data for the previous fiscal quarter and other financial data observed by the end of the previous quarter. We then compute institutional trading over the two quarters starting from the quarter before sorting. This approach is intended to capture trading based on early accounting releases.

arbitrageurs, we should observe significantly greater institutional buying in the long portfolio than in the short portfolio. To control for differences in the market capitalization of the stocks, we measure institutional trading using the changes in the percentage of shares held by institutions in the long and short portfolios (e.g., Gompers and Metrick, 2001).[27] This approach is analogous to value weighting the individual changes across all the stocks in the long and short portfolios.

Panel A of Table 5 presents tests designed to examine whether institutions attempt to exploit the annual anomaly over the full sample period, which spans 1982 to 2013. The unit of measurement is the variable "Long minus Short" which measures the difference between the changes in aggregate institutional holdings for the long and short legs of each anomaly-year. The observations are pooled across all the anomalies resulting in 448 observations (14 anomalies x 32 years).

INSERT TABLE 5 HERE

The first column of Panel A presents the trading behavior of all institutions in the 13F database. The results suggest that over the full sample period, the universe of institutions have not traded in a manner which exploits the anomalies: the -0.05 difference between net holdings changes in the long and short legs of the anomalies has the wrong sign and is not statistically different from zero. To examine if sophisticated institutional investors such as hedge funds are more active in exploiting these anomalies than less sophisticated institutions, in columns two through four we partition the sample of institutional investors into hedge funds, mutual funds, and others, respectively.[28] Furthermore, in columns five through eight we focus on the subset of each group classified as transient institutions. Over the full sample period, the results suggest that hedge funds and transient institutions trade significantly with the anomalies. For instance, on average, transient institutions increase their net ownership in the anomaly stocks by 0.26% over the two-quarter window around each ranking date.

[27] To address potential data errors, if for a given firm the total number of shares held by institutions is greater than the total number of shares outstanding, we cap the ratio at 100%. When considering the trading results this sometimes causes the sum of trading across different types of institutions to be slightly different than the aggregate trading figure. Deleting these observations deliver similar results.
[28] "Others" is defined as institutional investors not classified as hedge funds or mutual funds. This group includes insurance companies, pension funds, endowments, and banks.

Panel B presents results for trading in the quarterly anomalies. Consistent with the annual results we find little evidence that in aggregate, institutional investors trade in the direction of the anomaly. The results at the aggregate level are weaker using quarterly anomalies compared to using annual anomalies. However, when we focus on transient institutions, consistent with exploiting the anomalies we find that these investors increase their net ownership of the anomaly stocks by 0.34% overall around each ranking date. Furthermore, we observe significantly positive anomaly trading across all three transient institution subgroups. These results suggest that only a subset of investors, i.e., transient institutions, update their anomaly-based trading strategies more frequently than annually.

4.2 Anomaly Level Trading Analysis around the Journal Publication Date

Next, we examine if institutional trading in the anomalies has changed over time, and, in particular, around the publication of academic research about the anomaly. 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 know about and trade on the anomaly. For example, in their paper on momentum, Jegadeesh and Titman (1993) mention that a number of practitioners use relative strength rankings. If this is the case, publication may have a certification effect. Another possibility is that publication exposes the anomaly to institutions that are not aware of the strategy. For either case, we should observe that the aggregate change in institutional holdings in the anomalies increase around the journal publication date. Table 5 Panel C presents the results of OLS regressions where the dependent variable is again "Long minus Short" trading in the annual anomalies. The independent variables are dummies that identify the in-sample, pre-publication, post-publication and post-publication (early) periods. To avoid overlap between the post-publication and post-publication (early) period we estimate two separate regressions. We are interested in how institutional trading relates to the publication of the anomaly, reported in the first four rows of the panel. We are also interested in the difference in trading between the post-publication (early) and in-sample periods, reported in the last row of the panel. If institutions react to publication this difference should be positive.

The first column presents results for all institutions. The results indicate that during the in-sample, pre-publication, and post-publication periods, the long minus short trading variable is not significantly different from zero. However, during the post-publication (early) period, the aggregate holdings change in the long leg is significantly larger than the holdings change in the short leg.[29] The average change in total net ownership during the post-publication (early) period is 0.70% over the two-quarter window around each ranking date. From the in-sample to the post-publication (early) period, there is an average increase of 0.87% of the total net ownership in the long-short portfolio over the two-quarter window. This change is economically significant. A back-of-the-envelope calculation taking the average of the total market value of the long and short portfolios, averaged across anomalies and across time, suggests that a 0.87% ownership change corresponds to approximately $10 billion change in ownership. This result suggests that institutions, in aggregate, try to exploit the annual anomalies and that the timing of their decision is related to the journal publication of the anomalies. The finding that institutions don't trade with the anomalies in the full post-publication period is consistent with institutions reducing their trading as the returns to the strategy decay.

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

Next, we examine anomaly trading by transient institutions. Our results suggest that these institutions are active in exploiting the anomalies, and even anticipate their publication. In aggregate they trade with the anomaly in the in-sample and pre-publication periods. Because transient institutions trade on anomalies before publication, we observe less of a difference when we compare their trading in the post-publication (early) period to the in-sample period. This difference is only significant for the subsample of transient hedge funds where we observe a 0.18% average increase in the total net ownership in the long-short portfolio over the two-quarter window.

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

Table 5 Panel D replicates the above analysis using the portfolios sorted at the quarterly frequency. Among the full sample of institutions, we only observe elevated trading following publication among hedge funds. However, when we focus our analysis on transient institutions, we observe increases in trading activity when we compare the post-publication (early) with the in-sample period among all groups except other institutions. Again, we also see evidence that transient investors trade in anomalies before publication. For example, the average change in total net ownership is 0.44% during the pre-publication period and 0.19% during the in-sample period.

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

Figure 1 provides the graphical representation of the annual results above for hedge funds and transient institutions. Specifically, we plot the cumulative change in ownership for the long and short portfolios along with the difference. To control for time-specific trends in aggregate institutional trading, we examine the long minus neutral and short minus neutral portfolios where the neutral portfolio includes the middle 60% of stocks for a given anomaly ranking variable. Around publication there is a shift toward taking advantage of the anomalies. This shift occurs just before publication for hedge funds and several years prior to publication for transient institutions.

INSERT FIGURE 1 HERE

4. 3 Institutional Trading and Anomaly Returns

Thus far we have provided evidence of a decay in anomaly performance and increase in anomaly-based trading by institutions after publication. Figure 2 confirms this pattern by plotting the difference between the cumulative returns and changes in hedge fund and aggregate institutional ownership for the long and short portfolios from the previous December to the following June for the in-sample and post-publication (early) periods. Hedge funds and 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 anomalies after publication.

INSERT FIGURE 2 HERE

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

Table 6 summarizes the returns and trading activity for the ex-ante and ex-post portfolios. Panel A shows that there is a reduction in anomaly returns mostly driven by the long leg of the portfolio. The difference in the long leg is 0.46% per quarter, which is statistically significant.[30] Panel B shows institutional trading in the ex-post and ex-ante portfolios, and Panel C shows data on the subgroup of transient institutions. Consistent with our earlier pooled results, we do not observe anomaly trading among the full universe of institutions at the quarterly level. However, we do observe a significant difference between trading in the ex-post and ex-ante portfolios among hedge funds and transient institutions. This result implies a spike in trading among the most sophisticated investors following publication of the anomalies.

INSERT TABLE 6 HERE

[30] Note that in this analysis the sample period is smaller than the previous analyses, which reduces the power of the test.

4.4 VAR Analysis

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

$$y_t = c + A_1 y_{t-1} + A_2 y_{t-2} + \cdots + A_p y_{t-p} + e_t$$

The VAR is specified with a one-quarter lag based upon results from the Schwarz Bayesian information criterion.[31] We are interested in the matrix A of coefficients and performing a Granger-type causality test. If arbitrage activity occurs, we expect to observe a negative relation between institutional trading and future anomaly returns when estimating the VAR. We expect this relation to be strongest following anomaly publication due to the subsequent surge in institutional trading. Hence, we expect a negative coefficient on lagged trading for the return equation for the ex-post portfolio rather than the ex-ante portfolio.

Table 7 Panel A presents VAR results for trading and returns of the ex-post portfolio. The first column examines the relation between all institutional trading and future anomaly returns. Consistent with arbitrage activity, the results suggest that institutional trading is negatively related to future anomaly returns. Columns 2, 3, and 4 examine hedge fund, mutual fund, and others' trading, and columns 5-8 examine trading among transient institutions. Across all specifications, we consistently observe that institutional trading is significantly negatively related to future anomaly returns. Therefore, we identify a Granger-causal relation between trading and future anomaly returns.

Panel B presents VAR results for the ex-ante portfolio. Previous results show that institutions do not consistently trade with or against the anomalies prior to the anomaly publication. Consistent with these results, and inconsistent with an arbitrage process occurring

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

prior to anomaly publication, we do not observe a significant relation between institutional trading and future anomaly returns in the ex-ante portfolio.

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

INSERT TABLE 7 HERE

5. Comparison with Edelen et al. (2015)

In this section we replicate the results of Edelen et al. (2015) in an attempt to reconcile the discrepancy between our findings and theirs. On June 30th of each year we construct long and short portfolios for each anomaly. Following Edelen et al. (2015), for each stock we compute the change in the number of institutions and the change in the fraction of shares held. For the change in the number of institutions, as in Edelen et al. (2015), we scale the change in the number of institutions by the average number of institutions holding stocks in the same market capitalization decile. We then compute equal-weighted averages for the long and short portfolios, pool across anomalies each year, and report the annualized time-series averages for the long-short portfolio.[32] We consider various institution types and four different trading windows. Considering June 30th of the current year (the annual sorting date) as a reference point we examine: 1) December 31st two years ago to December 31st of the previous year ([-6, -2]); 2) December 31st two years ago to June 30th of the current year ([-6, 0]); 3) March 31st to June 30th of the current year ([-1, 0]); and 4) March 31st to September 30th of the current year ([-1, 1]). Panels A and B of Table 8 display the results.

INSERT TABLE 8 HERE

Edelen et al. (2015) examine the trading by all institutions in the [-6, 0] window. Consistent with their findings, we find that, for the [-6, -2] window the number of institutions in the long-short portfolio decreases by 8.74% (Panel A) and institutional ownership declines by 0.92% of shares outstanding in the long-short portfolio (Panel B). Both figures are statistically

[32] We use equal-weighted averages to be consistent with Edelen et al. (2015). We find qualitatively similar results if we use a value-weighted approach as in the previous analyses.

significant. There is also a negative, but insignificant, pattern when we examine aggregate institutional trading in the [-6, 0] window, as Edelen et al. (2015).[33] In contrast, we find that hedge funds and transient institutions trade with the anomalies in the [-6, 0] window, although the figure for hedge funds is only significant in Panel A. Furthermore, when we focus on trading across different institution types in the [-1, 0] and [-1, 1] windows the changes are all positive and mostly significant at the 5% level (28 of 32 specifications in Panels A and B). These contrasting findings may be driven by the availability of the information necessary to compute anomaly ranking data, which is generally made public by firms during the [-1, 0] window. As institutions do not have this information during much of the [-6, 0] window, we interpret the negative coefficient on institutional trading in the [-6, 0] window as evidence that institutions are not able to proactively anticipate the future anomaly rankings. On the other hand, the positive trading we observe in the [-1, 0] and [-1, 1] periods suggests that institutions react to the information once it is made public.

The lack of autocorrelation of the anomaly rankings, reported in Panel A of Table 2, may make it difficult for institutions to predict future rankings. However, the lack of predictability still does not explain why institutions trade against anomalies before knowing the anomaly rankings. One possibility, which is explored in Panels C and D of Table 8, is that these positions are affected by the previous year's rankings. Specifically, we focus on two subsamples of anomaly stocks: the "reversal sample" is the group of stocks that are in the long (short) portfolio in the current year and short (long) portfolio in the previous year; and the "persistent sample" is the group of stocks that are in the long (short) portfolio for both the current and previous years.[34] We also report results for the ex-post and ex-ante portfolios so that we can observe how trading behavior changes following publication. Panel C reports results for the change in the number of institutions whereas Panel D reports results for the change in the fraction of shares held (equal-weighted as in Edelen et al. 2015).

When we look at stocks that switch from long to short leg or vice versa (fourth column of Panels C and D), we find the same negative relation documented by Edelen et al. (2015):

[33] When we examine our six anomalies that overlap with those used by Edelen et al. (2015), we find that the results are negative and significant for the [-6, 0] window.

[34] For the reversal sample, we use 8 anomalies instead of 14 since 6 of the anomalies (CEI, NOA, GP, BM, OS, and ROA) have high autocorrelations and very few stocks go from the long to the short leg or vice versa from one year to the next.

institutions sell during the [-6, -2] window but start buying afterwards. However, when we look at stocks that remain in the long or short portfolio (seventh column), institutions no longer trade in the wrong direction suggesting that Edelen et al. results may partially be due to institutions reacting to previous year's anomaly rankings. Ex-post and ex-ante results are similar to those for all anomalies. But ex-post results are stronger than those for ex-ante portfolio as we would expect. Taken together these results provide evidence consistent with the rest of our paper. When institutions know about the anomalies or can anticipate the anomalies they correctly trade on them.

To summarize, the main difference between our paper and Edelen et al. (2015) is that we focus on institutional trading in anomalies conditional on the information about the anomalies being readily available to the institutions. First, we put emphasis on the period after the academic publication of each anomaly. Second, we highlight anomaly trading by hedge funds and transient institutions who, in addition to potentially having stronger incentives with respect to exploiting the anomalies, may also have richer information sets pertaining to the anomalies. Third, Edelen et al. (2015) examine institutional trading before the anomaly sorting starting from January of the previous year. Therefore, we reconcile their results as highlighting the inability of institutions to predict future anomaly rankings and take proactive positions. In contrast, we use a much narrower window spanning the two quarters surrounding the anomaly ranking date to ensure that institutions have access to the financial and accounting data necessary to compute rankings and trade on them. Thus, we see our results as highlighting the responsive, rather than anticipatory, behavior of institutions with respect to publicly available information.

6. Robustness Checks

6.1 Profitability of the Arbitrage Activity

The empirical findings from the previous section provide evidence of arbitrage activity by sophisticated institutional investors. A related question is whether institutional trading to exploit anomalies is profitable. This question is relevant because the profitability of the trading strategy is the driver of the arbitrage activity. To answer this question we need to observe the individual stocks in the long and short portfolios of each anomaly that are actually traded. Indeed, institutions could select the worst performing stocks among all the securities in the two portfolios. When examining returns on institutional trading, we are limited by the quarterly availability of institutional holdings data which prevents us from observing the timing of the trades and consequently assessing their direct trading profits. Thus, we can only provide indirect evidence of these profits by examining the future performance of stocks selected by institutions.

Each quarter we measure changes in aggregate institutional holdings for stocks in the long and short legs of the ex-ante and ex-post portfolios. We then sort stocks into two portfolios conditional on institutional trading: "buy in the long" portfolio which includes the long-leg stocks that institutions buy and "sell in the short" portfolio which has the short-leg stocks that institutions sell. We then compute the next quarter DGTW-adjusted returns for each portfolio. We also compute the return of a portfolio named "with anomaly" which is long the stocks in the "buy in the long" portfolio and short the stocks in the "sell in the short" portfolio. Examining the returns on these portfolios help us to determine if institutions profit from their trades in the anomaly stocks.

INSERT TABLE 9 HERE

Table 9 Panel A presents the value-weighted DGTW-adjusted returns of the ex-ante portfolio stocks. The first column shows results for the full sample of institutions and reports a significantly positive 1.90% abnormal return per quarter for the "with anomaly" portfolio. The alpha in the "sell in the short" portfolio is larger than the alpha in the "buy in the long" portfolio although they are both statistically significant. Columns 2-4 present results for the hedge funds, mutual funds, and other subgroups, and columns 5-8 present results for transient institutions. Across all groups we observe that the stocks selected by hedge funds deliver the highest performance, which is 2.56% per quarter.

Table 9 Panel B presents the DGTW-adjusted returns for the ex-post portfolio. Consistent with a post-publication decay in returns, across all specifications risk-adjusted returns in the ex-post portfolios are smaller than those earned in the ex-ante portfolio. Despite the decay, we observe significantly positive alphas across all specifications in the "with anomaly" portfolios. The decay is driven by stocks in the long portfolio. Indeed, whereas stocks in "buy in the long" portfolio delivered significant risk-adjusted returns in the ex-ante portfolio, now in the ex-post portfolio the alphas are insignificant. Taken together, these results provide evidence that institutional investors, and especially hedge funds, profit when they trade to take advantage of the anomalies. However, these profits are reduced after the publication of the anomalies with only stocks in the short leg being able to deliver alphas. According to Panel B of Table 2, short-leg stocks tend to be smaller and more illiquid and may thus be more susceptible to limits of arbitrage.

6.2 Fama-MacBeth Regressions

One concern is whether the increase in trading activity for the ex-post portfolio is robust after we control for common determinants of institutional trading. For instance, Gompers and Metrick (2001) find that institutional ownership is systematically related to size and book-to-market. We use Fama-MacBeth cross-sectional regressions to examine the institutional trading behavior in the stocks in the ex-ante and ex-post portfolios after controlling for stock characteristics related to institutional preferences. The analysis is performed using all the stocks that have both ex-ante and ex-post portfolio rankings, even if they are not in the long or short leg. The variables of interest are four dummy variables, ex-post long, ex-post short, ex-ante long, and ex-ante short, which indicate if the stock is in the long or short legs of the ex-post and ex-ante anomaly portfolios. Including separate variables for the long and short legs allows us to separately examine whether institutions change their trading behavior based on positive and negative anomaly signals. The control variables are measured on the ranking date and include the log of book-to-market, the 6-month cumulative stock returns, the average quarterly Amihud's (2002) illiquidity measure, and the log of market capitalization. Institutional trading is measured by the one-quarter (two-quarter) change in the fraction of a company’s stock that is owned by institutional investors starting from the ranking date (the quarter before ranking date).

Table 10 presents the results using one-quarter (Panel A) and two-quarter (Panel B) institutional trading. We examine both specifications because in previous analyses we consider both trading intervals. The increase in trading in the ex-post portfolio is confirmed. When a firm is in the ex-post long portfolio, institutions buy it; when it is in the ex-post short portfolio, institutions sell it. Columns 5 through 8 indicate that this result is especially strong for transient institutions. By contrast, the coefficients on the ex-ante dummy variables are generally insignificant. In the last six rows of the table, we test whether the difference between the ex-post and ex-ante coefficients are significant. Focusing on all the institutions, we find that the ex-post long (short) coefficient is significantly higher (lower) than the ex-ante long (short) coefficient in both the one-quarter and two-quarter specifications. We also test whether the difference between long and short is higher in the ex-post portfolio than in the ex-ante portfolio. The difference is positive for all 16 specifications and statistically significant for all but three. We observe stronger results when we use the two-quarter specification instead of the one-quarter specification.

The coefficients on the control variables suggest that aggregate institutional trading is increasing in growth and momentum and decreasing in illiquidity and size. These findings are consistent with previous literature, for example, a similar preference for trading in growth stocks is documented by Jiang (2010), for momentum stocks is documented by Grinblatt et al. (1995), and for liquid stocks is documented by Gompers and Metrick (2001). The preference for small stocks is consistent with the shift to smaller stocks documented by Bennett et al. (2003). Different from the rest of institutions, transient institutions appear to trade more in value stocks rather than growth stocks.

INSERT TABLE 10 HERE

6.3 Other Concerns

The 2008 financial crisis caused a liquidity crunch that may have limited the ability of institutions to exploit anomalies. The crisis occurred during the post-publication period for all but one (gross profitability) of the anomalies. Therefore, if the financial crisis reduced the capacity of institutional investors to trade on anomalies then including this period in our sample should bias us against finding results. Nonetheless, for robustness we rerun the regressions presented in Table 5 excluding the years 2008 and 2009 from the sample. The results, presented in Table 1 of a separate Internet Appendix, are indistinguishable to those when these years are included.

Chordia et al. (2014) document that an important determinant of the attenuation of anomaly returns is the increase in liquidity. To test whether liquidity or trading Granger causes the reduction in anomaly returns, we estimate a VAR model that includes a liquidity measure in addition to trading and returns. As a liquidity measure, we use either the aggregate Amihud measure or the share turnover for the long-short portfolio. Turnover is the quarterly average of the monthly share trading volume divided by shares outstanding. Table 2 of the Internet Appendix shows that for the return equation, the coefficient on lagged trading is negative and significant for the ex-post portfolio whereas the liquidity measure coefficient is insignificant. Therefore, it seems that liquidity is not the driver of the post-publication decay in anomaly returns.

A final concern is that the 13F data are available only for long positions and not the short positions. To fully exploit an anomaly, both a long and a short position are required. Although we do not observe short positions we have so far examined whether institutions sell existing shares of securities that fall into the short leg of an anomaly strategy. For robustness, we also examine the change in short interest for the long and short legs around publication dates. We obtain monthly short-interest data from Compustat. Consistent with Hwang and Liu (2014), we find that 58% of firms are missing short interest data before 2003, so we focus on the six annual anomalies that are published in mid to late 2000's: composite equity issues, net operating assets, gross profitability, asset growth, capital investments, and investment-to-assets. Short interest data is available for more than 90% of the total market capitalization of our sample after July 2003. Although the short interest data is not at the institution level, we can examine whether the stocks in the short portfolio are shorted more than the stocks in the long portfolio around anomaly publication.

Every June, we sort stocks into quintiles according to anomaly variables. We then compute the percentage of market capitalization sold short for the long and short legs at the end of previous, current, and following quarters and compute the changes from March to June and March to September. Figure 3 plots the difference between the changes in short interest for the long and short portfolios. Consistent with institutions following academic research and trading on them, the difference in differences is negative for the first four years following publication for March to June trading. In contrast, the average for the five years preceding publication is -0.006%.

INSERT FIGURE 3 HERE

7. Conclusion

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

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

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

REFERENCES

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

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

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

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

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

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

Bennett, J., R. Sias, and L. Starks, 2003, “Greener pastures and the impact of dynamic institutional preferences.” Review of Financial Studies 16, 1203–1238.

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

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

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

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

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

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

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

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

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

Cohen, R., P. Gompers, and T. Vuolteenaho, 2002, “Who underreacts to cash-flow news? Evidence from trading between individuals and institutions.” Journal of Financial Economics 66, 409–462.

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

Coval, J., T. Moskowitz, 2001, “The geography of investment: Informed trading and asset prices.” Journal of Political Economy 109, 811–841.

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

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

DeVault, L., R. Sias, and L. Starks, 2014, “Who are the sentiment traders? Evidence from the cross-section of stock returns and demand. Evidence from the Cross-Section of Stock Returns and Demand”. Working Paper.

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

Edelen, R., O. Ince, and G. Kadlec, 2015, “Institutional Investors and Stock Returns Anomalies”, Journal of Financial Economics forthcoming.

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

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

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

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

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

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

Fama, E. and K. French, 2010, “Luck versus skill in the cross-section of mutual fund returns.” Journal of Finance 65, 1915–1947.

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

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

Gibson, S., A. Safieddine, and R. Sonti, 2004, “Smart investments by smart money: evidence from seasoned equity offerings.” Journal of Financial Economics 72, 581–604.

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

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

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

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

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

Griffin, J. and J. Xu, 2009, “How smart are the smart guys? A unique view from hedge fund stock holdings.” Review of Financial Studies 22, 2531–2570.

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

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

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

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

Hendershott, T., D. Livdan, and N. Schürhoff, 2015, “Are institutions informed about news?” Journal of Financial Economics 117, 249–287.

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

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

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

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

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

Jagannathan, R., A. Malakhov, and D. Novikov, 2010, “Do hot hands exist among hedge fund managers? An empirical evaluation.” Journal of Finance, 65, 217–255.

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

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

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

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

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

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

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

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

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

McLean, D. and J. Pontiff, 2015, “Does academic research destroy stock return predictability?” Journal of Finance forthcoming.

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

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

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

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

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

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

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

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

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

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

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

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

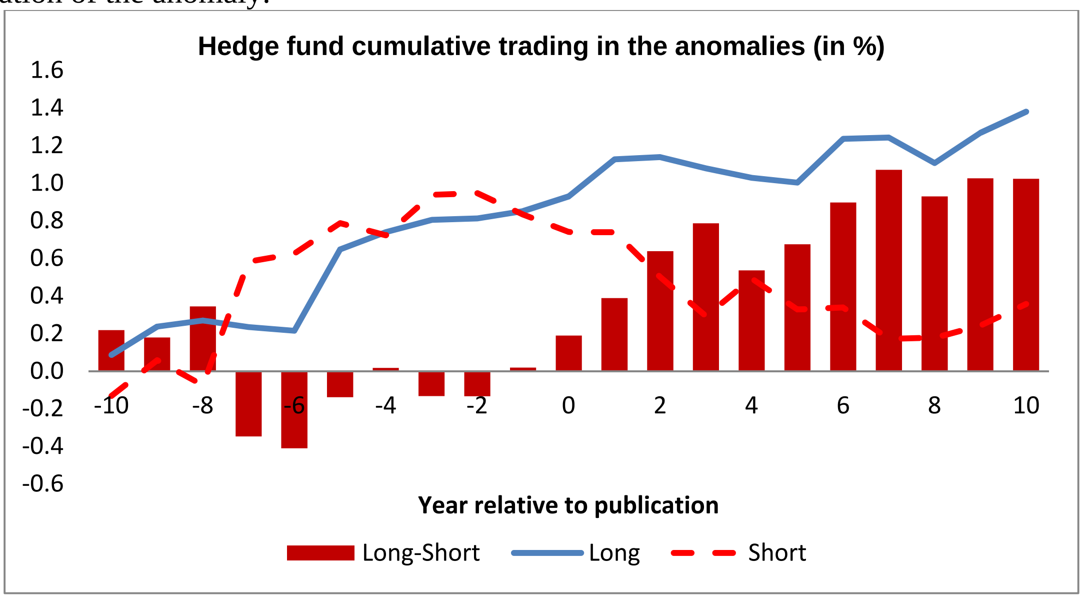
Xing, Y., 2008, “Interpreting the value effect through the Q-theory: an empirical investigation.” Review of Financial Studies 21, 1767–1795.

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

Figure 1

Hedge Fund and Transient Institution Cumulative Trading in the Long, Short, and Long-Short Portfolios Relative to Publication Date

This figure plots the average cumulative changes in hedge fund (top chart) and transient institutional (bottom chart) ownership for the long and short portfolios, and the difference between the two portfolios. The long portfolio contains underpriced securities that should be bought and the short portfolio includes overpriced securities that should be sold (short). Every June we sort stocks into quintiles according to the anomaly variables and measure the changes in percentage of shares outstanding held by hedge funds or transient institutions in the long and short portfolios between the end of March and the end of September. The trading is detrended by subtracting the concurrent change in percentage of shares outstanding held in the neutral portfolio (middle 60% of stocks for anomaly ranking variable). We take the average across the 14 anomalies for the adjusted changes in the long and short portfolios, and the difference between the two portfolios, and we cumulate this average over time. Year 0 is the year of publication of the anomaly.



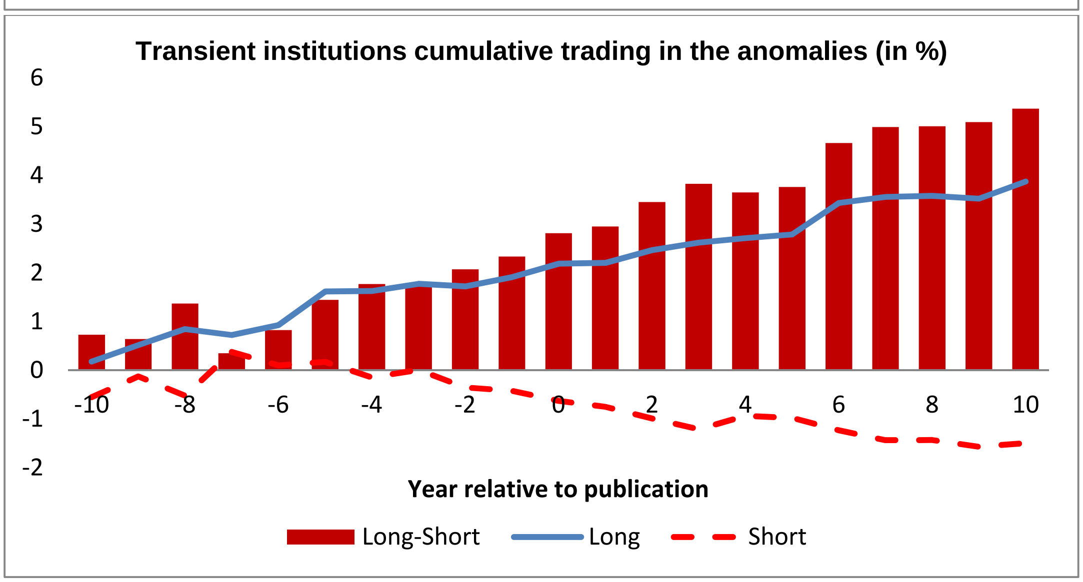
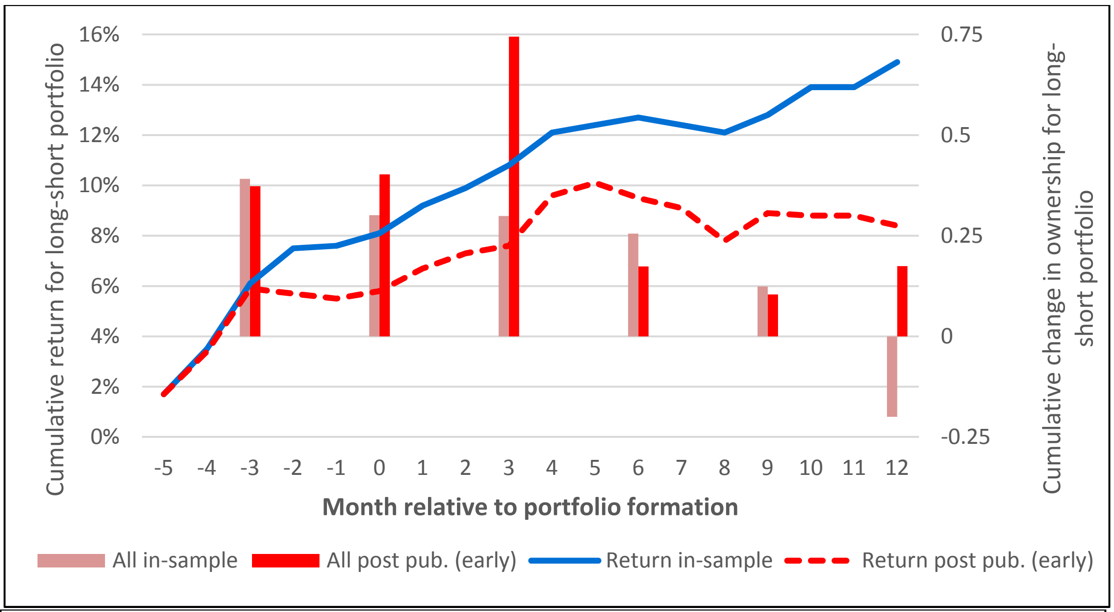


Figure 2

Cumulative Institutional Trading and Anomaly Returns by Periods

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



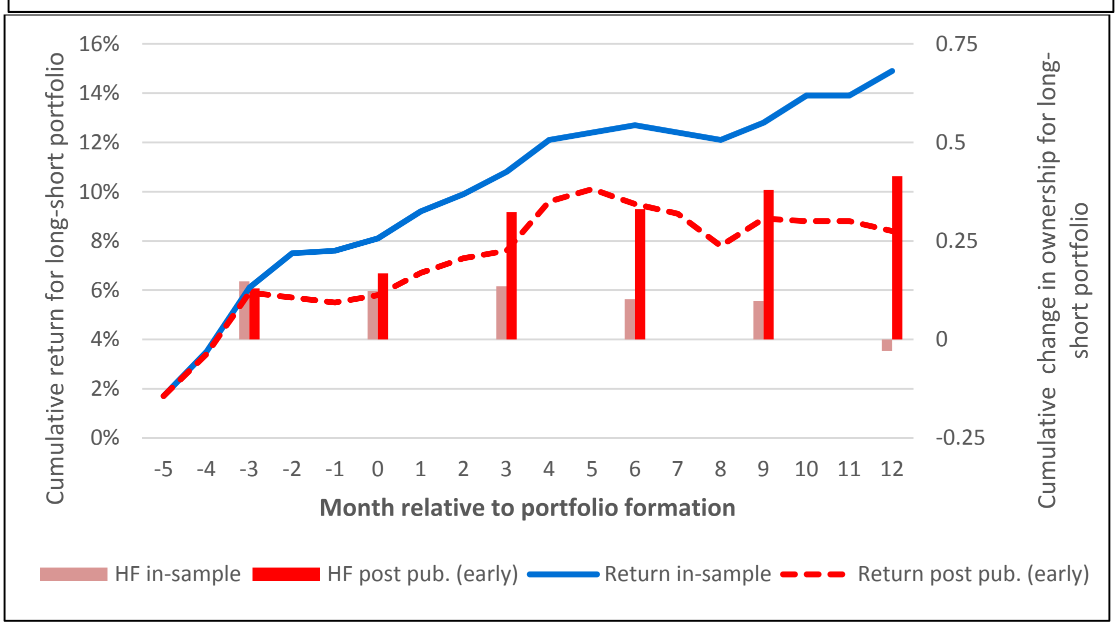


Figure 3
Change in Short Interest around Publication Date

This figure plots the average difference between the changes in short interest for the long and short portfolios. Every June, we sort stocks into quintiles according to the anomaly variables. We then compute the percentage of market capitalization sold short for the long and short legs at the end of previous, current, and following quarters and calculate the changes from March to June and March to September. Given that short interest data is only available after July 2003, we focus on six annual anomalies that are published in mid to late 2000's: composite equity issues, net operating assets, gross profitability, asset growth, capital investments, and investment-to-assets. Year 0 is the year of publication of the anomaly.

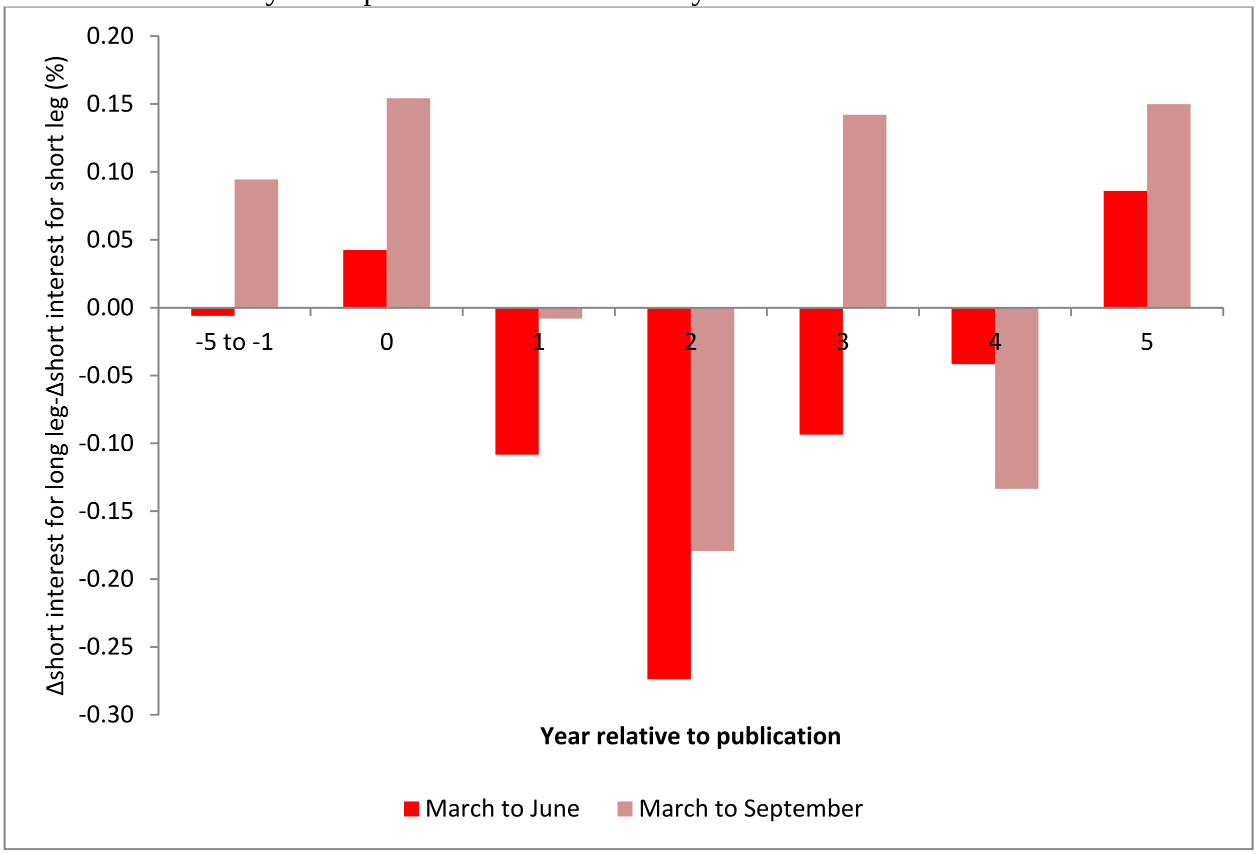


Table 1
Sample of Anomalies

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

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

Table 2

Correlations and Portfolio Characteristics

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

Panel A	**NSI**	**CEI**	**ACC**	**NOA**	**GP**	**AG**	**CI**	**IVA**	**BM**	**MOM**	**DIS**	**OS**	**ROA**	**PEAD**
First-order autocorrelation	0.37	0.87	0.26	0.68	0.89	0.29	0.28	0.37	0.79	0.01	0.31	0.76	0.65	-0.18
NSI		0.44	0.11	0.12	0.09	0.33	0.01	0.19	0.18	0.03	0.13	0.06	0.09	-0.01
CEI			0.09	0.13	0.12	0.24	-0.01	0.17	0.15	0.02	0.18	0.09	0.12	0.00
ACC				0.23	-0.08	0.31	0.07	0.25	0.09	0.06	-0.02	0.01	-0.10	0.05
NOA					0.06	0.40	0.11	0.46	-0.10	0.05	-0.03	-0.02	-0.03	0.04
GP						-0.04	-0.02	-0.02	-0.21	0.03	0.21	0.13	0.38	0.02
AG							0.17	0.60	0.29	0.06	-0.10	-0.10	-0.20	0.04
CI								0.28	0.03	0.05	-0.01	-0.06	-0.04	0.08
IVA									0.16	0.07	-0.02	-0.06	-0.11	0.07
BM										0.08	-0.12	-0.24	-0.32	-0.07
MOM											0.32	0.02	0.10	0.21
DIS												0.46	0.56	0.33
OS													0.54	0.18
ROA														0.34

Panel B	**Long leg**	**Short leg**	**Difference**	**p-value**
Size	2.62	1.76	0.85	0.00
Book-to-market	3.13	2.76	0.37	0.00
Momentum	3.77	2.62	1.14	0.00
Illiquidity	2.25	2.73	-0.48	0.00

Table 3
Anomaly Returns

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

Panel A: Long-short performance with annual ranking						
	In-sample			Post-publication		
	Returns	Alphas	DGTW	Returns	Alphas	DGTW
NSI	1.41	1.09	1.03	0.97	1.62	0.96
	(0.00)	(0.00)	(0.00)	(0.21)	(0.01)	(0.04)
CEI	1.38	1.57	1.09	0.20	1.40	0.42
	(0.02)	(0.00)	(0.00)	(0.83)	(0.06)	(0.50)
ACC	0.95	1.38	0.50	0.60	0.80	0.40
	(0.15)	(0.02)	(0.23)	(0.34)	(0.22)	(0.44)
NOA	1.01	1.16	0.73	0.20	0.07	0.61
	(0.02)	(0.01)	(0.03)	(0.79)	(0.93)	(0.24)
GP	0.99	1.50	0.93	-0.30		-1.99
	(0.02)	(0.00)	(0.01)	(0.84)		(0.12)
AG	1.16	0.81	1.07	0.87	0.32	0.56
	(0.03)	(0.03)	(0.00)	(0.42)	(0.77)	(0.42)
CI	1.08	1.05	0.51	0.05	0.09	0.15
	(0.01)	(0.01)	(0.11)	(0.95)	(0.91)	(0.79)
IVA	1.21	1.06	0.92	0.71	1.26	0.89
	(0.00)	(0.00)	(0.00)	(0.53)	(0.28)	(0.19)
BM	1.77	1.65	1.25	1.27	1.14	0.81
	(0.01)	(0.01)	(0.05)	(0.13)	(0.19)	(0.24)
MOM	1.16	2.35	0.86	-0.09	0.16	-0.28
	(0.21)	(0.01)	(0.31)	(0.95)	(0.89)	(0.80)
DIS	0.80	2.38	0.01	-1.41	0.55	-0.56
	(0.43)	(0.00)	(0.98)	(0.39)	(0.66)	(0.51)
OS	1.45	1.81	0.93	1.04	3.08	1.88
	(0.14)	(0.00)	(0.01)	(0.46)	(0.00)	(0.01)
ROA	0.52	1.56	0.80	0.46	1.75	0.49
	(0.56)	(0.05)	(0.15)	(0.69)	(0.02)	(0.42)
PEAD	0.93	3.15	0.39	0.22	0.20	0.09
	(0.41)	(0.00)	(0.53)	(0.66)	(0.70)	(0.80)
EW Portfolio	1.12	1.54	0.97	0.80	1.05	0.61
	(0.00)	(0.00)	(0.00)	(0.04)	(0.01)	(0.04)

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

Table 4

Anomaly Returns by Publication Period and for Each Quarter after June

This table uses OLS regressions to examine the quarterly mean return of the anomalies surrounding dates relevant to the publication of each anomaly. The unit of observation in the regression is anomaly-year and the sample period is 1982 to 2013. The observations are pooled resulting in 448 observations (14 anomalies x 32 years). Every June of year t we sort stocks into quintiles based on accounting data for the last fiscal year end in calendar year t – 1, which becomes available to market participants by the end of March. For MOM, DIS, OS, ROA, and PEAD we focus on June's ranking. Next, we calculate value-weighted portfolio returns over the following four quarters. The dependent variable is the quarterly mean DGTW-adjusted returns on the anomaly (the difference between the return of the long and short portfolios) in the first, second, third, and fourth quarter after the anomaly sorting as specified in columns 1 through 4, respectively. The independent variables identify how the return date relates to the publication of the anomaly. Specifically, in-sample indicates if the return date falls in the sample period of the original anomaly publication, pre-publication indicates if the return date falls in the period from the end of the publication period and to just before the publication date of the paper, post-publication indicates if the return date is starting from the publication date of the paper through 2013, and post-publication (early) period indicates if the return date falls in the four years (t = 0, t =3) including and after the publication date of the paper. To avoid overlap between the post-publication and post-publication (early) period we estimate two separate regressions. Robust standard errors are calculated and p-values are reported below the coefficient estimates.

DGTW returns	**RetQ1**	**RetQ2**	**RetQ3**	**RetQ4**
In-sample	1.71	0.75	0.17	0.77
	(0.00)	(0.01)	(0.61)	(0.01)
Pre-publication	0.59	0.89	0.38	0.82
	(0.38)	(0.31)	(0.63)	(0.13)
Post-publication	0.94	0.58	0.16	0.31
	(0.02)	(0.20)	(0.74)	(0.36)
Post-publication (early)	1.80	1.26	0.01	-0.25
	(0.03)	(0.06)	(0.99)	(0.70)

Table 5
Institutional Trading in the Anomaly

This table examines the trading activity of institutional investors in the 14 anomalies. The unit of measure is the variable "Long minus Short" which measures the difference between the aggregate institutional holdings changes in the long and short legs of each anomaly. Institutional holdings (expressed in percent) are measured by the percentage of shares held by institutions in the long and short portfolios. Institutional trading is measured by the two-quarter change in institutional holdings starting from the quarter before ranking date. Observations are pooled across the anomalies. Panel A presents average trading across the full sample period in the anomalies sorted once a year and Panel B presents average trading in the anomalies sorted every quarter. Panel C presents results of a regression of trading on dummies that identify dates surrounding the publication of each anomaly, and Panel D presents the same analysis when stocks are sorted every quarter instead of once a year. The first column of each panel presents results for all institutions. The second through fourth columns present results for the subgroup of traders identified as hedge funds (HF), mutual funds (MF) and all the other institutions (Others). The fifth through eighth columns present results for institutions identified as transient. The last rows of Panels C and D also report the difference between trading in the post-publication (early) period and the in-sample period. To avoid overlap between the post-publication and post-publication (early) period we estimate two separate regressions. Robust standard errors are calculated and p-values are reported below the coefficient estimates.

Panel A: Annual anomaly trading in full sample period

	Full sample				**Transient institutions**			
	All	**HF**	**MF**	**Others**	**All**	**HF**	**MF**	**Others**
Full Sample	-0.05	0.08	0.00	-0.13	0.26	0.07	0.18	0.02
	(0.59)	(0.03)	(0.99)	(0.01)	(0.00)	(0.01)	(0.00)	(0.00)

Panel B: Quarterly anomaly trading in full sample period

	Full sample				**Transient institutions**			
	All	**HF**	**MF**	**Others**	**All**	**HF**	**MF**	**Others**
Full Sample	-0.09	0.02	-0.03	-0.07	0.34	0.09	0.23	0.02
	(0.09)	(0.37)	(0.29)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)

Panel C: Annual anomaly trading in sub-sample periods								
	Full sample				**Transient institutions**			
	All	**HF**	**MF**	**Others**	**All**	**HF**	**MF**	**Others**
In-sample	-0.17	-0.01	0.08	-0.29	0.21	0.01	0.17	0.02
	(0.17)	(0.82)	(0.28)	(0.00)	(0.01)	(0.77)	(0.00)	(0.00)
Pre-publication	0.24	0.23	-0.04	0.10	0.40	0.15	0.25	0.01
	(0.44)	(0.03)	(0.84)	(0.42)	(0.01)	(0.02)	(0.02)	(0.70)
Post-publication	0.03	0.15	-0.09	0.02	0.28	0.11	0.16	0.01
	(0.83)	(0.01)	(0.35)	(0.82)	(0.00)	(0.00)	(0.00)	(0.19)
Post-publication (Early)	0.70	0.29	0.29	0.12	0.39	0.19	0.21	0.00
	(0.01)	(0.00)	(0.08)	(0.37)	(0.00)	(0.00)	(0.02)	(0.98)
Post-publication (Early)	0.87	0.31	0.20	0.41	0.18	0.18	0.03	-0.02
- In-sample	(0.00)	(0.00)	(0.26)	(0.01)	(0.22)	(0.01)	(0.73)	(0.15)

Panel D: Quarterly anomaly trading in sub-sample periods								
	Full sample				**Transient institutions**			
	All	**HF**	**MF**	**Others**	**All**	**HF**	**MF**	**Others**
In-sample	-0.12	-0.02	0.04	-0.14	0.19	0.02	0.15	0.02
	(0.07)	(0.46)	(0.35)	(0.00)	(0.00)	(0.26)	(0.00)	(0.00)
Pre-publication	0.07	0.04	0.02	-0.01	0.44	0.10	0.33	0.02
	(0.67)	(0.57)	(0.82)	(0.87)	(0.00)	(0.04)	(0.00)	(0.06)
Post-publication	-0.08	0.06	-0.14	0.01	0.51	0.19	0.32	0.01
	(0.37)	(0.06)	(0.01)	(0.86)	(0.00)	(0.00)	(0.00)	(0.09)
Post-publication (Early)	-0.08	0.10	-0.06	-0.09	0.62	0.25	0.36	0.01
	(0.62)	(0.07)	(0.58)	(0.15)	(0.00)	(0.00)	(0.00)	(0.14)
Post-publication (Early)	0.05	0.11	-0.10	0.06	0.43	0.22	0.21	-0.01
- In-sample	(0.78)	(0.05)	(0.40)	(0.44)	(0.00)	(0.00)	(0.02)	(0.19)

Table 6

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

This table presents the average risk-adjusted returns and 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. We assign a percentile rank to each stock based on each anomaly and compute the equal-weighted average rank for ex-ante and ex-post anomalies. We drop a stock if more than half the anomaly variables are missing. We rank the stocks again based on the average rank and the top and bottom quintiles form the long and short portfolios, respectively. Panel A presents the DGTW-adjusted returns of each portfolio. Panel B (Panel C) presents institutional trading in the long-short portfolio for aggregate (transient) institutions and separately for hedge funds, mutual funds, and the rest of institutions. Institutional trading is measured by the two-quarter change in the fraction of a company's stock that is owned by institutional investors in the long portfolio minus the change in the short portfolio starting from the quarter before ranking date. Newey-West standard errors are calculated and p-values are reported below the coefficient estimates.

Panel A: DGTW-adjusted returns

	Long	Short	Long-Short
Ex-post portfolio	0.16	-1.13	1.29
	(0.53)	(0.03)	(0.05)
Ex-ante portfolio	0.62	-1.06	1.68
	(0.01)	(0.00)	(0.00)
Ex-post minus ex-ante portfolio	-0.46	-0.07	-0.39
	(0.05)	(0.89)	(0.47)

Panel B: Trading - All Institutions

	All	Hedge funds	Mutual funds	Others
Ex-post portfolio	-0.08	0.26	-0.24	-0.13
	(0.73)	(0.00)	(0.12)	(0.30)
Ex-ante portfolio	-0.39	-0.06	-0.23	-0.12
	(0.01)	(0.39)	(0.01)	(0.24)
Ex-post minus ex-ante portfolio	0.31	0.31	-0.01	-0.01
	(0.27)	(0.00)	(0.96)	(0.94)

Panel C: Trading - Transient Institutions

	All	Hedge funds	Mutual funds	Others
Ex-post portfolio	1.32	0.51	0.77	0.04
	(0.00)	(0.00)	(0.00)	(0.00)
Ex-ante portfolio	0.28	0.04	0.22	0.02
	(0.00)	(0.33)	(0.00)	(0.04)
Ex-post minus ex-ante portfolio	1.04	0.47	0.55	0.02
	(0.00)	(0.00)	(0.00)	(0.14)

Table 7

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

This table reports the results of the vector autoregressive (VAR) model which includes quarterly institutional trading and quarterly DGTW-adjusted returns for the long-short leg of 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. Institutional trading is measured by the one-quarter change in the fraction of a company's stock that is owned by institutional investors starting from the quarter of the ranking date. The VAR is specified with a one-quarter lag based upon the Schwarz Bayesian information criterion. Panel A presents VAR results for trading and returns of the ex-post portfolio and Panel B presents VAR results for the ex-ante portfolio. The first column presents results for all institutions, while the second through fourth column focus on the hedge fund, mutual fund and the others subgroups, respectively. The fifth through eighth columns presents results for the subsample of traders identified as transient. p-values are reported below the coefficient estimates.

Panel A: Ex-post portfolio

	Full sample				**Transient institutions**			
	All	**HF**	**MF**	**Others**	**All**	**HF**	**MF**	**Others**
Return								
Lag Ret	0.08	0.14	0.11	0.13	0.21	0.20	0.20	0.17
	(0.42)	(0.15)	(0.25)	(0.21)	(0.03)	(0.05)	(0.03)	(0.09)
Lag Trading	-0.01	-0.03	-0.02	-0.01	-0.03	-0.05	-0.03	-0.15
	(0.00)	(0.01)	(0.00)	(0.17)	(0.00)	(0.01)	(0.00)	(0.05)
Constant	0.01	0.01	0.00	0.01	0.02	0.02	0.02	0.01
	(0.19)	(0.05)	(0.58)	(0.09)	(0.01)	(0.02)	(0.02)	(0.04)
Trading								
Lag Ret	-3.40	0.39	-0.87	-3.13	0.83	0.26	0.73	-0.11
	(0.35)	(0.62)	(0.66)	(0.07)	(0.56)	(0.64)	(0.48)	(0.42)
Lag Trading	0.07	0.19	0.10	-0.03	0.13	0.17	0.06	-0.12
	(0.48)	(0.06)	(0.33)	(0.80)	(0.22)	(0.10)	(0.55)	(0.24)
Constant	-0.34	0.02	-0.33	-0.04	0.21	0.09	0.11	0.02
	(0.14)	(0.70)	(0.01)	(0.69)	(0.03)	(0.02)	(0.11)	(0.01)

Panel B: Ex-ante portfolio								
	Full sample				**Transient institutions**			
	All	**HF**	**MF**	**Others**	**All**	**HF**	**MF**	**Others**
Return								
Lag Ret	0.16	0.13	0.17	0.14	0.12	0.11	0.19	0.15
	(0.13)	(0.21)	(0.11)	(0.17)	(0.31)	(0.29)	(0.13)	(0.13)
Lag Trading	0.00	0.02	-0.01	-0.01	0.01	0.02	-0.01	0.00
	(0.80)	(0.08)	(0.53)	(0.50)	(0.56)	(0.13)	(0.61)	(0.95)
Constant	0.01	0.02	0.01	0.01	0.02	0.02	0.01	0.02
	(0.01)	(0.00)	(0.02)	(0.01)	(0.01)	(0.00)	(0.01)	(0.01)
Trading								
Lag Ret	3.18	0.82	2.79	-0.24	2.73	0.63	1.93	0.10
	(0.15)	(0.40)	(0.03)	(0.86)	(0.06)	(0.38)	(0.04)	(0.49)
Lag Trading	-0.05	0.05	-0.10	0.04	0.04	-0.08	0.10	-0.02
	(0.67)	(0.63)	(0.33)	(0.71)	(0.76)	(0.47)	(0.39)	(0.84)
Constant	-0.46	-0.08	-0.27	-0.12	-0.07	-0.05	-0.02	0.00
	(0.00)	(0.13)	(0.00)	(0.10)	(0.34)	(0.23)	(0.60)	(0.93)

Table 8

Institutional Trading before Anomaly Sorting

This table examines institutional trading in the quarters leading up to the anomaly sorting. On June 30th of each year we construct long and short portfolios for each anomaly. For each stock we compute the change in the number of institutions and change in the fraction of shares held for various institution types for four different windows: 1) December 31st two years ago to December 31st of the previous year ([-6, -2]); 2) December 31st two years ago to June 30th of the current year ([-6, 0]); 3) March 31st to June 30th of the current year ([-1, 0]); and 4) March 31st to September 30th of the current year ([-1, 1]). We then compute equal-weighted averages for the long and short portfolios, pool across anomalies each year, and report the annualized time-series averages for the long-short portfolio. Panels A and B display the results for the full sample of aggregate (transient) institutions and separately for hedge funds, mutual funds, and others for the change in number of institutions and in fraction of shares held, respectively. Focusing only on all institutions, Panels C and D present separate results for two subgroups of stocks and for the ex-ante and ex-post portfolios. The *reversal sample* is the group of stocks which are in the long (short) portfolio in the current year and short (long) portfolio previous year. The *persistent sample* is the group of stocks that are in the long (short) portfolio both this year and past year. p-values are reported below the coefficient estimates.

Panel A: Change in number of institutions

	Full sample				**Transient institutions**			
	All	**HF**	**MF**	**Others**	**All**	**HF**	**MF**	**Others**
[-6, -2]	-8.74	-7.51	-8.02	-9.97	-7.06	-3.06	-6.60	-14.51
	(0.00)	(0.00)	(0.00)	(0.00)	(0.02)	(0.52)	(0.03)	(0.01)
[-6, 0]	-0.70	4.61	1.31	-4.10	8.60	11.99	9.20	-2.57
	(0.45)	(0.01)	(0.31)	(0.00)	(0.00)	(0.01)	(0.00)	(0.48)
[-1, 0]	10.66	15.55	13.74	6.45	24.36	23.10	25.48	20.63
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.03)
[-1, 1]	7.68	11.73	9.52	4.91	17.33	17.60	17.66	16.80
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)

Panel B: Change in fraction of shares held

	Full sample				**Transient institutions**			
	All	**HF**	**MF**	**Others**	**All**	**HF**	**MF**	**Others**
[-6, -2]	-0.92	-0.11	-0.44	-0.39	0.18	0.10	0.08	0.00
	(0.00)	(0.02)	(0.00)	(0.00)	(0.02)	(0.01)	(0.10)	(0.80)
[-6, 0]	-0.23	0.03	-0.09	-0.19	0.66	0.26	0.39	0.01
	(0.11)	(0.43)	(0.39)	(0.00)	(0.00)	(0.00)	(0.00)	(0.03)
[-1, 0]	0.60	0.09	0.25	0.19	1.03	0.31	0.67	0.05
	(0.03)	(0.34)	(0.21)	(0.16)	(0.00)	(0.00)	(0.00)	(0.00)
[-1, 1]	0.66	0.23	0.28	0.16	0.88	0.31	0.53	0.04
	(0.00)	(0.00)	(0.03)	(0.13)	(0.00)	(0.00)	(0.00)	(0.00)

Panel C: Change in number of institutions, by year – 1 sorting									
	All stocks			**Reversal sample**			**Persistent sample**		
	All anomalies	**Ex-post**	**Ex-ante**	**All anomalies**	**Ex-post**	**Ex-ante**	**All anomalies**	**Ex-post**	**Ex-ante**
[-6, -2]	-8.74	-19.67	-10.54	-27.40	-61.28	-40.44	2.98	11.89	-0.93
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.73)
[-6, 0]	-0.70	1.69	1.40	-8.40	-20.57	-6.89	7.14	20.16	2.61
	(0.45)	(0.56)	(0.53)	(0.00)	(0.00)	(0.29)	(0.00)	(0.00)	(0.28)
[-1, 0]	10.66	33.00	14.04	21.24	54.07	44.14	8.88	22.43	6.52
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.12)
[-1, 1]	7.68	27.09	10.35	13.99	37.23	33.19	7.03	20.74	5.06
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.07)

Panel D: Change in fraction of shares held, by year – 1 sorting									
	All stocks			**Reversal sample**			**Persistent sample**		
	All anomalies	**ex-post**	**ex-ante**	**All anomalies**	**Ex-post**	**Ex-ante**	**All anomalies**	**Ex-post**	**Ex-ante**
[-6, -2]	-0.92	-2.46	-1.07	-2.22	-5.57	-3.76	0.14	0.48	-0.23
	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)	(0.45)	(0.45)	(0.64)
[-6, 0]	-0.23	-0.37	0.12	-0.33	-2.06	-0.25	0.37	1.53	0.29
	(0.11)	(0.40)	(0.68)	(0.12)	(0.01)	(0.75)	(0.04)	(0.02)	(0.43)
[-1, 0]	0.60	3.08	1.38	2.71	4.51	5.53	0.33	3.25	0.36
	(0.03)	(0.00)	(0.01)	(0.00)	(0.01)	(0.02)	(0.31)	(0.01)	(0.67)
[-1, 1]	0.66	2.31	1.53	1.66	2.29	3.80	0.59	2.25	0.96
	(0.00)	(0.00)	(0.00)	(0.00)	(0.03)	(0.02)	(0.02)	(0.00)	(0.11)

Table 9

Anomaly Stock Performance Conditional on Institutional Trading

This table reports value-weighted DGTW-adjusted returns of stocks selected conditional on institutional trading. Each quarter we measure aggregate institutional holdings changes in stocks in the long and short legs of the ex-ante (Panel A) and ex-post portfolios (Panel B). We then sort stocks conditional on institutional trading into two portfolios: “buy in the long” portfolio, which is the long-leg stocks institutions buy, and “sell in the short” portfolio, which is the short-leg stocks institutions sell. We then compute the next-quarter DGTW-adjusted returns for each portfolio. We also compute the return of a portfolio termed "with anomaly” which is long the stocks in the “buy in the long” portfolio and short the stocks in “sell in the short” portfolio. The first column depicts portfolios formed from the trades of all institutions, while the second through fourth columns focus on the hedge fund, mutual fund and the others subgroups, respectively. The fifth through eighth columns present results for the subsample of traders identified as transient. p-values are presented below each risk-adjusted return.

Panel A: Ex-ante portfolio

	Full sample				**Transient institutions**			
	All	**HF**	**MF**	**Others**	**All**	**HF**	**MF**	**Others**
Buy in the long portfolio	0.78	0.75	0.59	0.71	0.55	0.49	0.44	0.65
	(0.01)	(0.01)	(0.05)	(0.04)	(0.06)	(0.10)	(0.13)	(0.03)
Sell in the short portfolio	-1.12	-1.81	-1.26	-1.14	-1.31	-1.38	-1.11	-1.08
	(0.02)	(0.00)	(0.02)	(0.01)	(0.01)	(0.01)	(0.03)	(0.01)
With anomaly portfolio	1.90	2.56	1.85	1.84	1.86	1.88	1.56	1.73
	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)	(0.02)	(0.00)

Panel B: Ex-post portfolio

	Full sample				**Transient institutions**			
	All	**HF**	**MF**	**Others**	**All**	**HF**	**MF**	**Others**
Buy in the long portfolio	0.28	0.25	0.12	0.31	0.23	0.02	0.23	-0.09
	(0.39)	(0.42)	(0.71)	(0.28)	(0.48)	(0.94)	(0.46)	(0.79)
Sell in the short portfolio	-1.39	-1.63	-1.38	-1.62	-1.51	-1.36	-1.23	-1.59
	(0.03)	(0.02)	(0.03)	(0.01)	(0.02)	(0.04)	(0.04)	(0.01)
With anomaly portfolio	1.67	1.88	1.50	1.92	1.74	1.38	1.46	1.50
	(0.03)	(0.02)	(0.04)	(0.01)	(0.02)	(0.09)	(0.04)	(0.03)

Table 10

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 versus 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. 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 one quarter institutional trading in Panel A (two quarters in Panel B). The control variables, which are measured on the ranking date, are the following: log of book-to-market, 6-month cumulative stock returns, average quarterly Amihud (2002) illiquidity measure, and log of market capitalization of the specified stock. Institutional trading is measured by the change in the fraction of a company's stock that is owned by institutional investors starting from the ranking date for Panel A (the quarter before ranking date for Panel B). Newey-West standard errors are calculated and p-values are reported below the coefficient estimates.

Panel A: One quarter trading								
	Full sample				**Transient institutions**			
	All	**HF**	**MF**	**Others**	**All**	**HF**	**MF**	**Others**
Constant	1.48	0.68	0.67	0.11	0.87	0.48	0.40	-0.01
	(0.00)	(0.00)	(0.02)	(0.60)	(0.00)	(0.00)	(0.01)	(0.51)
Ex-post long (a)	0.12	0.07	-0.03	0.08	0.30	0.14	0.16	0.01
	(0.01)	(0.00)	(0.46)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Ex-post short (b)	-0.17	-0.05	-0.07	-0.04	-0.17	-0.07	-0.09	0.00
	(0.00)	(0.03)	(0.16)	(0.09)	(0.00)	(0.00)	(0.00)	(0.53)
Ex-ante long (c)	-0.01	0.01	0.00	-0.02	0.06	0.01	0.05	0.01
	(0.90)	(0.53)	(0.91)	(0.47)	(0.07)	(0.69)	(0.01)	(0.20)
Ex-ante short (d)	0.02	-0.04	0.01	0.05	-0.04	-0.02	-0.02	0.00
	(0.74)	(0.17)	(0.87)	(0.02)	(0.29)	(0.26)	(0.50)	(0.48)
BM	-0.08	0.00	-0.03	-0.05	0.08	0.04	0.04	0.00
	(0.00)	(0.82)	(0.03)	(0.00)	(0.00)	(0.00)	(0.00)	(0.75)
Illiquidity	-0.09	-0.04	-0.04	-0.01	-0.05	-0.03	-0.02	0.00
	(0.00)	(0.00)	(0.00)	(0.24)	(0.00)	(0.00)	(0.01)	(0.89)
Momentum	0.31	0.04	0.11	0.17	0.04	0.00	0.03	0.01
	(0.00)	(0.03)	(0.00)	(0.00)	(0.18)	(0.95)	(0.15)	(0.00)
Size	-0.15	-0.07	-0.07	-0.02	-0.11	-0.05	-0.06	0.00
	(0.01)	(0.00)	(0.06)	(0.65)	(0.00)	(0.00)	(0.00)	(0.74)
a-c	0.12	0.05	-0.03	0.10	0.25	0.13	0.11	0.01
	(0.06)	(0.10)	(0.53)	(0.00)	(0.00)	(0.00)	(0.00)	(0.19)
b-d	-0.19	-0.01	-0.07	-0.09	-0.13	-0.05	-0.08	-0.01
	(0.01)	(0.74)	(0.21)	(0.00)	(0.04)	(0.11)	(0.07)	(0.36)
(a-c)-(b-d)	0.31	0.07	0.04	0.19	0.38	0.18	0.19	0.01
	(0.00)	(0.16)	(0.55)	(0.00)	(0.00)	(0.00)	(0.00)	(0.09)

Panel B: Two quarters trading								
	Full sample				**Transient institutions**			
	All	**HF**	**MF**	**Others**	**All**	**HF**	**MF**	**Others**
Constant	2.89	1.24	1.26	0.43	1.19	0.72	0.51	-0.03
	(0.00)	(0.00)	(0.01)	(0.18)	(0.00)	(0.00)	(0.03)	(0.39)
Ex-post long (a)	0.37	0.18	0.02	0.18	0.80	0.36	0.42	0.02
	(0.00)	(0.00)	(0.70)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Ex-post short (b)	-0.59	-0.19	-0.31	-0.08	-0.72	-0.30	-0.43	0.00
	(0.00)	(0.00)	(0.00)	(0.04)	(0.00)	(0.00)	(0.00)	(0.58)
Ex-ante long (c)	-0.02	0.01	-0.03	-0.01	0.11	0.01	0.09	0.01
	(0.68)	(0.68)	(0.52)	(0.69)	(0.04)	(0.70)	(0.00)	(0.06)
Ex-ante short (d)	0.10	-0.02	0.04	0.06	-0.01	0.00	-0.01	0.00
	(0.21)	(0.61)	(0.49)	(0.11)	(0.93)	(0.99)	(0.89)	(0.98)
BM	-0.25	-0.03	-0.08	-0.15	0.12	0.05	0.07	0.00
	(0.00)	(0.05)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.43)
Illiquidity	-0.21	-0.08	-0.08	-0.04	-0.07	-0.05	-0.02	0.00
	(0.00)	(0.00)	(0.00)	(0.02)	(0.00)	(0.00)	(0.04)	(0.40)
Momentum	1.04	0.24	0.48	0.33	0.66	0.25	0.39	0.02
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Size	-0.28	-0.12	-0.11	-0.05	-0.16	-0.08	-0.09	0.00
	(0.00)	(0.00)	(0.05)	(0.35)	(0.00)	(0.00)	(0.01)	(0.69)
a-c	0.39	0.16	0.05	0.20	0.69	0.35	0.33	0.01
	(0.00)	(0.00)	(0.47)	(0.00)	(0.00)	(0.00)	(0.00)	(0.14)
b-d	-0.70	-0.16	-0.35	-0.13	-0.72	-0.30	-0.42	0.00
	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)	(0.71)
(a-c)-(b-d)	1.09	0.33	0.40	0.33	1.40	0.64	0.75	0.01
	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.23)