Liquidity Characteristics of Market Anomalies and Institutional Trading

Abstract

This study examines the liquidity characteristics of market anomalies and how liquidity affects institutional trading on those anomalies. We find pervasive, horizon-dependent, liquidity exposure of long-short anomaly portfolios. For long-horizon anomalies, the long legs of the portfolios are less liquid and suffer from deteriorating liquidity relative to the short legs. Short-horizon anomaly portfolios exhibit the opposite pattern. Consistent with such liquidity characteristics and institutional liquidity preference, aggregate institutional trades appear to be in the right direction for short-horizon anomalies but in the wrong direction for long-horizon anomalies. Perverse institutional trading on long-horizon anomalies disappears after we control for liquidity. Analysis based on exogenous measures of institutional liquidity preferences, and difference-in-difference analysis based on exogenous liquidity shocks, further highlight the causal effect of liquidity on institutions' anomaly trading patterns. Finally, we find that liquidity-driven and non-liquidity components of institutional trades have different impact on market mispricing. The magnitude of long-horizon anomalies is exacerbated by the liquidity-driven institutional trading when such trading is in the wrong direction, but not affected by the direction of the non-liquidity component of institutional trading.

I Introduction

Existing studies present intriguing findings regarding the impact of institutional investors on market efficiency, especially in correcting mispricing in the form of market anomalies. Many studies show that market anomalies are weaker among stocks with higher institutional ownership or more active institutional trading; see, e.g., Bartov, Radhakrishnan, and Krinsky (2000), Ali, Hwang, and Trombley (2003), Collins, Gong and Haribar (2003), Nagel (2005), and Lam and Wei (2011). However, two prominent papers in the relative recent literature find that institutional investors do not actively exploit market anomalies. Lewellen (2011) finds that the aggregate stock portfolio held by institutional investors closely resembles the market portfolio and does not tilt toward stocks predicted to have high returns by well-known anomalies. Edelen, Ince, and Kadlec (2016) provide evidence that further challenges the sophisticated institutions hypothesis. They show that institutions often trade in the wrong direction of market anomalies; that is, they buy stocks predicted by anomalies to have low returns, and sell stocks predicted to have high returns. Further, when institutional investors trade in the wrong direction of an anomaly, the magnitude of the anomaly is often exacerbated. Such findings suggest that the price impact of institutions could well be the cause of stock mispricing.

This study examines the role of liquidity in driving the puzzling patterns of institutional trading on anomalies. We find that the liquidity characteristics of anomaly portfolios are heterogeneous, depending on the return-predictive horizons of the anomalies. Such liquidity characteristics, combined with institutional investors' liquidity preference, cause their aggregate trades to be in the wrong direction of some anomalies while in the right direction of others. However, the component of institutional trading not driven by liquidity is either uncorrelated with or in the right direction of anomalies. Further, we find that the perverse impact of institutional trading on the magnitude of market anomalies is mainly due to liquidity-driven institutional trades. Our findings suggest that liquidity goes a long way in explaining the anomaly trading patterns by institutions as well as the impact of institutional trading on mispricing.

We investigate market anomalies in eleven broadly representative categories that cover a majority of individual anomalies documented in existing studies. We show that based on the return predictive horizon, these anomalies can be clustered into two groups. Seven categories of anomaly variables, including value, investment, financing, quality, efficiency, intangible investments and gross profitability, predict stock returns at relatively long horizons, for example, beyond one year. Anomaly variables in the other four categories, including momentum, short-term profitability, distress, and uncertainty, predict stock returns at relatively short horizons, for example, within one year.[1] More interestingly, we find that the way institutions trade on an anomaly is closely related to the anomaly's return predictive horizon. Institutions tend to be wrong on long-horizon anomalies, but right on short-horizon ones. Specifically, we measure net institutional trading on an anomaly as the difference in changes of institutional ownership between the long and short legs of the anomaly portfolio. Net institutional trading is significantly negative for five out of seven long-horizon categories, but significantly positive for all four short-horizon categories. Such heterogeneous, horizon-dependent, anomaly-trading patterns by institutions add to the intrigue already documented in Edelen, Ince, and Kadlec (2016).

What may drive institutions to trade in the right direction of one set of anomalies but in the opposite of another set? We find that the liquidity characteristics of the anomalies offer an intuitive and powerful explanation. Across anomalies, both the level and change of liquidity at the long and short legs of an anomaly portfolios is closed related to its return-predictive horizon. For long-horizon anomalies, stocks in the long legs tend to be illiquid, with deteriorating liquidity, while the short legs tend to be liquid, with improving liquidity. For short-horizon anomalies, the liquidity pattern is reversed: both the level and change in liquidity are higher for stocks in the long legs than those in the short legs.

It has been well-known in the existing literature (e.g., Gompers and Metrick, 2001) that institutional investors exhibit strong liquidity preference – due to their large portfolio size and concerns about trading costs, institutions tend to hold liquid stocks. In this study, we find that the liquidity preference translates into two patterns on institutional trading. First, the stocks institutions buy and sell are similarly liquid, consistent with the fact that most institutional investors are long-only and the stocks they sell are from what they already hold. Second, to maintain liquid positions, institutions tend to sell stocks that have become

[1] Daniel, Hirshleifer, and Sun (2020) have noted the difference in return-predictive horizon across anomalies. Our findings are consistent with, and further extend, theirs.

less liquid and buy stocks that have become more liquid. Thus, based on the liquidity characteristics of the anomalies, even if institutions do not intentionally pursue any market anomaly but merely follow a liquidity preference, they can appear to trade correctly on the short-horizon anomalies but incorrectly on long-horizon ones.

To see the extent to which liquidity preference drives institutional investors' trading on anomalies in the data, we perform three sets of analysis. In the first set, we perform an intuitive decomposition of institutional trading into a liquidity-driven and a non-liquidity component. Averaged across long-horizon anomalies, net liquidity-driven institutional trading is significantly negative, while the net non-liquidity component is not significant. This result suggests that the perverse institutional trading on long-horizon anomalies is mainly driven by liquidity. Moreover, averaged over short-horizon anomalies, both the net liquidity-driven and net non-liquidity components of institutional trading are significantly positive. This result suggests that institutions' tendency to trade on short-horizon anomalies is not completely due to liquidity.

The analysis based on the liquidity decomposition of institutional trades may be subject to a reverse causality concern. We use two additional sets of analyses to sharpen our inference on the causal effect of liquidity on institutional trading patterns. In the one set of analysis, we compare the trades of institutions with different liquidity preferences, where the liquidity preference is measured by exogenous portfolio characteristics not directly related to how institutional trading. We find that institutions with strong liquidity preferences tend to trade in the wrong direction of long-horizon anomalies while in the right direction of short-horizon ones. By contrast, institutions with weak liquidity preferences either exhibit an insignificant trading pattern or an opposite pattern to institutions with strong liquidity preference. In another set of analysis, we take advantage of exogenous liquidity shocks during two quasi-natural experiments – the minimum tick size changes in 1997 and 2001. Following the liquidity shocks, institutional trading turns into the right direction of long-horizon anomalies. A difference-in-difference analysis shows that following the tick size changes (relative to the period before), institutions significantly increase their net purchase of stocks experiencing high liquidity shocks (relative to those with low liquidity shocks) on both the long and short legs of the long-horizon anomaly portfolios, and they do so more aggressively on the long leg. Thus, exogenous liquidity changes do significantly impact institutional trading on anomalies.

Having shown that liquidity is important for understanding the patterns of institutional trading on anomalies, we further explore two questions on the relation between institutional trading and the magnitude of market anomalies. First, since institutional preference for liquidity can give rise to liquidity premium, it is natural to ask to what extent liquidity premium explains the returns to the anomaly portfolios. We find that during the sample period of 1980–2018, the conventionally measured liquidity premium—the return difference between illiquid and liquid stocks—is no longer significant. What remains significant is a liquidity change premium, i.e., a positive return difference between stocks with deteriorating liquidity and those with improving liquidity. The liquidity change premium fully explains the magnitude of the value anomaly. However, anomaly portfolio returns for the other 10 categories remain significant after we control for the liquidity change premium. Thus, the liquidity premium or liquidity change premium does not completely explain away anomalies.

Second, we re-examine whether market anomalies are aggravated by institutions' tendency to trade in the wrong direction. We separate the long-short portfolio of an anomaly into two subportfolios: one on which institutions trade in the right direction, and the other on which institutions trade in the wrong direction. Our analysis confirms that for long-horizon anomalies, the abnormal returns to the subportfolios where institutional trading is in the wrong direction are significantly higher than those on the subportfolios where institutional trading is in the right direction.[2] Further, this result is mainly due to the liquidity-driven institutional trading, while the direction of the non-liquidity institutional trading is not significantly related to the magnitude of these anomalies. We also show that the liquidity change premium can account for the return differences between the subportfolios with the right and wrong institutional trading directions. These findings suggest that liquidity is important for understanding the perverse impact of institutional trading on the magnitude of anomalies, in addition to understanding the perverse direction of institutional trading.

The contributions of this study are the following. First, to our knowledge, we are the first to document systematic liquidity characteristics of market anomalies. These anomalies are often used to construct "market-neutral" long-short portfolios. Interestingly, we find that such "market-neutral" portfolios are not liquidity neutral, but rather have clear directional

[2]For short-horizon anomalies, we find no significant difference in the magnitude of anomalies between the subportfolios with the right and wrong directions of institutional trading.

exposures to liquidity and liquidity change. When dissecting the Long Term Capital Management failure, several authors including Perold (1999) and Lowenstein (2000) have noted anecdotally that certain popular fixed-income trading strategies—such as the one based on the on-the-run/off-the-run spread in the Treasury market—take long positions in illiquid securities and short positions in liquid positions, to the extent that the returns to these strategies can be viewed as compensation for liquidity provision. We show that long-short portfolios based on stock anomalies similarly exhibit directional liquidity exposures. Also interestingly, the directions of the portfolio liquidity exposures are not uniform, but intricately related to the return-predictive horizons of the anomalies.

Second, we link the intriguing pattern of institutional trading documented in the literature to the liquidity characteristics of market anomalies. The existing literature, including Edelen et al. (2016) and subsequent studies by Calluzzo, Moneta, and Topaloglu (2018) and McLean, Pontiff, and Reilly (2020), find that institutional trading tends to be in the wrong direction of market anomalies. By contrast, we discover heterogeneous patterns of institutional trading—institutions tend to be in the wrong direction of long horizon anomalies but in the right direction of short-horizon anomalies. More importantly, we show that the liquidity characteristics of anomalies, combined with institutional liquidity preference, explain such heterogenous institutional trading patterns as well as the resulting impact on market mispricing.[3]

Finally, we join several recent studies to provide possible explanations for the perverse pattern of institutional trading on anomalies. Akbas, Amstrong, Socescu, and Subrahmanyam (2015) point out that fund flows can cause mutual funds to be "dumb money" in stock trading that intensifies market anomalies. Calluzzo, Moneta, and Topaloglu (2018) show that institutions are more likely to trade in the right direction of an anomaly when the anomaly becomes well-publicized. Ince and Kadlec (2019) find that institutional investors increasingly trade with more sophisticated and more informed counterparties such as firms and corporate insiders. McLean, Pontiff, and Reilly (2020) examine the trades of nine types

[3]Empirical studies on mutual funds have also documented rich patterns of fund trading on anomalies; e.g., Grinblatt, Titman, and Wermers (1995), Carhart (1997), Ali, Chen, Yao, and Yu (2006; 2020), and Wermers, Yao, and Zhao (2012). These studies find that mutual funds tend to trade on certain anomalies such as the price momentum and the post earnings announcement drift, but not on others such as on the accruals anomaly. Relatively to these studies, we provide a more systematic way to understand what anomalies institutions are more likely to trade on and what anomalies they are more likely to trade against.

of market participants on a large number of anomalies. They find that more sophisticated market participants including firms and short sellers often trade in the right direction of anomalies and take the opposite side of institutions and retail investors. Relative to these studies, our explanation is unique in that we relate the heterogeneity of institutional trading directions to the heterogeneity in return-predictive horizons and the liquidity characteristics of the anomalies.

The remainder of the paper is organized as follows. Section II describes the 11 categories of anomalies, data, and empirical methodologies. Section III presents the empirical results on how institutions' liquidity preference affects their trading on market anomalies. Section IV addresses the issue of reverse causality using exogenous liquidity preference measures and using two quasi-natural experiments of liquidity shocks. It further examines the extent to which the liquidity premium explains the abnormal returns to anomaly portfolios and the effect of institutional trading on the magnitude of market anomalies. Section V concludes the paper.

II Data, Sample, and Variables

II.1 Market Anomalies

Existing studies have documented several hundred market anomalies (e.g., Green, Hand, and Zhang, 2013, 2017; Harvey, Liu, and Zhu, 2016; McLean and Pontiff, 2016; Hou, Xue, and Zhang, 2020; Jensen, Kelly, and Pedersen, 2021). Despite the large number, many anomalies are related to each other conceptually and statistically and can be classified into a relatively small number of categories. For example, anomalies represented by the book-to-market ratio, earnings-to-price ratio, cash flow-to-price ratio, sales growth, and long-term growth forecasts are collectively known as the value anomaly (e.g., Lakonishok, Shleifer, and Vishny, 1994; Fama and French, 1996), while price momentum, standardized unexpected earnings, and return surprise in earnings announcement window are referred to as momentum signals (Chan, Jegadeesh, and Lakonishok, 1996). Further, a dozen price momentum signals can be constructed using different portfolio formation periods and holding periods (Jegadeesh and Titman, 1993; Hou, Xue, and Zhang, 2020).

The approach of this study is to focus on the relatively small number of but nonetheless broadly representative anomaly categories. Specifically, we examine the following 11 anomaly categories: value, investment, financing, quality, efficiency, intangible, long-term profitability, momentum, short-term profitability, distress, and uncertainty. For each category, we select one to three representative anomalies. Altogether, we include 24 individual anomalies. Similar anomaly classifications have been used in the literature; e.g., Daniel, Hirshleifer, and Sun (2020), and Hou, Xue, and Zhang (2020). The anomaly categories and individual anomalies belonging to each category are the following.

1. **Value**: book-to-market ratio (BP), earning-to-price ratio (EP), and sales growth (SG)
2. **Investment**: capital expenditure (CAPEX), abnormal investments (AI), and asset growth (AG)
3. **Financing**: net equity issues (NS) and a composite measure of external financing (XFIN)
4. **Quality**: accruals (ACC) and discretionary accruals (DACC)
5. **Efficiency**: asset turnover (ATTO) and net operating assets (NOA)
6. **Intangible**: R&D expenses (RD), and selling, general and administrative expenses (SGA)
7. **Long-term (LT) profitability**: gross profit (GP)
8. **Momentum**: 12-month price momentum (PrRet), standardized unexpected earnings (SUE), and analyst forecast revision (FRV)
9. **Short-term (ST) profitability**: return on equity (ROE) and gross margin (GM)
10. **Distress**: O-score (OSCORE) and failure probability (CHS)
11. **Uncertainty**: idiosyncratic volatility (IVOL) and analyst forecast dispersion (DISP)

The Appendix provides details on the construction of the individual anomaly variables. As we will show, the first seven categories (Value, Investment, Financing, Quality, Efficiency, Intangible, and LT Profitability) have long return-predictive horizons and the remaining four categories (Momentum, ST Profitability, Distress, and Uncertainty) have short return-predictive horizons. These 11 categories include a large proportion of individual anomalies examined in the literature. In the Internet Appendix, we show that a majority of anomalies examined by Green, Hand, and Zhang (2017), Hou, Xue, and Zhang (2020), and Jensen, Kelly, and Pedersen (2021) fall into these 11 categories.

The anomaly categories in this study include and extend those of Edelen et al. (2016). The seven individual anomalies examined by Edelen et al. (2016) include five long-horizon ones in the value, investment, financing, long-term profitability, and efficiency categories, and two short-horizon ones in the momentum and distress categories. We additionally include anomalies in the quality, intangible, short-term profitability, and uncertainty categories.

II.2 Data and Anomaly Portfolios

Our data for anomaly variables are from CRSP, Compustat, and IBES. Quarterly institutional holdings are from Refinitiv (formerly Thomson-Reuters) 13F data. Our sample period is from 1980 to 2018.

The stock sample is selected in the following way. We start with all common stocks (with share code 10 or 11) in the CRSP database, and exclude financial firms (with 4-digit SIC code between 6000 and 6999). We then exclude stocks with share prices below $5 at the end of each portfolio formation quarter to mitigate concerns about market microstructure noises in measuring returns.

The anomaly variables are constructed quarterly. We use the following procedure to ensure that the information used to construct an anomaly variable is available at the time of portfolio formation. For anomalies involving Compustat annual data, we assume that financial statements are available six months after the fiscal year-end. For anomalies constructed from Compustat quarterly data, we use the earnings reporting dates from Compustat to determine data availability. If the earnings reporting date is missing, we assume that the data become available four months after the fiscal quarter-end.

The anomaly portfolios are formed in the following way. At the end of each quarter, we sort stocks into terciles based on each anomaly variable, and form an equal-weighted portfolio within each tercile. The long leg of an anomaly portfolio is the tercile portfolio predicted by the anomaly to have high returns, and the short leg is the tercile portfolio predicted to have low returns.

II.3 Liquidity Measures

Our main liquidity measure is the Amihud (2002) illiquidity ratio (ILLIQ), defined as

$$\text{ILLIQ} = \frac{1}{T}\sum_{t=1}^{T}\frac{|r_t|}{S_t P_t} \tag{1}$$

where r_t is the daily stock return, S_t is the daily number of shares traded, P_t is the daily closing price, and T is the total number of trading days during the measurement period. ILLIQ is estimated at the end of every quarter, using the daily data. We require a minimum of 360 daily observations when liquidity is measured 6 quarters, and a minimum of 120 daily observations when liquidity is measured over 2 quarters.

Liquidity in the U.S. stock market improves over time. To control for this time trend, we rely on the cross-sectional percentile ranking of ILLIQ. Further, until recent years, NASDAQ has reported trading volume differently from NYSE and AMEX. To account for this reporting difference, we follow the literature (e.g., Lee and Swaminathan, 2000) to rank separately among NYSE/AMEX stocks and among NASDAQ stocks. The resulting ranked illiquidity measure is denoted as ILQ. It takes a value between 0 and 99, with a higher value indicating lower liquidity.

Our subsequent analysis relates liquidity change to institutional trading. We measure liquidity change, ΔILQ, over the same horizon of institutional trading. Specifically, for long-horizon anomalies, ΔILQ is the change in ILQ from the end of quarter t-6 to the end of quarter t (the portfolio formation quarter). For short-horizon anomalies, ΔILQ is the change in ILQ from the end of quarter t-2 to the end of quarter t. A positive value of ΔILQ indicates deteriorating liquidity.

To ensure the robustness of inference, we cross-validate our results using alternative measures of liquidity in Section III.6.1.

II.4 Institutional Holding and Trading

We measure institutional trading by change in institutional ownership. A stock's institutional ownership, denoted as %Inst, is the total number of shares held by the institutions divided by the total shares outstanding of the stock. Correspondingly, institutional trading, Δ%Inst, is the change in %Inst, with Δ%Inst measured over past six quarters from the end of quarter t-6 to the end of quarter t, where quarter t is the portfolio formation quarter) for long-horizon anomalies. For short-horizon anomalies, Δ%Inst is measured over 2 quarters from the end of quarter t-2 to the end of quarter t. To alleviate the influence of outliers on statistical inference, we winsorize institutional trading at the 0.5-th and 99.5-th percentiles across all stocks in each quarter.

In addition to Δ%Inst, we use an alternative measure of institutional trading based on the change in the number of institutions holding a stock. The detailed are provided in Section III.6.2.

III Empirical Evidence: Liquidity Characteristics and Institutional Trading

III.1 Return-Predictive Horizons of Anomalies

We first show that anomalies have different return predictive horizons, based on the returns to anomaly portfolios at various holding quarters. As described in Section II.2, we form equal-weighted long-short anomaly portfolios at the end of each calendar quarter from 1980 to 2018. The long leg of an anomaly portfolio is the tercile portfolio predicted to have high returns, and the short leg the tercile portfolio predicted to have low returns. Returns to individual anomaly portfolios are further averaged within a category to obtain the category-level anomaly portfolio return.

Table 1 reports the returns to the long and short legs, as well as to the hedged (i.e., long-short) portfolios of the 11 anomaly categories during multiple quarters after portfolio formation.[4] To keep the length of the table in check, we report holding period returns for eight quarters after portfolio formation on the long-horizon categories and for four quarters on the short-horizon categories.

Table 1 reveals substantial heterogeneity in the return-predictive horizon of the 11 anomaly categories. Returns to the long-short hedge portfolios of seven categories—Value, Investment, Financing, Quality, Efficiency, Intangible, and Long-term Profitability—are signifi-

[4] Anomaly portfolios are rebalanced at the beginning of each holding quarter to keep equal weights. If a stock drops out of the sample (due to delisting or stock price dropping below $5) by the beginning of a holding quarter, it is removed from the portfolio and the remaining stocks in the portfolio are reweighted to keep equal weights. If a stock is delisted during a holding quarter, we include the delisting return from CRSP to compute its holding period return. Following Shumway (1997), if the CRSP delisting return is missing, we replace it with -30% if delisting is performance related, and zero otherwise.

cantly positive at horizons beyond four quarters. By contrast, returns to the long-short portfolios of three categories—Momentum, Short-term Profitability, and Uncertainty—are only significant for less than four quarters after portfolio formation. The returns to the long-short portfolio of the Distress category are significant for four quarters, but become insignificant afterward (untabulated). Based on these patterns, we classify the first seven categories as long-horizon anomalies and the remaining four as short-horizon anomalies.[5]

Two caveats are noted. First, following a few prominent studies that examine market anomalies systematically (e.g., McLean and Pontiff, 2016; Green, Hand, and Zhang, 2017; Hou, Xue, and Zhang, 2020), we report the simple returns of long-short anomaly portfolios, which serve as an intuitive indication of the return predictability of anomaly variables. We do not examine whether these anomalies survive the state-of-the-art factor models, an ongoing debate in the literature. Second, the anomaly portfolios are equal weighted instead of value weighted. The returns to the value-weighted anomaly portfolios are weaker (e.g., Hou, Xue, and Zhang, 2020); therefore institutions conscientiously exploiting these anomalies would be unlikely to follow a value-weighted strategy.

III.2 Institutional Trading on Anomalies

We now examine institutional trading on anomalies. We measure institutional trading on an individual stock using the change in the percentage of institutional ownership $\Delta\%$Inst. In each quarter, we calculate the averages of $\Delta\%$Inst over stocks in the long leg and short leg of an anomaly separately, and then calculate the net institutional trading as the long-short difference. We then average net institutional trading over individual anomalies within a category, and finally, estimate the time series averages and corresponding t-statistics at the category level. Institutional trading is measured over six quarters for long-horizon anomalies and two quarters for short-horizon anomalies. To take into account the serial correlations,

[5]Interestingly, depending on specific measures, profitability is in both the long- and short-horizon categories. Existing studies have noted that the single long-horizon profitability variable, gross profitability (GP), could derive its long-horizon predictive power from its relation with other long-horizon anomaly variables. Novy-Marx (2013) and Campbell (2018) point out that the numerator of gross profitability is related to selling, general, and administrative (SGA) expenses, an anomaly variable in the Intangible category. Hou, Xue, and Zhang (2020) point out that via its denominator, gross profitability is related to asset growth, an anomaly variable in the Investment category.

we calculate the time series t-statistics using the Newey-West (1987) standard errors.[6]

The results are reported in Table 2. The pattern is not uniform across anomaly categories, and the direction of institutional trading appears to be related to the return-predictive horizon of the anomalies. Judging by the sign and t-statistic of net institutional trading, we note that institutions are in the wrong direction for five out of seven long-horizon categories, and significantly so for the categories of Value, Financing, and Intangible. Further, they are in the right direction for all four short-horizon categories, and significantly so for the categories of Momentum, ST Profitability, and Distress. Averaged over the seven long-horizon anomaly categories, the net institutional trading is significantly negative (at -0.42%, with a t-statistic of -4.73). Averaged over the four short-horizon categories, the net institutional trading is significantly positive (at 0.75%, with a t-statistic of 5.84).

The results suggest that institutional trading is not uniformly wrong on all anomalies. Rather, across anomalies, institutional trading exhibits a pattern related to the return-predictive horizons of anomalies. Institutions are more likely to be on the wrong side of long-horizon anomalies and on the right side of short-horizon anomalies. In the next set of analysis, we relate such institutional trading patterns to the liquidity characteristics of anomalies and the liquidity preference of institutional investors.

III.3 Liquidity Characteristics of Market Anomalies

We now turn to the liquidity characteristics of anomalies. Consistent with how we measure institutional trading on anomalies, in each quarter we calculate the average liquidity level (ILQ, the percentile rank of the Amihud illiquidity ratio) and the average liquidity change (ΔILQ) for the stocks in the long and short leg of an anomaly, and then calculate the difference between the two legs. The liquidity change is measured over six quarters for long-horizon anomalies and two quarters for short-horizon anomalies. We then average the liquidity levels and changes across anomalies in the same category and take the time series averages.

Panels A and B of Table 3 report the liquidity level and change respectively for the 11 anomaly categories. For long-horizon anomalies, the long legs tend to consist of stocks that

[6]Throughout the paper, we systematically use the Newey-West standard errors when calculating the t-statistics for institutional trading, liquidity, and liquidity change.

are less liquid and with deteriorating liquidity, relative to the short legs. Specifically, the long-short difference in ILQ is positive for six out of the seven categories, with the exception of the Quality category. Further, the long-short difference in ΔILQ is positive for six out of seven categories, with the exception of the LT Profitability category. For the four short-horizon categories, the long legs all have lower ILQ and lower ΔILQ than the short legs. The long- and short-horizon anomalies thus tend to have opposite liquidity characteristics.

The magnitude of the liquidity characteristics reported in Panel A of Table 3 can be understood in the following way. Take the Value category for example. The short leg has an average illiquidity percentile rank of 42.97. This value suggests that the short leg consists of stocks with illiquidity below the median (i.e., 50), that is, relatively liquid stocks. The long leg has an average illiquidity percentile rank of 56.17, which is above the median and suggests that this leg consists of relatively illiquid stocks. The long-short difference in the illiquidity percentile rank is 13.20, quite a large gap. The magnitude of the liquidity change in Panel B of Table 3 can be interpreted similarly. The short leg of the Value category experiences an average drop of 3.57 percentile in the illiquidity rank over six quarters, while the long leg experiences an increase of 1.28 percentile in the illiquidity rank. The long-short difference is 4.85 percentile change in the illiquidity rank.

In Table A4 of the Internet Appendix, we present another way of interpreting the magnitude of the liquidity characteristics of the anomaly portfolios. There, we convert the raw Amihud illiquidity ratio into a return impact variable, which can be interpreted as the impact on absolute stock returns of $1 million (in 2018 dollars) of trading. Panel A of Table A4 shows that for the Value anomaly, the return impact of the stocks in the short leg is 0.59% per million dollar of trading, and that of the long leg is much higher, at 1.70% per million dollar of trading. Thus by this return impact measure, the long leg is much more illiquid than the short leg. Further, Panel B of Table A4 shows that the short-leg stocks of the Value anomaly experience a reduction of return impact of 0.06% per million dollar of trading during the past six quarters, while the long-leg stocks experience an increase of 0.04% of return impact per million dollar of trading. The difference in the change of the return impact between the two legs is 0.09%, significantly positive with a t-statistic of 4.02.

Although evidence in the literature has hinted toward the liquidity patterns of anomalies, it has not yet provided a systematic picture. Lee and Swaminathan (2000) find that value stocks tend to have low trading volume while glamor stocks tend to have high trading volume. Asness, Moskowitz, and Pedersen (2013) find that value anomalies have a positive exposure to liquidity risk while momentum anomalies have a negative exposure to liquidity risk. Akbas, Amstrong, Sorescu, and Subrahmanyam (2015) examine the correlation of aggregate market liquidity with returns to long-short hedge portfolios based on 11 anomalies. They find significantly positive correlations for five anomalies (Return on assets, Oscore, Gross profitability, Net stock issues, and Composite equity issues) and insignificant correlations for six anomalies (Failure probability, Accruals, Investment-to-assets, Net operating assets, Asset growth, and Price Momentum). The new finding reported in this study is a more systematic pattern of liquidity and liquidity change, which can be related to the return-predictive horizons of the anomalies.

III.4 Institutional Preference for Liquidity

Due to their large portfolio size and associated concern about trading costs, institutional investors tend to avoid illiquid stocks. It has been well documented that institutions tilt their portfolio weights toward liquid stocks (e.g., Gompers and Metrick, 2001). In this subsection, we document institutional liquidity preferences in both holdings and trades.

Panel A of Table 4 reports the average liquidity and liquidity change for stock deciles sorted by the percentage of institutional ownership, %Inst. The stocks in the bottom decile, those with the lowest level of institutional ownership, have an average illiquidity ranked at the 76th perentile, which is quite illiquid. The stocks in the top decile, i.e., those with the highest level of institutional ownership, have an average illiquidity ranked at the 30th percentile, quite liquid. Note that the average percentile rank of the illiquidity ratio ILQ decreases monotonically as the institutional ownership decile rank increases. This finding is consistent with the notion that institutions tend to hold liquid stocks. The liquidity change measure ΔILQ, over both two quarters and six quarters, also declines with institutional ownership decile ranks. This finding suggests that stocks held more by institutions are those with improving liquidity. However, the magnitude of the difference in ΔILQ between the top and bottom institutional ownership deciles is economically small, compared with the difference in the illiquidity level ILQ.

Panel B of Table 4 reports the average liquidity and liquidity change for stock deciles sorted by institutional trading Δ%Inst, which is measured over both two quarters and six quarters. Δ%Inst has an inverse U-shaped relation with ILQ. That is, stocks with large net institutional purchases and net institutional sales are both liquid. This result is consistent with the notion that a majority of the institutions in the 13F data are long-only. The stocks long-only institutions sell must be from what they hold, which tend to be liquid.

Perhaps a more novel pattern revealed in Panel B of Table 4 is the monotonically negative relation between institutional trading Δ%Inst and illiquidity rank change ΔILQ. For example, when institutional trading is measured over six quarters, the change in illiquidity ranking ΔILQ (also over six quarters) is 1.12 (as a percentile rank change) for the bottom Δ%Inst decile, indicating deteriorating illiquidity for stocks sold the most by institutions. By contrast, the illiquidity percentile rank is reduced by -7.86 for the top Δ%Inst decile, indicating improved liquidity for stocks bought the most by institutions. The difference in ILQ is -8.99 (percentile rank change) between the bottom and top Δ%Inst deciles, significantly negative. The negative relation between Δ%Inst and ΔILQ suggests that institutions tend to buy stocks with improving liquidity and sell stocks with deteriorating liquidity. This result is consistent with the institutional preference for maintaining liquid stock holdings. Specifically, when stock liquidity changes over time, institutions trade to replace stocks that have become less liquid with those that have become more liquid.

Overall, the results in Table 4 suggest a positive relation between institutional holding and liquidity, and a positive relation between institutional trading and liquidity improvement. Both are consistent with the liquidity preference of institutional investors. The question is then to what extent such institutional liquidity preference affects institutional trading on market anomalies. We examine this issue next.

III.5 Liquidity-driven and Non-liquidity Components of Institutional Trading and Market Anomalies

To assess how liquidity preference affects institutional trading on anomalies, we decompose institutional trading into a liquidity-driven component and a non-liquidity one and examine the magnitude of each component of trading for the long and short legs of anomaly portfolios. The liquidity-driven component of institutional trading on a stock, denoted $\Delta\%\text{Inst}_{LIQ}$, is measured intuitively as the average Δ%Inst for all stocks in the same ΔILQ decile the stock belongs to during a given period. The non-liquidity component, denoted $\Delta\%\text{Inst}_{NLQ}$, is the institutional trading measure on a stock in excess of the liquidity-driven component; that is, $\Delta\%\text{Inst}_{NLQ} = \Delta\%\text{Inst} - \Delta\%\text{Inst}_{LIQ}$. For long-horizon (short-horizon) anomalies, both institutional trading and liquidity change are consistently measured over six (two) quarters. In each quarter, we average the liquidity-driven and non-liquidity components of institutional trading over the long and short legs of each individual anomaly and calculate the long-short difference, and then average them over anomalies within the same category.

Panel A of Table 5 shows that, for long-horizon anomalies, the liquidity-driven institutional trading over the long legs tends to be lower than that over the short legs. Net liquidity-driven institutional trading, i.e. the long-short difference in liquidity-driven institutional trading, is significantly negative for the Value, Investment, Financing, Quality, and Intangible categories and insignificantly negative for Efficiency (although significantly positive for LT Profitability). Averaged over the seven long-horizon categories, net liquidity-driven institutional trading is negative at -0.55%, with a significant t-statistic of -10.02. Among the four short-horizon categories, Momentum and ST Profitability exhibit significantly positive net liquidity-driven institutional trading, while the statistics for the other two categories are not significant. Averaged over the four short-horizon anomaly categories, net liquidity-driven institutional trading is significantly positive at 0.22%, with a t-statistic of 3.21. Therefore, even if institutional investors do not intentionally trade on any anomalies, their liquidity preference appears to drive their trading in the wrong direction of long-horizon anomalies and in the right direction of short-horizon anomalies.

Panel B of Table 5 shows that for five out of seven long horizon anomaly categories, non-liquidity institutional trading is higher for the long legs than the short legs, and significantly so for two categories (Investment and Efficiency). Value is the only category for which the difference in non-liquidity institutional trading between the long and short legs is significantly negative. Averaged over the seven long-horizon categories, the net non-liquidity component of institutional trading (i.e., the long-short difference) is significantly positive at 0.13%, with a t-statistic of 2.06. Thus, after controlling for liquidity preference, institutions tend to trade in the right direction of long-horizon anomalies. In other words, the perverse pattern of institutional trading on long-horizon anomalies is mainly due to liquidity. By contrast, the net non-liquidity institutional trading measures are all significantly positive across the four short-horizon categories. Averaged over the four categories, net non-liquidity institutional trading is significantly positive at 1.10%, with a t-statistic of 4.95. Thus, the tendency for institutions to trade in the right direction of short-horizon anomalies is not completely driven by liquidity.

One important conclusion from these findings is that liquidity largely explains why institutional trading tends to be in the wrong direction of long-horizon anomalies. The direction of the non-liquidity component of institutional trading, which should reflect more of institutions' intention to exploit mispricing, does not contradict the long-horizon anomalies and is consistent with the short-horizon anomalies.

III.6 Robustness: Alternative Measures of Liquidity and Institutional Trading

III.6.1 Alternative Liquidity Measures

Liquidity is a multi-faceted concept and multiple liquidity measures are available in the literature. We choose the Amihud illiquidity ratio (ILLIQ) as the main measure of illiquidity, because existing studies show that it performs well in capturing the price impact component of trading costs, which is the most relevant liquidity concept for institutional investors with large portfolios. Goyenko, Holden, and Trzcinka (2009) find that ILLIQ does well in measuring price impact and outperforms other low-frequency estimators of trading costs. Hasbrouck (2009) reports that, among proxies based on data at a daily frequency, ILLIQ is the most strongly correlated with the price impact measure based on intra-day data.

To ensure the robustness of inference, we perform an analysis using two alternative liquidity measures based on the intra-day TAQ data. Specifically, we obtain the measures from the WRDS Intraday Indicators Database (WRDS IID), with variables based on the second-timestamped data (i.e., monthly TAQ) for the period of 1993-2002 and the corresponding variables based on the millisecond-timestamped data (i.e., daily TAQ) for the period of 2003-2018. The first alternative measure of illiqidity, Spread, is the value-weighted percentage effective spread, which is the variable "ESpreadPCT_VW1" in the second-timestamped data (before 2003) and the variable "EffectiveSpread_Percent_DW" in the millisecond-timestamped data (after 2003). The second alternative measure, Impact, is the value-weighted percentage price impact, which is the variable "PriceImpact-PCT_VW1" in the second-timestamped data (before 2003) and the variable "PercentPriceImpact_LR_DW" in the millisecond-timestamped data (after 2003).

We average each measure over six quarters (for long-horizon anomalies) and two quarters (for short-horizon anomalies). We then cross-sectionally rank stocks into percentiles based on it, with a higher ranking indicating higher illiquidity. The change in illiquidity is the change of the percentile ranking over six and two quarters respectively, with a high value indicating increased illiquidity (or reduced liquidity).

We use these measures to repeat the analysis in Table 3. The results on the difference in the level and change of liquidity between the long and short legs of each anomaly category are reported in Table 6. Due to data availability, the sample period for this analysis is from 1993 to 2018. The results for both the level and change of liquidity in Table 7 confirm those reported in Table 3. That is, the differences in the level of illiquidity and illiquidity change between the long and short legs of the long-horizon anomaly portfolios tend to be positive, while the opposite pattern holds for the short-horizon anomalies.

Further, we decompose institutional trading into a liquidity-driven component and a non-liquidity component, in the same way as described in Section III.5 but using alternative liquidity measures. The results, reported in Table 7, are similar to those in Table 5; that is, the liquidity-driven component of institutional trading tends to be in the wrong direction of long-horizon anomalies and in the right direction of short-horizon anomalies. The non-liquidity component of institutional trading is not related to long-horizon anomalies and remains in the right direction of short-horizon anomalies.

III.6.2 An Alternative Measure of Institutional Trading

We also perform an analysis using the second institutional trading measure of Edelen et al. (2016), based on the change in the size-scaled number of institutional owners. The size-scaled number of institutions, #Inst, is the number of institutions holding the stock divided by the average number of institutions holding stocks in the same size decile. The corresponding institutional trading measure, Δ#Inst, is the change in the number of institutions holding the stock over six quarters for long-horizon anomalies or two quarters for short-horizon anomalies, divided by the average number of institutions holding stocks in the same size decile at the beginning of the change window. We winsorize the measure at the 0.5-th and 99.5-th percentiles to alleviate the influence of outliers.

Further, we decompose this measure into the liquidity-driven and non-liquidity components, in the same way as described in Section III.5. The liquidity-driven component $\Delta\#\text{Inst}_{LIQ}$ is the average institutional trading (measured by $\Delta\#$Inst) on all stocks in the same ΔILQ decile during the same period. The non-liquidity component, denoted $\Delta\#\text{Inst}_{NLQ}$, is the institutional trading measure on a stock in excess of the liquidity-driven component; that is, $\Delta\#\text{Inst}_{NLQ} = \Delta\#\text{Inst} - \Delta\#\text{Inst}_{LIQ}$.

Table 8 reports institutional trading on anomalies, based on $\Delta\#$Inst as well as its liquidity-driven and non-liquidity components. The table is constructed similarly to Tables 2 and 5, and its results are qualitatively similar to those based on $\Delta\%$Inst. Institutional trading and its liquidity-driven component appear to be in the wrong direction of long-horizon anomalies and in the right direction of short-horizon anomalies. The non-liquidity component of institutional trading is, on average, not related to long-horizon anomalies, but is positively related to short-horizon anomalies.

III.6.3 Regression Analysis and Additional Robustness Checks

Our analysis so far relies on a sorted portfolio approach and focuses on the top and bottom terciles of stocks ranked by anomaly variables (i.e., the long and short legs of the anomaly portfolios). This approach leaves out stocks in the middle terciles. To make the analysis more inclusive, we perform Fama-MacBeth regressions that involve the entire cross section of stocks.

Specifically, we perform cross-sectional regressions to examine the relation between institutional trading and anomalies, with and without controlling for liquidity change. The dependent variable is the institutional trading measure, either $\Delta\%$Inst or $\Delta\#$Inst. The main explanatory variable is the cross-sectional percentile rank of an anomaly category. To obtain this variable, we first obtain the cross-sectional percentile rank of a stock based on an individual anomaly variable, and then take the average rank across all variables in the same anomaly category. The key control variable in the regression is the liquidity change ΔILQ. We also include the logarithm of market capitalization (Ln(Size)) as an additional control.

The results in Table 9 show that without controlling for liquidity change, the coefficients of both institutional trading measures are significantly negative for long-horizon anomalies and significantly positive for short-horizon anomalies. Once we control for liquidity change, the coefficients on institutional trading measures become insignificant for long-horizon anomalies, while remaining significantly positive for short-horizon anomalies. These results suggest that liquidity is the main reason that institutions are on the wrong side of long-horizon anomalies. They are consistent with the results based on sorted portfolios, as reported in Tables 2 and 5.

Finally, we we discuss two sets of additional analyses performed to ensure the robustness of our findings. We only discuss the results briefly here and provide more details in the Internet Appendix.

First, we show that the return-predictive horizons, liquidity characteristics, and institutional trading patterns on the 24 individual anomalies are largely consistent with those at the anomaly category level.

Second, Edelen et al. (2016) find different institutional trading patterns over long versus short horizons and provide a caution on the use of short-horizon institutional trading to make inference. When analyzing short-horizon anomalies, we rely on institutional trading over two quarters. To check the robustness of the results, we additionally examine institutional trading over six quarters on these short-horizon anomalies. The results confirm that using a longer-horizon institutional trading measure does not alter our key inference on how institutions trade on short-horizon anomalies.

IV Further Analysis

The analysis in Section III shows that how institutional investors' liquidity preference affects their trading on market anomalies. The analysis relies on a decomposition of institutional trading into the liquidity-driven and non-liquidity component. Such analysis may have a lingering concern on reverse causality; that is, the liquidity changes experienced by stocks in the long and short legs of anomaly portfolios are caused by institutional trading. To address this concern, we perform two additional sets of analysis. In Section IV.1, we exploit the exogenous heterogeneity in institutions' liquidity preferences to show that the cross-sectional differences in liquidity preference drive different patterns of institutional trading on anomalies. In Section IV.2, we use quasi-natural experiments to show how exogenous shocks to liquidity affect institutional trading on anomalies.

Further, given the wrong direction of institutional trading on (long-horizon) anomalies, we examine how institutional trading affects the magnitude of anomalies. Section IV.3 examines whether the stock return premia associated with liquidity and liquidity change explain the magnitude of anomalies. Section IV.4 examines how the direction of institutional trading affects the magnitude of anomalies and to what extent liquidity can explain such effects.

IV.1 Trading by Institutions with Different Liquidity Preferences

In this section, we use an alternative approach to demonstrate how liquidity preference affects institutional trading on anomalies. Instead of examining institutional investors in aggregate, we classify institutions into groups based on their liquidity preference, and analyze the trading behavior of each group. Because the liquidity preference measures we use do not rely in any direct way on institutional trading, such analysis is not subject to the reverse-causality concern that the liquidity change of a stock is caused by institutional trading.

We consider two proxies for institutional liquidity preference. The first is the total value of an institution's equity holdings, based on the idea that larger institutions tend to hold larger positions on individual stocks and are thus more concerned about liquidity. The second measure is the liquidity of an institution's stock holdings, based on the simple idea of revealed preference: institutions with stronger liquidity preference likely hold more liquid portfolios. We measure the illiquidity of an institution's stock holding by the weighted average illiquidity (ILQ) of its stock holdings. In each quarter, we classify institutional investors into terciles based on each of these two liquidity preference proxies. Large (small) institutions are those ranked in the top (bottom) tercile based on the size of equity holdings. Institutions with illiquid (liquid) portfolios are those ranked in the top (bottom) tercile based on the illiquidity of their holdings. Our prediction is that due to stronger liquidity preference, trades by large institutions and institutions with liquid portfolios are more likely to be in the wrong direction of long-horizon anomalies and in the right direction of short-horizon ones.

In Table 10, we report the net institutional trading Δ%Inst for each type of institution on the eleven categories of anomalies. Panel A shows that large institutions' net trading is significantly negative on long-horizon anomalies and significantly positive on short-horizon ones. In contrast, Panel B shows that small institutions' net trading on long-horizon anomalies is insignificant, and their net trading on short-horizon anomalies is significantly negative. The contrasts are consistent with the difference in liquidity preferences between large and small institutions.

Further, Panels C and D of Table 10 show that the net trading of institutions with liquid portfolios is significantly negative for long-horizon anomalies, but significantly positive for short-horizon anomalies. Interestingly, the pattern is different for institutions with illiquid portfolio; their net trading is significantly positive on long-horizon anomalies but significantly negative on short-horizon anomalies.[7] Again, this result is consistent with the prediction based on their different liquidity preference.

Note that existing studies have also reported heterogeneous trading patterns by different types of institutions. For example, Edelen, et al. (2016), Calluzzo, et al (2018), and McLean, et al. (2020) find that mutual funds tend to be on the wrong side of (long-horizon) anomalies, while hedge funds and short-sellers are often on the right side. Hedge funds and short-sellers are typically smaller and nimbler than mutual funds and other traditional long-only institutions. These patterns are therefore consistent with the difference in liquidity preference across these types of institutions.

IV.2 Evidence based on Quasi-natural Experiments

We further address the reverse causality concern using two quasi-natural experiments with large exogenous liquidity shocks to stocks – the minimum tick size changes at major U.S. stock exchanges from one-eighth to one sixteenth of a dollar in 1997, and further to one cent (i.e., decimalization) in 2001. Prior studies (e.g., Bessembinder, 2003; Chordia, Roll, and Subrahmanyam, 2008) show that these two events largely reduced the bid-ask spreads and improved liquidity in the stock market. Because these tick size changes are regulator-mandated and systematically implemented by all stock exchanges, a large number of studies have used them as exogenous shocks to liquidity (e.g., Fang, Noe, and Tice, 2009; Han and Lesmond, 2011; Bharath, Jayaraman, and Nagar, 2013; Fang, Tian, and Tice, 2014). In a recent study, Eaton, Irvine, and Liu (2021) identify 26 papers in the recent ten years that use the 2001 decimalization event as an exogenous liquidity shock to study various issues.

[7] However, it is somewhat puzzling that small institutions and institutions with illiquid portfolios trade in the wrong direction of the short-horizon anomalies.

We follow prior studies to treat these events as exogenous liquidity shocks (as opposed to the result of institutional trading) and examine how institutional trading on anomalies is affected by such shocks. Because institutional trading is only available at the quarterly frequency, we define the "treatment period", where stocks experience large liquidity shocks, in the following way. First, the transition from the minimum tick size of one eighth to one sixteenth is implemented from May 7, 1997 to June 24, 1997. However, this period coincides with the implementation of a set of "order handling rules" (e.g., quote display rule, actual size rule, excess spread rule) on NASDAQ by SEC from January 20, 1997 to October 13, 1997. We therefore set the year 1997 to be the treatment period. Accordingly, we set the entire year of 1996 as the corresponding pre-treatment period. Second, NYSE and AMEX transition to one cent from August 28, 2000 to January 29, 2001, with a small number of stocks in a pilot program making the tick size change by December 4, 2000, and the majority of stocks making the change by January 29, 2001. NASDAQ's decimalization is from March 12, 2001 to April 9, 2001. Accordingly, we define the treatment period as the first half of year 2001 (2001H1) and set the second half of year 2000 (2000H2) as the corresponding pre-treatment period. Note that in 2001 the stock market also experienced the burst of the tech bubble. To avoid this potentially confounding effect, for the 2001 event, we exclude all technology stocks from the analysis (based on the Fama-French 10-industry classification).

In Panel A of Table 11, we first report the overall effect of minimum tick size change on liquidity and institutional trading (without relating institutional trading to anomalies yet). The liquidity measure we use here is the value-weighted percentage effective spread described in Section III.6.1, as the tick size changes most directly affect the spreads among all liquidity measures. Institutional trading is based on ΔInst. The panel shows that the percentage effective spread, averaged across all stocks, is significantly reduced by 3.53% and 2.16% during the two treatment periods (1997 and 2001) relative to their respective pre-treatment periods. Further, for the two events, net institutional trading measures are 4.81% and 1.82% in the two treatment periods respectively, significantly higher (by 4.91% and 1.04%) than those in the corresponding pre-treatment periods. This evidence suggests that the improvement in liquidity increases institutional trading.

Prior studies show that the two events affect the liquidity across stocks in an uneven way. We confirm this by classifying stocks into two groups based on the change in effective spread from the pre-treatment to the treatment period. The group with high (low) liquidity shock consists of stocks with above-median (below-median) *reduction* in effective spread. Panel A of Table 11 shows that during both the 1997 and 2001 events, the difference in the change of effective spread between the two groups is quite large – -8.97% for the 1997 event and -5.74% for the 2001 event. Institutional trading also exhibit large differences between the two groups. For the group with high liquidity shock, institutional trading increases by 6.22% and 1.87% from the pre-treatment period to the treatment period for the 1997 and the 2001 events respectively. By contrast, for the group with low liquidity shock, institutional trading increases by 3.59% for the 1997 event and 0.22% for the 2001 event. The evidence suggests that the overall increase in institutional trading from the pre-treatment period to the treatment period for both events is mainly driven by stocks with high liquidity shocks.

Panel B of Table 11 provides illustrative statistics on how liquidity change affects institutional trading on anomalies during these two events. For each event, the long and short legs of the anomaly portfolios are defined as of the end of the treatment period. For brevity we only report the results for the two aggregated categories of long-horizon and short-horizon anomalies. The panel shows that for the long-horizon anomaly, during the 1997 event (relative to its pre-treatment period of 1996), both the long and short legs of the long-horizon anomaly experience a spread reduction (3.58% and 3.79% respectively), with the long-leg experiencing more spread reduction than the short leg by a significant 0.21%. During the 1997 event, institutional investors buy more stocks on the long leg of the long-horizon anomaly (5.33%) than they do on the short leg (4.09%), with a significantly positive long-short difference of 1.24%. This is in a sharp contrast with the pre-treatment period of 1996, where institutional trading is in the wrong direction of the long-horizon anomaly, with a long-short difference of Δ%Inst a significantly negative -2.80%. There are similar patterns for the liquidity and institutional trading on the long-horizon anomaly during the 2001 event. Relative to the pre-treatment period, during the treatment period the effective spread is reduced for stocks on both the long and the short legs, with more reduction for the long leg (2.40%) than for the short leg (1.79%). Accordingly, institutional trading increases more on the long leg (1.48%) than on the short leg (0.90%), from the pre-treatment period to the treatment period. These results intuitively suggest that the liquidity shocks of 1997 and 2001 cause institutions to trade in the right direction of long-horizon anomalies.

The same panel also shows that, for the short-horizon anomalies during both the 1997 and 2001 shocks, the effective spread is reduced for both long and short legs. Institutions buy more at the long leg than at the short leg, i.e., trade in the right direction, during both the treatment and the pre-treatment periods. The net (long-short) institutional trading significantly increases during the treatment period of 1997, but the increase is not significant during the treatment period of 2001 (all relative to their respective pre-treatment periods).

Prior studies take advantage of the fact that the impact of the minimum tick size changes on liquidity is different across stocks, and design difference-in-difference (DiD) analysis based on such differential impact on liquidity. We follow this strategy and conduct a further DiD analysis to identify the causal impact of liquidity change on institutional trading. For this analysis, we identify a group of "treated" stocks, which experience large positive liquidity shocks. We also identify a group of "control" stocks, which experience relatively low liquidity shocks. In identifying "treated" and "control" stocks, we further adopt a procedure to ensure the samples identified satisfy the "parallel trend" assumption, an important condition for the validity of the DiD approach. The "parallel trend" in the context of our analysis refers to the condition that the "treated" and "control" stocks should exhibit a similar trend of institutional trading prior to the shock. Our empirical procedure to ensure the "parallel trend" during the pre-treatment period is as follows.[8] On each anomaly leg, we first sort stocks into deciles based on the change in institutional trading during the pre-treatment period. Specifically, the pre-treatment trend (change) in ΔInst is measured from 1995 to 1996 for the 1997 event, and from 2000H1 to 2000H2 for the 2001 event. Then, within each decile, we sort stocks into two groups based on the change in effective spread from the pre-treatment period to the treatment period to form the portfolio of stocks with high and low liquidity shocks. Within an anomaly portfolio leg, the treated group consists of stocks with high liquidity shocks (large spread reductions) across all pre-treatment-trend deciles, and the control group consists of stocks with low liquidity shocks, across all pre-treatment-trend deciles. This procedure ensures that stocks on each leg that experience high and low liquidity shocks due to the tick size change have the same trend of institutional trading prior to the

[8]We have also performed an analysis using the propensity score matching (PSM) approach, where the propensity score is based on the pre-treatment level and change of spread as well as the stock size. We obtain similar (untabulated) results.

event.

Panel C of Table 11 reports the results of the DiD analysis. We first confirm that our procedure above enables the treated stocks and the control stocks to have the same parallel trend prior to the liquidity shock event. For example, as shown in the second to last column of the panel, for the 1997 event, the difference in the pre-treatment trend of ΔInst is 0.04% and 0.06% (both insignificant), respectively, for the short and long legs of long-horizon anomaly. For the 2001 event, the difference in the pre-treatment trend of ΔInst is 0.41% and 0.08% for the short and long legs of long-horizon anomaly, again both insignificant.

The third to last column of this panel shows that during the treatment period, the treated and control groups on the same leg of the portfolio have significantly different institutional trading. During the 1997 event, for the long horizon anomaly, ΔInst for the treated stocks on the short leg is 6.12%, significantly higher than the corresponding number of 2.09% for the control stocks on the same leg; ΔInst for the treated stocks on the long leg is 7.15%, also significantly higher than the corresponding number of 3.53% for the control stocks on the same leg. Similarly, during the 2001 event, for the long horizon anomaly, ΔInst for the treated stocks on the short leg is 2.71%, significantly higher than the corresponding number of 0.59% for the control stocks on the same leg; ΔInst for the treated stocks on the long leg is 3.28%, also significantly higher than the corresponding number of 0.89% for the control stocks on the same leg. The pattern of the short-horizon anomaly is similar.

The difference-in-difference (DiD) statistics are reported in the last column of the panel. During the 1997 event, the treated stocks on the short leg of the long-horizon anomaly experience an increase of ΔInst of 4.17% (from pre-treatment to treatment period), while the corresponding control stocks experience an increase of 1.19%. The difference ("Treated - Control" under "Short Leg") of 2.98% is significantly positive. During the 2001 event, the treated stocks on the short leg of the long-horizon anomaly experience an increase of ΔInst of 2.08% (from pre-treatment to treatment period), while the corresponding control stocks experience a decrease of 0.27%. The difference ("Treated - Control" under "Short Leg") of 2.35% is significantly positive. The results for the long leg of the long-horizon anomaly is similar – a difference in the increase of ΔInst by 4.17% between treated and control stocks in the long leg for the 1997 event , and a difference of 3.03% for the 2001 event, both statistically significant. We also find similar results for the short-horizon anomaly. These results suggest that exogenous liquidity shocks significantly affect how institutional investors trade on stocks within both long and short legs of the anomaly portfolio.

The findings in Section IV.1 and IV.2 combined provide evidence that the liquidity characteristics of anomalies and the liquidity preference of institutional investors have causal effect on how institutions trade on long- and short-horizon anomalies.

IV.3 Liquidity Premium and Market Anomalies

Investors' preference for liquidity can give rise to a liquidity premium—a higher return to more illiquid stocks. Given that the long legs and short legs of anomaly portfolios have substantially different liquidity characteristics, it is natural to ask whether the returns of anomaly portfolios are explained by the liquidity premium.

To address this question, we first discuss the pattern on the liquidity premium. In Panel A of Table 12, we report the return difference between the top and bottom decile portfolios sorted by level of illiquidity, ILQ. The table shows that this intuitive measure of liquidity premium is insignificant throughout the eight quarters after portfolio ranking. That is, the premium associated with illiquidity has disappeared during the sample period we study (1980-2018).

Interestingly, we find significant evidence for the premium associated with liquidity change. As Panel A shows, the return difference between the top and bottom decile portfolios sorted by the two-quarter change of illiquidity (ΔILQ) is significantly positive for five quarters after portfolio ranking (except for the first quarter). Further, the top-bottom return difference for portfolios sorted by the six-quarter change of illiquidity is significantly positive for the first four quarters as well as for the sixth quarter after portfolio ranking.[9]

Given the above findings, we further examine whether the return premium associated with liquidity change affects the magnitude of the market anomalies. For each stock in each quarter, we calculate its liquidity-adjusted return as the quarterly stock return in excess

[9] In untabulated analysis, we find that during the period of 1963-1979, the top-bottom return difference for ILQ-sorted portfolios is significant for at least eight quarters after portfolio ranking. Therefore, in early years the liquidity premium is much stronger and is a long-horizon phenomenon. Similarly, we find that the premium associated with liquidity change ΔILQ is even stronger during this period. Finally, we perform an analysis using the TAQ-based liquidity measures of the effective spread (Spread) and the price impact (Impact). Based on these two measures and during the period of 1993-2018, again there is no significant premium associated with the level of illiquidity, but there is a significantly positive premium associated with the change in illiquidity.

of a liquidity benchmark return, which is calculated as the average return to stocks in the same decile of liquidity change (over six or two quarters). We then calculate the average liquidity-adjusted return for the long and short legs of the anomaly portfolios.

Panel B of Table 12 reports the results of the long-short difference in the liquidity-adjusted returns for the 11 anomaly-category portfolios. The long-short return difference for the value anomaly portfolio, after liquidity adjustment, is no longer significant at any horizon. Therefore the value anomaly appears to be mainly driven by the liquidity change premium during the sample period. The magnitudes of other anomalies also appear to be somewhat reduced after the adjustment for the liquidity change premium, but to a much lesser extent. The average adjusted-return difference across seven long-horizon categories remains significant over eight quarters and the average across four short-horizon categories remains significant over three quarters. These patterns for liquidity-adjusted returns are quite similar to those in Table 1 for unadjusted returns.

Therefore, although the long and short legs of anomaly portfolios tend to have significantly different characteristics in terms of the level and change of liquidity, with the exception of the value anomaly, anomaly portfolio returns are not completely driven by the liquidity premium or the liquidity change premium.

IV.4 Magnitude of Market Anomalies Conditional on Institutional Trading Directions

A remaining important issue is the impact of institutional trading on stock mispricing. Given our findings on how liquidity drives institutional trading, we address three relevant questions. First, does the direction of institutional trading matter for the magnitude of long- and short-horizon anomalies? Second, do the directions of the liquidity-driven and non-liquidity components of institutional trading matter for the magnitude of anomalies? And finally, does the liquidity change premium matter in explaining the different magnitudes of the anomalies associated with institutional trading directions?

We use a double-sorting procedure to analyze the magnitude of anomalies conditional on the direction of institutional trading. In each quarter, we sort stocks into quintiles based on institutional trading (over six or two quarters, depending on the anomaly horizon). Then, for each anomaly portfolio, we identify a subportfolio on which institutions trade in the wrong direction. The long leg of this subportfolio consists of the long-leg stocks in the bottom quintile of institutional trading (denoted "LL" (Long+Low)), and the short leg of this subportfolio consists of the short-leg stocks in the top quintile of institutional trading ("SH" (Short + High)). Similarly, we identify an anomaly subportfolio on which institutions trade in the right direction. The long leg of this subportfolio consists of the long-leg stocks in the top quintile of institutional trading ("LH" (Long+High)), and the short leg of this subportfolio consists of the short-leg stocks in the bottom quintile of institutional trading ("SL" (Short+Low)).

To concisely summarize the return patterns over multiple portfolio holding quarters, we follow the approach of Jegadeesh and Titman (1993) to combine portfolios with overlapping holding periods. Specifically, consider a portfolio that is held for K quarters after the initial portfolio ranking (with quarterly rebalancing). In each quarter t, there are K such portfolios, formed during quarters t-K to t-1. We combine these K portfolios into a single portfolio using equal weights, and compute its return during quarter t. This way, we obtain a time series of non-overlapping quarterly returns, based on which we further compute the average returns. We set K=4 quarters for long-horizon anomalies and K=2 quarters for short-horizon anomalies and apply this approach to the subportfolios on which institutions trade in the wrong and right directions, respectively.

As reported in Panel A of Table 13, for long-horizon anomalies, we find a pattern consistent with that reported by Edelen et al. (2016). The magnitude of these anomalies, as measured by the long-short return difference, tends to be larger for the subportfolios on which institutional investors trade in the wrong direction (LL-SH), relative to the subportfolios on which institutions trade in the right direction (LH-SL). Averaged over the seven long-horizon categories, the return difference between the two subportfolios (labeled "Wrong - Right", i.e., (LL-SH) - (LH-SL)) is 0.93%, significantly positive. Therefore, when institutions trade in the wrong direction of long-horizon anomalies, the magnitude of the anomalies is exacerbated. However, for the four short-horizon anomaly categories, the return differences between the "wrong" and "right" subportfolios are all insignificant. That is, the direction of institutional trading does not affect the magnitude of short-horizon anomalies.

To see if the patterns are different for liquidity-driven trading and non-liquidity trading, we further construct subportfolios on which the liquidity-driven and non-liquidity components are in the wrong and right directions, respectively. We then repeat the analysis of Panel A using these subportfolios. Panel B of Table 13 shows that, when institutions' liquidity-driven trades are in the wrong direction, the magnitude of long-horizon anomalies tends to be larger. Averaged over the seven long-horizon categories, the return difference between the two subportfolios ("Wrong - Right") is 1.56%, significantly positive. For short-horizon anomalies, however, the pattern is reversed. Averaged over the four categories, the return difference between the two subportfolios ("Wrong - Right") is -0.27%.

Further, Panel C of Table 13 shows that when the institutional trading direction is defined on the non-liquidity component, the return difference between the "wrong" and "right" subportfolios is insignificant for all 11 anomaly categories, and insignificant for the averages of the long- and short-horizon categories. Thus, non-liquidity institutional trading does not impact the magnitude of mispricing.

Panel D of Table 13 addresses the third question, whether the liquidity change premium matters for the different magnitudes of anomalies associated with institutional trading direction. This panel reports the liquidity-adjusted returns, that is, return adjusted for the liquidity change premium, estimated in same way as in Table 13. The panel shows that the differences in the liquidity-adjusted returns between the "wrong" and "right" subportfolios (labeled "Wrong-Right") become insignificant for all seven long-horizon anomaly categories. Thus, despite that the liquidity change premium does not explain away the average magnitude of the anomalies, it fully explains the impact of institutional trading direction on the magnitude of long-horizon anomalies. In other words, the significant relation between the institutional trading direction and the magnitude of long-horizon anomalies might not necessarily be an indication that institutional trading exacerbates stock mispricing, but rather an incarnation of the liquidity change premium.

Panel D of Table 13 also shows that the differences in the liquidity-adjusted returns between the "wrong" and "right" subportfolios are negative for all four short-horizon anomalies. Averaged over the four anomalies, the number is significantly negative (-0.69% with a t-statistic of -1.69). Combined with the pattern that institutional trading is often in the right direction of short-horizon anomalies, this finding suggests that institutional trading tends to reduce the magnitude of short-horizon anomalies, after the liquidity change premium is controlled for.

To sum up, we find that, while the magnitude of long-horizon anomalies is higher when institutional trading is in the wrong direction, this effect is mainly driven by liquidity and is closely related to the liquidity change premium. By contrast, the magnitude of short-horizon anomalies tends to be unaffected by the direction of institutional trading. After controlling for the liquidity change premium, we find evidence that institutional trading attenuates the short-horizon anomalies.

V Conclusions

In this study, we examine the liquidity characteristics of market anomalies. We show that the long-short portfolios formed on various market anomalies are not liquidity neutral; but rather, they have different characteristics in terms of the level and change of liquidity. Further, the directions of the liquidity exposure of long-short anomaly portfolios are heterogeneous and intricately related to the return-predictive horizons of the anomalies. For long-horizon anomalies, the long legs tend to be illiquid and with decreased liquidity, relative to the short legs. In a sharp contrast, the pattern appears to be the opposite for the short-horizon anomalies. To our knowledge, these findings are novel in the literature on institutional trading and market anomalies.

We further investigate the connection between the liquidity characteristics of market anomalies and how institutional investors trade on anomalies. Recent studies have reported that institutions tend to trade in the wrong direction of many anomalies, which is quite puzzling and challenges the commonly perceived role of institutional investors in improving market efficiency. We find that the relation between institutional trading and market anomalies is also heterogeneous. Institutional investors are often on the wrong side of long-horizon anomalies, but on the right side of short-horizon anomalies. Further, the wrong direction of institutional trading on long-horizon anomalies is explained by the liquidity characteristics of these anomalies and institutional preference for liquidity. The non-liquidity component of institutional trading tends to be in the right direction of anomalies. We also show that it is important to factor liquidity into understanding the perverse relation between the direction of institutional trading and the magnitude of long-horizon anomalies. Our findings highlight that the liquidity-driven and non-liquidity components of institutional trading have different implications for market efficiency.

Appendix: Individual Market Anomalies

Below are details on the construction of the 24 individual anomaly variables. Compustat data items are indicated in parentheses.

1. Book-to-price ratio (BP): Book equity to market equity ratio, where book equity is the book value of stockholders' equity (item SEQ), plus balance sheet deferred taxes and investment tax credit (item TXDITC, if available], minus the book value of preferred tax [items PSTKRV, PSTKL, PSTK, in that order]; market equity is market cap at the end of the fiscal year. If SEQ is missing, SEQ is computed as the sum of common equity (item CEQ) and preferred equity (item PSTK), or the difference between total assets (item AT) and total liability (item LT), in that order. The data are from Compustat annual files.

2. Earnings-to-price ratio (EP): NIBE/ME, where NIBE is earnings before extraordinary items (item IB), and ME is market cap at end of the fiscal year. We only include firms with positive NIBE. The data are from Compustat annual files.

3. Sales growth (SG): Percent change in sales (item SALE) over the previous year. The data are from Compustat annual files.

4. Capital Investment (CAPX): Capital expenditure (item CAPX) divided by book assets (item AT) in the beginning of the year. The data are from Compustat annual files.

5. Abnormal Investment (AI): $3CE_{t-1}$ / (CE_{t-2} + CE_{t-3} + CE_{t-4}) -1, in which CE is capital expenditure (item CPAX) scaled by lagged sales (item SALE). The data are from Compustat annual files.

6. Asset Growth (AG): Percentage change in book assets (item AT) over the previous year. The data are from Compustat annual files.

7. Net Equity Issues (NS): the change in the natural log of the split-adjusted shares outstanding during the previous fiscal year. The split-adjusted shares outstanding is shares outstanding (item CSHO) times the adjustment factor (item AJEX_C). The data are from Compustat annual files.

8. External Financing (XFIN): Total financing obtained from equity and debt markets, including cash flow from common and preferred stock markets (Equity) and from private and public debt markets (Debt). Equity represents net cash received from the sale (and/or repurchase) of common and preferred stock less cash dividends paid (item SSTK less item PRSTKC less item DV). Debt represents net cash received from the issuance (and/or reduction) of debt (item DLTIS, less item DLTR, plus item DLCCH). We require the availability of Compustat data for each of the above variables, with the exception of item DLCCH (change in current debt), which is set to zero if it is missing. We notice that while the equity financing included in XFIN covers both common and preferred equity, while NS is just a measure of common stock issuance. The data are from Compustat annual files.

9. Accruals (ACC): (ΔCA - ΔCASH - ΔCL - ΔSTD - ΔTP - DEP)/LAT, where CA is current assets (item ACT); CASH is cash/cash equivalents (item CHE); CL is the current liabilities (item LCT);STD is Debt in Current Liabilities (item DLC); TP is income taxes payable (item TXP); DEP is depreciation and amortization expense (item DP); and LTA is the lagged total assets (item AT). The data are from Compustat annual files.

10. Discretionary Accruals (DACC): We follow Xie (2001) and use the Jones model to estimate normal accruals and abnormal accruals in cross-section for each two-digit SIC code and year combination, formed separately for NYSE/AMEX firms and for NASDAQ firms. We denote the residual values from the Jones model as discretionary accruals (DACC). The data are from Compustat annual files.

11. Asset Turnover (ATTO): Total sales revenue (item SALE) divided by average total assets (item AT). The data are from Compustat annual files.

12. Net Operating Asset (NOA): The difference between (AT-CHE) and (AT-DLC-DLTT-MIB-PSTK-CEQ), divided by lagged book asset (item AT). The data are from Compustat annual files.

13. Research and development (RD): R&D expenditure (item XRD) / ME, where ME is market cap at the fiscal year-end. RD is set to missing if it is zero. The data are from Compustat annual files.

14. Selling and General Administrative Expenses (SGA): Selling, general and administrative expenses (item XSGA) / ME, where ME is market cap at the fiscal year-end. SGA is set to missing if it is zero. The data are from Compustat annual files.

15. Gross Profit (GP): Sales (item Sale) minus Cost of Goods Sold (item COGS), divided by book assets (item AT). The data are from Compustat annual files.

16. Price momentum (MOM): Stock returns from month t-12 to t-1, where month t is the portfolio formation month. The data are from CRSP.

17. Standardized Unexpected Earnings (SUE): Change in split-adjusted EPS (item EPSFXQ / item ADJEXS) from quarter t-3 to t, divided by the standard deviation of 4-quarter EPS changes. The standard deviation is measured using 4-quarter EPS changes during past 8 quarters, with a minimum of 4 quarters of observations required. The data are from Compustat quarterly files.

18. Analyst forecast revision (FRV): Average unadjusted analyst EPS forecast for the currently unreported fiscal year FY1 during month t, in excess of the average unadjusted EPS forecast for the same fiscal year made during month t-6, divided by the unadjusted stock price in month t when the average forecast is measured. The data are from IBES.

19. Return on Equity (ROE): Net income (item NIQ) divided by common equity (item CEQQ). The data are from Compustat quarterly files.

20. Gross Margin (GM): Sales (item SALEQ) minus Cost of Goods Sold (item COGSQ), then divided by Sales (item SALEQ). The data are from Compustat quarterly files.

21. O-Score (OSCORE): We follow Franzen, Rodgers and Simin (2007) and define O-Score as

$$OScore = -1.32 - 0.407 * size + 6.03 * tlta - 1.43 * wcta + 0.0757 * clca$$

$$-2.37 * nita - 1.83 * ffotl + 0.285 * intwo - 1.72 * oeneg - 0.521 * chin$$

where Size is the log of total assets (item AT), tlta is total liabilities (Item LT) divided by total assets (Item AT), wcta is working capital defined as current assets (Item ACT) less current liabilities (Item LCT) divided by total assets (Item AT), clca is current liabilities (Item LCT) divided by current assets (Item ACT), nita is net income (Item NI) divided by total assets (Item AT), ffotl is funds from operations defined as pretax income (Item PI) plus depreciation (Item DP) divided by total liabilities (Item LT),intwo is a dummy variable equal to 1 when the firm has negative net (Item NI) in the 2 prior years and otherwise, oeneg is a dummy variable set equal to 1 if the firm has negative book value of equity (if total liabilities exceed total assets) and 0 otherwise, and chin is change in net income (Item NI), defined as

$$(netincome_t - netincome_{t-1})/(|netincome_{t-1}| + |netincome_t|)$$

The data are from Compustat annual files.

22. Failure Probability (CHS): We apply the coefficients in the 3rd column in Table 4 of Campbell, Hilscher, and Szilagyi (2008) and define CHS as

$$CHS = -9.16 - 20.26 * nimtaavg + 1.42 * tlmta - 7.13 * exretavg + 1.41 * stdev$$
$$-0.045 * rsize - 2.13 * cashmta + 0.075 * mtb - 0.058 * price$$

where nimtaavg and exretavg are the moving average of lagged four quarterly nimta and 12 monthly excess returns (exret), respectively, with geometrically declining weights on lags, nimta is net income (item NIQ) divided by the sum of market equity (the product of number of shares outstanding and month end stock prices) and total liability (item LTQ),exret is the monthly log excess return on each firm's equity relative to the S&P 500 index, tlmta is the ratio of total liabilities (item LTQ) divided by the sum of market equity and total liabilities (item LTQ), stdev is the annualized three-month rolling sample standard deviation, rsize is the relative size of each firm measured as the log ratio of its market equity to that of the S&P 500 index, cashmta is the ratio of cash and short term investments (item CHEQ) divided by the sum of market equity and total liabilities, mtb is the ratio of market-to-book equity, where book equity is the sum of stockholders' equity (item SEQQ) and deferred tax credit (item TXDITCQ) minus preferred stockholders' equity (item PSTKQ) and book equity is adjusted by adding 10% of the difference between market and book equity, and price is the log price per share (truncated above at the $15). We winsorize all eight predictive variables at the 5t̂h and 95t̂h percentiles of their pooled distributions to compute CHS Score for each firm every month. The data are from CRSP daily and monthly files and Compustat quarterly files.

23. Idiosyncratic Volatility (IVOL): Standard deviation of residual returns from regressing daily stock returns onto the Fama-French 3 factors. The regression is performed using daily returns during the portfolio formation quarter with a minimum of 45 observations. The data are from CRSP.

24. Analyst forecast dispersion (DISP): Standard deviation of unadjusted analyst EPS forecasts for the unreported fiscal year FY1, divided by the unadjusted stock price at the end of the portfolio formation quarter. The data are from IBES.

References

Acharya, V., and L. H. Pedersen, 2005. Asset Pricing with Liquidity Risk. Journal of Financial Economics 77, 375-410.

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.

Asness, C., T. Moskowitz, and L. Pedersen, 2013. Value and Momentum Everywhere. Journal of Finance 68, 929-985.

Ali, A., X. Chen, T. Yao, and T. Yu, 2008. Do Mutual Funds Profit from the Accruals Anomaly? Journal of Accounting Research 46, 1-26.

Ali, A., X. Chen, T. Yao, and T. Yu, 2020. Can Mutual Funds Profit from Post Earnings Announcement Drift? The Role of Competition. Journal of Banking and Finance, forthcoming.

Ali, A., L. S. Hwang, and M. Trombley, 2003. Arbitrage Risk and the Book-to-market Anomaly. Journal of Accounting and Economics 69, 355-373.

Amihud, Yakov, 2002. Illiquidity and Stock Returns: Cross-section and Time-series Effects. Journal of Financial Markets 5, 31-56.

Bartov, E., S. Radhakrishnan, and I. Krinsky, 2000. Investor Sophistication and Patterns in Stock Returns after Earnings Announcements. The Accounting Review 75, 43-63.

Bessembinder, H., 2003. Trade Execution Costs and Market Quality after Decimalization. Journal of Financial and Quantitative Analysis 38, 747–777.

Bharath, S.T., S. Jayaraman, and V. Nagar, 2013. Exit as Governance: An Empirical Analysis. Journal of Finance 68, 2515–2547.

Carhart, M., 1997. On Persistence in Mutual Fund Performance. Journal of Finance 52, 57-82.

Calluzzo, P., F. Moneta, and S. Topaloglu, 2018. When Anomalies are Publicized Broadly, Do Institutions Trade Accordingly? Management Science 65, 4555-4574.

Chan, L., N. Jegadeesh, and J. Lakonishok, 1996. Momentum Strategies. Journal of Finance 51, 1681-1713.

Campbell, J., 2018. Financial Decisions and Markets: A Course in Asset Pricing. Princeton University Press: Princeton, NJ.

Campbell, J., J. Hilscher, and J. Szilagyi, 2008. In Search of Distress Risk. Journal of Finance 63, 2899-2939.

Chordia, T., R. Roll, and A. Subrahmanyam, 2008. Liquidity and Market Efficiency. Journal of Financial Economics 87, 249–268.

Collins, D., G. Gong, and P. Hribar, 2003. Investor Sophistication and the Mispricing of Accruals. Review of Accounting Studies 8, 251-276.

Daniel, K., D. Hirshleifer, and L. Sun, 2020. Short- and Long-Horizon Behavioral Factors. Review of Financial Studies 33, 1673-1736.

Eaton, G., P. Irvine, and T. Liu, 2021. Measuring Institutional Trading Costs and the Implications for Finance Research: The Case of Tick Size Reductions. Journal of Financial Economics 139, 832-851.

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

Fama, E. F., and K. R. Frech, 1996. Multifactor Explanations of Asset Pricing Anomalies. Journal of Finance 51, 55-84.

Fang, V., T. Noe, and S. Tice, 2009. Stock Market Liquidity and Firm Value. Journal of Financial Economics 94, 150–169.

Fang, V., X. Tian, and S. Tice, 2014. Does Stock Liquidity Enhance or Impede Firm Innovation? Journal of Finance 69, 2085–2125

Gompers, P., and A. Metrick, 2001. Institutional Investors and Equity Prices. Quarterly Journal of Economics 116, 229-259.

Goyenko, R., C. Holden, and C. Trzcinka, 2009. Do Liquidity Measures Measure Liquidity? Journal of Financial Economics 92, 153-181.

Green, J., J. Hand, and F. Zhang, 2013. The Supraview of Return Predictive Signals. Review of Accounting Studies 18, 692-730.

Green, J., J. Hand, and F. Zhang, 2017. The Characteristics that Provide Independent Information about Average U.S. Monthly Stock Returns. Review of Financial Studies 30, 4389-4436.

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.

Han, Y. and D. Lesmond, 2011. Liquidity Biases and the Pricing of Cross-sectional Idiosyncratic Volatility. Review of Financial Studies 24, 1590–1629.

Hasbrouck, J., 2009. Trading Costs and Returns for U.S. Equities: Estimating Effective Costs from Daily Data. Journal of Finance 64, 1445-1477.

Harvey, C., Y. Liu, and H. Zhu, 2016. ... and the Cross-Section of Expected Returns. Review of Financial Studies 29, 5-68.

Hou, K., and T. Moskowitz, 2005. Market Frictions, Price Delay, and the Cross-section of Expected Returns. Review of Financial Studies 18, 981-1020.

Hou, K., C. Xue, and L. Zhang, 2020. Replicating Anomalies. Review of Financial Studies 33, 2019-2133.

Ince, O., and G. Kadlec, 2019. Institutional Counterparties and Performance. Working Paper, Virginia Tech.

Jensen, T., B. Kelly, and L. Pedersen, 2021. Is There a Replication Crisis in Finance? Working Paper, Yale School of Management.

Lam, E., and K.C. Wei, 2011. Limits-to-arbitrage, Investment Frictions, and the Asset Growth Anomaly. Journal of Financial Economics 102, 127-149.

Lakonishok, J., A. Shleifer, and R. Vishny, 1994. Contrarian Investment, Extrapolation, and Risk. Journal of Finance 49, 1541-1578.

Lee, C., and B. Swaminathan, 2000. Price Momentum and Trading Volume. Journal of Finance 55, 1217-1269.

Lewellen, J., 2011. Institutional Investors and the Limits of Arbitrage. Journal of Financial Economics 102, 62-80.

Lowenstein, R., 2000. When Genius Failed: The Rise and Fall of Long-Term Capital Management. Random House: New York.

McLean, R.D. and J. Pontiff, 2016. Does Academic Research Destroy Stock Return Predictability? The Journal of Finance 71, 5–32.

McLean, R.D., J. Pontiff, and C. Reilly, 2020. Taking Sides on Return Predictability. Working Paper, Georgetown University.

Nagel, S., 2005. Short Sales, Institutional Investors and the Cross-section of Stock Returns. Journal of Financial Economics 78, 277-309.

Newey, W. and K. West, 1987. A Simple, Positive Semi-definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix. Econometrica 55, 703-708.

Novy-Marx, R., 2013. The Other Side of Value: The Gross Profitability Premium. Journal of Financial Economics 108, 1-28.

Perold, A., 1999. Long-Term Capital Management, L.P. (A), Harvard Business School Case 9-200-007. Harvard University, Boston, MA.

Shumway, T., 1997. The Delisting Bias in CRSP Data. Journal of Finance 52, 327–340.

Wermers, R., T. Yao, and J. Zhao, 2012. Forecasting Stock Returns though An Efficient Aggregation of Mutual Fund Holdings. Review of Financial Studies 25, 3490-3529.

Table 1. Return-predictive Horizons of Market Anomalies

This table reports average quarterly returns to 11 anomaly category portfolios. Stocks are sorted quarterly into equal-weighted terciles using each of the 24 individual anomaly variables. The long (short) leg of an anomaly portfolio is the tercile predicted to have high (low) returns. We compute the average quarterly return differences between the long and short legs during the subsequent quarters, and then average them across anomalies in the same category. The table reports the time series averages of the return differences between the long and short legs during the subsequent 8 quarters (Qtr) for long-horizon anomalies and 4 quarters for short-horizon anomalies. Returns are expressed in percentage points. LT Avg and ST Avg are the long-short return differences averaged across 7 long-horizon categories and 4 short-horizon categories respectively. Value, Investment, Financing, Quality, Efficiency, Intangible, and LT Profit are long-horizon categories. Momentum, ST Profit, Distress, and Uncertainty are short-horizon categories. *a*, *b*, and *c* denote significance at 1%, 5%, and 10% respectively. The sample period is from 1980 to 2018.

Qtr	Value	Investment	Financing	Quality	Efficiency	Intangible	LT Profit	LT Avg
1	1.08^b	1.03^a	1.68^a	0.94^a	1.29^a	1.96^a	1.78^a	1.39^a
2	0.97^b	0.73^a	1.45^a	0.64^a	1.12^a	1.63^a	1.57^a	1.16^a
3	0.93^b	0.62^a	1.34^a	0.58^a	0.99^a	1.53^a	1.41^a	1.06^a
4	0.79^b	0.43^b	1.19^a	0.44^a	0.89^a	1.34^a	1.29^a	0.91^a
5	0.70^c	0.42^b	1.14^a	0.36^b	0.89^a	1.44^a	1.19^a	0.88^a
6	0.64	0.39^b	1.04^a	0.35^b	0.80^a	1.32^a	1.10^a	0.80^a
7	0.59	0.36^c	0.90^b	0.24^c	0.71^a	1.29^a	1.08^a	0.74^a
8	0.46	0.30	0.79^b	0.30^b	0.63^a	1.11^a	0.98^a	0.65^a

Qtr	Momentum	ST Profit	Distress	Uncertainty	ST Avg
1	1.72^a	1.77^a	1.21^a	1.25^b	1.49^a
2	0.86^a	1.24^a	1.11^a	1.00^b	1.05^a
3	0.16	0.58^b	0.97^a	0.70	0.60^b
4	-0.38	0.32	0.74^b	0.47	0.29

Table 2. Institutional Trading on Market Anomalies

This table reports institutional trading measures on the 11 anomaly category portfolios. Institutional trading Δ%Inst is the change in percentage of shares held by institutions, measured over 6 quarters for long-horizon anomalies and over 2 quarters for short-horizon anomalies. In each quarter, we first calculate the average institutional trading for the long leg and short leg of an individual anomaly portfolio, and the difference in institutional trading between the two legs (L-S). We then average them across anomalies within the same category, and average over time. LT Avg and ST Avg are the averages across 7 long-horizon categories and 4 short-horizon categories respectively. Institutional trading measures are reported in percentage points. The t-statistics for the differences between the long and short legs are computed using the Newey-West standard errors. a, b, and c denote significance at 1%, 5%, and 10% respectively.

	Value	Investment	Financing	Quality	Efficiency	Intangible	LT Profit	LT Avg
Short	3.47	2.91	3.58	2.95	2.81	2.98	2.58	3.04
Long	2.13	2.73	2.18	2.89	3.04	2.37	2.98	2.62
L-S	-1.34^a	-0.18	-1.40^a	-0.05	0.24	-0.61^a	0.40^b	-0.42^a
t-stat	(-7.95)	(-1.42)	(-7.61)	(-0.53)	(1.82)	(-3.30)	(2.37)	(-4.73)

	Momentum	ST Profit	Distress	Uncertainty	ST Avg
Short	-0.04	0.82	0.83	0.82	0.61
Long	2.01	1.25	1.09	1.07	1.36
L-S	2.05^a	0.44^a	0.26^b	0.25	0.75^a
t-stat	(11.43)	(4.75)	(2.15)	(1.38)	(5.84)

Table 3. Liquidity Characteristics of Anomaly Portfolios

This table reports the illiquidity level and change of 11 anomaly category portfolios. Panel A reports the level of illiquidity ILQ and Panel B reports the change of illiquidity ΔILQ. We measure stock illiquidity (ILQ) by the cross-sectional percentile rank of the Amihud illiquidity ratio. Illiquidity change ΔILQ is the change of ILQ over 6 quarters for long-horizon anomalies and over 2 quarters for short-horizon anomalies. In each quarter we first calculate the average ILQ and ΔILQ for the long and short legs of individual anomalies, and the difference in ILQ and ΔILQ between the long and short legs (L-S). We then average them over anomalies in the same category, and average over time. LT Avg and ST Avg are the averages across 7 long-horizon anomaly categories and 4 short-horizon anomaly categories respectively. The t-statistics for the differences between the long and short legs are computed using the Newey-West standard errors. a, b, and c denote significance at 1%, 5%, and 10% respectively.

Panel A: Level of Illiquidity, ILQ

	Value	Investment	Financing	Quality	Efficiency	Intangible	LT Profit	LT Avg
Short	42.97	46.39	47.62	51.16	47.77	41.75	48.52	46.60
Long	56.17	54.74	47.95	49.22	53.00	57.09	49.45	52.52
L-S	13.20^a	8.35^a	0.33^a	-1.93^a	5.23^a	15.33^a	0.93^a	5.92^a
t-stat	(16.56)	(14.95)	(0.28)	(−5.83)	(9.17)	(23.92)	(1.42)	(12.44)

	Momentum	ST Profit	Distress	Uncertainty	ST Avg
Short	50.67	55.03	59.54	53.40	54.66
Long	44.44	42.95	41.82	36.63	41.46
L-S	-6.23^a	-12.08^a	-17.72^a	-16.77^a	-13.20^a
t-stat	(−14.15)	(−31.01)	(−38.02)	(−23.00)	(−35.57)

Panel B: Change in Illiquidity, ΔILLIQ

	Value	Investment	Financing	Quality	Efficiency	Intangible	LT Profit	LT AVG
Short	−3.57	−2.68	−3.89	−1.54	−1.24	−2.57	−0.35	−2.26
Long	1.28	0.84	0.73	−0.57	−0.92	1.43	−1.33	0.21
L-S	4.85^a	3.52^a	4.62^a	0.98^a	0.33^a	4.00^a	-0.99^a	2.47^a
t-stat	(17.20)	(18.26)	(14.39)	(7.24)	(1.70)	(12.56)	(−3.57)	(12.76)

	Momentum	ST Profit	Distress	Uncertainty	ST Avg
Short	2.24	0.23	0.10	0.23	0.70
Long	−3.04	−0.95	−0.66	−0.85	−1.37
L-S	-5.28^a	-1.18^a	-0.76^a	-1.08^a	-2.07^a
t-stat	(−26.93)	(−9.94)	(−4.56)	(−4.13)	(−12.90)

Table 4. Liquidity Characteristics of Institutional Holding and Trading

This table reports the illiquidity level and change of stock portfolios sorted by institutional holding and trading. Stock illiquidity (ILQ) is measured by the cross-sectional percentile rank of the Amihud illiquidity ratio. Illiquidity change ΔILQ is the change of ILQ over both 2 quarters and 6 quarters. Institutional holding is measured by the percentage of shares held by institutions (%Inst) and institutional trading is measured by the change in percentage of shares held by institutions (Δ%Inst) over both 2 quarters and 6 quarters. Panel A reports the average level and change in illiquidity (ILQ, ΔILQ over 2 quarters, and ΔILQ over 6 quarters) for stock deciles sorted by institutional holding %Inst. Panel B reports the average level and change in illiquidity (ILQ, ΔILQ over 2 quarters, and ΔILQ over 6 quarters) for stock deciles sorted by institutional trading Δ%Inst, over 2 quarters and 6 quarters, respectively. We estimate the level and change of illiquidity for each decile portfolio in each quarter, and then average them over time. H-L is the difference between top and bottom decile portfolios. The t-statistics for H-L are computed using the Newey-West standard errors. a, b, and c denote significance at 1%, 5%, and 10% respectively.

Panel A: Level and Change of Illiquidity for Portfolios Sorted by Institutional Ownership

	Portfolios sorted by %Inst		
	ILQ	ΔILQ over 2 quarters	ΔILQ over 6 quarters
Low	75.67	−0.42	0.73
2	71.33	−0.20	0.87
3	64.53	−0.32	0.59
4	55.95	−0.31	0.25
5	49.65	−0.29	0.03
6	45.12	−0.32	−0.30
7	41.45	−0.30	−0.43
8	37.16	−0.29	−0.63
9	33.60	−0.37	−1.04
High	30.28	−0.65	−1.86
H-L	-45.39^{a}	−0.23	-2.59^{a}
(t-stat)	(−25.31)	(−1.62)	(−7.33)

Panel B: Level and Change of Illiquidity for Portfolios Sorted by Institutional Trading

	Portfolios sorted by Δ%Inst over 2 qtrs		Portfolios sorted by Δ%Inst over 6 qtrs	
	ILQ	ΔILQ over 2 qtrs	ILQ	ΔILQ over 6 qtrs
Low	44.54	0.70	45.97	1.12
2	47.13	0.81	48.46	1.03
3	50.22	0.65	52.07	0.64
4	56.03	0.37	53.97	0.44
5	56.27	0.40	51.26	0.18
6	51.94	0.20	49.23	−0.11
7	49.77	−0.15	48.64	−0.53
8	48.31	−0.61	48.79	−1.30
9	46.38	−1.73	48.70	−3.32
High	45.79	−4.87	48.44	−7.86
H-L	1.25	-5.56^a	2.47^a	-8.99^a
(t-stat)	(1.59)	(−16.54)	(2.65)	(−16.74)

Table 5. Liquidity-driven and Non-liquidity Institutional Trading on Market Anomalies

This table reports the liquidity-driven and non-liquidity components of institutional trading on the 11 anomaly categories. Institutional trading is measured by the change in percentage of shares held by institutions (Δ%Inst). The liquidity-driven component of institutional trading on a stock, $\Delta\%\text{Inst}_{LIQ}$, is the average institutional trading measure across all stocks in the same liquidity change (ΔILQ) decile. The non-liquidity component of institutional trading, $\Delta\%\text{Inst}_{NLQ}$, is the institutional trading measure in excess of the liquidity-driven component. Both institutional trading and liquidity change are measured over 6 quarters for long-horizon anomalies and over 2 quarters for short-horizon anomalies. We calculate the liquidity-driven and non-liquidity components of institutional trading for the long and short legs, as well as the long-short difference (L-S), of an individual anomaly portfolio in each quarter, and then average them over anomalies in the same category. Institutional trading components are reported in percentage points. LT Avg and ST Avg are the averages across 7 long-horizon categories and 4 short-horizon categories respectively. The t-statistics for the differences between the long and short legs are computed using the Newey-West standard errors. a, b, and c denote significance at 1%, 5%, and 10% respectively.

Panel A: Liquidity-Driven Institutional Trading, $\Delta\%\text{Inst}_{LIQ}$ (%)

	Value	Investment	Financing	Quality	Efficiency	Intangible	LT Profit	LT Avg
Short	3.34	3.13	3.50	2.92	2.85	3.07	2.65	3.07
Long	2.24	2.43	2.28	2.72	2.80	2.32	2.82	2.52
L-S	-1.10^a	-0.70^a	-1.22^a	-0.19^a	-0.05	-0.75^a	0.17^a	-0.55^a
t-stat	(−12.52)	(−11.39)	(−10.56)	(−5.41)	(−1.28)	(−8.20)	(2.74)	(−10.01)

	Momentum	ST Profit	Distress	Uncertainty	ST Avg
Short	2.59	2.54	2.63	2.81	2.64
Long	3.00	2.94	2.80	2.69	2.86
L-S	0.41^a	0.41^a	0.17^b	-0.12	0.22^a
t-stat	(6.96)	(7.22)	(2.14)	(−0.96)	(3.21)

Panel B: Non-liquidity Institutional Trading, $\Delta\%\text{Inst}_{NLQ}$ (%)

	Value	Investment	Financing	Quality	Efficiency	Intangible	LT Profit	LT Avg
Short	0.12	−0.23	0.07	0.03	−0.04	−0.09	−0.07	−0.03
Long	−0.11	0.30	−0.11	0.17	0.24	0.05	0.16	0.10
L-S	-0.23^b	0.53^a	-0.18	0.14	0.29^a	0.14	0.24	0.13^b
t-stat	(−1.98)	(4.94)	(−1.60)	(1.26)	(2.63)	(0.95)	(1.46)	(2.06)

	Momentum	ST Profit	Distress	Uncertainty	ST Avg
Short	−1.21	−0.37	−0.42	−0.46	−0.62
Long	1.29	0.27	0.17	0.19	0.48
L-S	2.50^a	0.64^a	0.59^a	0.65^b	1.10^a
t-stat	(7.65)	(3.94)	(2.69)	(2.39)	(4.95)

Table 6. Liquidity Characteristics of Anomaly Portfolios Using Alternative Liquidity Measures

This table reports the illiquidity level and change of 11 anomaly category portfolios using two alternative liquidity measures based on the intraday data of TAQ – the value-weighted percentage effective spread (Spread) and value-weighted percentage price impact (Impact). These measures are averaged from the daily measures provided by the WRDS Intraday Indicator Dataset, over 6 quarters for long-horizon anomalies and over 2 quarters for short-horizon anomalies, and then cross-sectionally ranked into percentiles, with a higher ranking indicating lower liquidity. Measures of illiquidity change ΔSpread and ΔImpact are the changes of the cross-sectional percentile rank of Spread and Impact over 6 quarters for long-horizon anomalies and over 2 quarters for short-horizon anomalies. In each quarter we first calculate the average level and change in illiquidity for the long and short legs of individual anomalies, and the difference in them between the long and short legs (L-S). The table reports the time-series averages of the long-short differences in the level and change of illiquidity rank over anomalies in the same category. LT Avg and ST Avg are the averages across 7 long-horizon categories and 4 short-horizon categories respectively. Panels A and B report the level and change of illiquidity respectively. The t-statistics are computed using the Newey-West standard errors. a, b, and c denote significance at 1%, 5%, and 10% respectively.

Panel A: Difference in Illiquidity Level (Spread and Impact) Between Long and Short Legs

	Value	Investment	Financing	Quality	Efficiency	Intangible	LT Profit	LT Avg
Spread	4.35^a	5.31^a	-11.74^a	-2.50^a	4.63^a	18.88^a	2.75^a	3.10^a
Impact	7.11^a	7.46^a	-9.06^a	-0.92^a	4.49^a	19.64^a	0.97^a	4.24^a

	Momentum	ST Profit	Distress	Uncertainty	ST Avg
Spread	-5.80^a	-11.57^a	-16.09^a	-27.73^a	-15.30^a
Impact	-6.98^a	-12.61^a	-16.94^a	-25.56^a	-15.52^a

Panel B: Difference in Illiquidity Change (ΔSpread and ΔImpact) Between Long and Short Legs

	Value	Investment	Financing	Quality	Efficiency	Intangible	LT Profit	LT Avg
ΔSpread	4.17^a	2.49^a	3.74^a	0.55^a	0.48^a	3.35^a	-0.48^a	2.04^a
ΔImpact	4.10^a	2.47^a	3.15^a	0.43^a	0.33^a	4.59^a	-0.36^a	2.10^a

	Momentum	ST Profit	Distress	Uncertainty	ST Avg
ΔSpread	-4.45^a	-0.90^a	-0.64^a	-0.86^a	-1.72^a
ΔImpact	-5.74^a	-1.25^a	-1.10^a	-1.98^a	-2.52^a

Table 7. Liquidity-driven and Non-liquidity Institutional Trading on Market Anomalies Using Alternative Illiquidity Measures

This table reports the liquidity-driven and non-liquidity components of institutional trading on the 11 anomaly categories, under two alternative liquidity measures Spread (Panels A and B) and Impact (Panels C and D) respectively. Institutional trading is measured by the change in percentage institutional ownership Δ%Inst. The liquidity-driven component of institutional trading on a stock, $\Delta\%\text{Inst}_{LIQ}$, is the average institutional trading across all stocks in the same liquidity change (ΔILQ) decile. The non-liquidity component of institutional trading, $\Delta\%\text{Inst}_{NLQ}$, is the institutional trading measure in excess of the liquidity-driven component. Both institutional trading and liquidity change are measured over 6 quarters for long-horizon anomalies and over 2 quarters for short-horizon anomalies. We calculate the liquidity-driven and non-liquidity components of institutional trading for the long and short legs, as well as the long-short difference (L-S), of an individual anomaly portfolio in each quarter, and then average them over anomalies in the same category. Institutional trading components are reported in percentage points. LT Avg and ST Avg are the averages across 7 long-horizon categories and 4 short-horizon categories respectively. The t-statistics are computed using the Newey-West standard errors. a, b, and c denote significance at 1%, 5%, and 10% respectively. The sample period is from 1993 to 2018.

Panel A: Liquidity-driven Component of Institutional Trading $\Delta\%\text{Inst}_{LIQ}$ (%) on Anomalies, Based on Spread

	Value	Investment	Financing	Quality	Efficiency	Intangible	LT Profit	LT Avg
Short	3.16	2.90	3.27	2.71	2.69	2.92	2.49	2.88
Long	2.03	2.28	2.15	2.56	2.58	2.11	2.62	2.33
L-S	-1.13^a	-0.62^a	-1.12^a	-0.15^a	-0.11^b	-0.81^a	0.13	-0.54^a
t-stat	(−10.75)	(−9.61)	(−10.00)	(−3.00)	(−2.46)	(−8.26)	(1.76)	(−10.27)

	Momentum	ST Profit	Distress	Uncertainty	ST Avg
Short	0.51	0.90	0.92	0.93	0.82
Long	1.43	1.06	1.02	1.01	1.13
L-S	0.92^a	0.16^a	0.09	0.08	0.31^a
t-stat	(9.18)	(4.14)	(1.68)	(1.04)	(5.25)

Panel B: Non-liquidity Component of Institutional Trading $\Delta\%\text{Inst}_{NLQ}$ (%) on Anomalies, Based on Spread

	Value	Investment	Financing	Quality	Efficiency	Intangible	LT Profit	LT Avg
Short	0.20	−0.08	0.40	0.11	0.05	−0.08	−0.04	0.08
Long	−0.20	0.17	−0.34	0.17	0.25	0.10	0.17	0.05
L-S	-0.39^b	0.25	-0.75^a	0.07	0.20	0.17	0.21	−0.03
t-stat	(−2.45)	(1.55)	(−3.55)	(0.43)	(1.23)	(1.00)	(0.92)	(−0.40)

	Momentum	ST Profit	Distress	Uncertainty	ST Avg
Short	−0.62	−0.02	−0.05	0.03	−0.17
Long	0.57	0.11	−0.04	−0.06	0.15
L-S	1.19^a	0.14	0.02	−0.09	0.31^b
t-stat	(7.48)	(1.52)	(0.14)	(−0.46)	(2.39)

Panel C: Liquidity-driven Component of Institutional Trading $\Delta\%\text{Inst}_{LIQ}$ (%), Based on Impact

	Value	Investment	Financing	Quality	Efficiency	Intangible	LT Profit	LT Avg
Short	3.06	2.83	3.12	2.64	2.64	2.92	2.54	2.82
Long	2.12	2.33	2.23	2.56	2.57	2.09	2.56	2.35
L-S	-0.94^a	-0.50^a	-0.89^a	−0.09	−0.08	-0.83^a	0.02	-0.47^a
t-stat	(−5.73)	(−6.67)	(−5.52)	(−1.69)	(−1.58)	(−6.09)	(0.18)	(−5.85)

	Momentum	ST Profit	Distress	Uncertainty	ST Avg
Short	0.56	0.90	0.92	0.89	0.82
Long	1.37	1.05	1.01	1.03	1.11
L-S	0.81^a	0.15^a	0.09	0.13	0.30^a
t-stat	(5.89)	(4.15)	(1.55)	(1.53)	(4.32)

Panel D: Non-liquidity Component of Institutional Trading $\Delta\%\text{Inst}_{NLQ}$ (%) on Anomalies, Based on Impact

	Value	Investment	Financing	Quality	Efficiency	Intangible	LT Profit	LT Avg
Short	0.29	−0.01	0.55	0.17	0.10	−0.08	−0.09	0.13
Long	−0.29	0.13	−0.41	0.18	0.27	0.11	0.23	0.03
L-S	-0.59^a	0.13	-0.97^a	0.01	0.17	0.19	0.32	−0.11
t-stat	(−4.27)	(0.81)	(−4.72)	(0.04)	(1.02)	(0.95)	(1.45)	(−1.13)

	Momentum	ST Profit	Distress	Uncertainty	ST Avg
Short	−0.67	−0.03	−0.05	0.07	−0.17
Long	0.62	0.13	−0.03	−0.08	0.16
L-S	1.30^a	0.15	0.02	−0.14	0.33^b
t-stat	(8.02)	(1.54)	(0.17)	(−0.72)	(2.41)

Table 8. Institutional Trading on Market Anomalies Based on Δ#Inst and Its Components

This table reports institutional trading on the 11 anomaly category portfolios using an alternative institutional trading measure, which is the size-adjusted change in number of institutional owners, Δ#Inst, over 6 quarters for long-horizon anomalies and over 2 quarters for short-horizon anomalies. The liquidity-driven component of institutional trading on a stock, $\Delta\#\text{Inst}_{LIQ}$, is the average institutional trading measure across all stocks in the same liquidity change (ΔILQ) decile. The non-liquidity component of institutional trading, $\Delta\#\text{Inst}_{NLQ}$, is the institutional trading measure in excess of the liquidity-driven component. We calculate the institutional trading measure and its components for the long and short legs, as well as the long-short difference (L-S), of an individual anomaly portfolio in each quarter, and then average them over anomalies in the same category. LT Avg and ST Avg are the averages across 7 long-horizon categories and 4 short-horizon categories respectively. Panels A, B, and C report the results for institutional trading, the liquidity-driven component, and the non-liquidity components respective. The t-statistics are computed using the Newey-West standard errors. a, b, and c denote significance at 1%, 5%, and 10% respectively.

Panel A: Institutional Trading, Δ#Inst

	Value	Investment	Financing	Quality	Efficiency	Intangible	LT Profit	LT Avg
Short	27.80	23.74	27.77	22.10	20.00	22.99	16.85	23.04
Long	14.80	18.64	16.00	21.58	23.51	17.24	24.21	19.43
L-S	-13.00^a	-5.10^a	-11.77^a	-0.52	3.51^a	-5.75^a	7.35^a	-3.61^a
t-stat	(-9.82)	(-7.20)	(-10.41)	(-1.18)	(2.65)	(-4.99)	(5.21)	(-4.52)

	Momentum	ST Profit	Distress	Uncertainty	ST Avg
Short	-0.90	4.47	5.39	5.38	3.59
Long	14.42	8.69	7.62	6.91	9.41
L-S	15.33^a	4.22^a	2.23^a	1.53^a	5.83^a
t-stat	(25.56)	(12.17)	(6.40)	(3.03)	(15.80)

Panel B: Liquidity-Driven Institutional Trading, $\Delta\#\text{Inst}_{LIQ}$

	Value	Investment	Financing	Quality	Efficiency	Intangible	LT Profit	LT Avg
Short	25.37	23.71	25.94	21.92	21.07	23.08	19.26	22.91
Long	16.48	17.72	17.30	20.08	21.16	16.82	21.67	18.75
L-S	-8.89^a	-5.98^a	-8.64^a	-1.84^a	0.09	-6.26^a	2.42^a	-4.16^a
t-stat	(−12.10)	(−13.19)	(−11.75)	(−6.55)	(0.19)	(−10.74)	(3.33)	(−9.98)

	Momentum	ST Profit	Distress	Uncertainty	ST Avg
Short	3.66	5.97	6.32	6.34	5.57
Long	9.65	7.12	6.66	6.61	7.51
L-S	5.98^a	1.16^a	0.34	0.27	1.94^a
t-stat	(16.95)	(8.65)	(1.87)	(0.92)	(10.33)

Panel C: Non-liquidity Institutional Trading, $\Delta\#\text{Inst}_{NLQ}$

	Value	Investment	Financing	Quality	Efficiency	Intangible	LT Profit	LT Avg
Short	2.43	0.03	1.83	0.18	−1.07	−0.09	−2.40	0.13
Long	−1.68	0.92	−1.29	1.51	2.35	0.42	2.53	0.68
L-S	-4.12^a	0.88	-3.12^a	1.33^a	3.42^a	0.51	4.94^a	0.55
t-stat	(−5.35)	(1.35)	(−5.52)	(3.10)	(3.83)	(0.59)	(5.74)	(1.05)

	Momentum	ST Profit	Distress	Uncertainty	ST Avg
Short	−4.57	−1.50	−0.93	−0.95	−1.99
Long	4.78	1.57	0.97	0.30	1.90
L-S	9.35^a	3.06^a	1.89^a	1.26^a	3.89^a
t-stat	(24.46)	(11.22)	(7.05)	(3.52)	(13.75)

Table 9. Fama-MacBeth Regressions of Institutional Trading on Market Anomalies

This table reports results of Fama-MacBeth regression of institutional trading on anomaly ranks, with and without controlling for liquidity change. The regressions are performed quarterly across all sample stocks. The dependent variable is one of the two institutional trading measures on individual stocks, Δ%Inst in Panel A and Δ#Inst in Panel B. The main explanatory variable is the average anomaly-category percentile rank (Anomaly). To obtain this variable, we first cross-sectionally rank stocks in a given quarter by an anomaly into percentiles, and then average over the percentiles across all anomalies in the same category. We further average the anomaly-category percentile ranks across 7 long-horizon and 4 short-horizon anomaly categories respectively, to obtain LT Avg and LT Avg. The main control variable is the liquidity change, ΔILQ. We also control for the log of market capitalization, Ln(Size). Both institutional trading and liquidity change are measured over 6 quarters for long-horizon anomalies and over 2 quarters for short-horizon anomalies. The t-statistics are computed using the Newey-West standard errors. The regression includes an intercept, which is not tabulated. *a*, *b*, and *c* denote significance at 1%, 5%, and 10% respectively.

Panel A: Δ%Inst as Dependent Variable

	Value	Investment	Financing	Quality	Efficiency	Intangible	LT Profit	LT Avg
				Without Controlling for ΔILQ				
Anomaly	-0.044^a	-0.010^a	-0.029^a	-0.002	0.005	-0.013^a	0.005^b	-0.041^a
(t-stat)	(−8.33)	(−2.73)	(−8.56)	(−1.02)	(1.42)	(−4.30)	(2.27)	(−5.59)
Ln(Size)	-0.181^a	-0.076	-0.023	-0.064	-0.055	-0.126^c	-0.060	-0.109^c
(t-stat)	(−2.79)	(−1.14)	(−0.37)	(−0.99)	(−0.86)	(−1.87)	(−0.91)	(−1.66)
				Controlling for ΔILQ				
Anomaly	-0.012^a	0.013^a	-0.007^a	0.003	0.006^c	0.002	0.003	0.002
(t-stat)	(−2.93)	(4.28)	(−2.85)	(1.41)	(1.88)	(0.62)	(1.30)	(0.37)
ΔILQ	-0.213^a	-0.224^a	-0.216^a	-0.220^a	-0.219^a	-0.224^a	-0.220^a	-0.219^a
(t-stat)	(−14.31)	(−14.86)	(−14.36)	(−14.29)	(−14.19)	(−13.93)	(−14.27)	(−14.25)
Ln(Size)	-0.189^a	-0.141^b	-0.150^b	-0.162^a	-0.149^b	-0.149^b	-0.156^b	-0.152^b
(t-stat)	(−2.94)	(−2.21)	(−2.46)	(−2.63)	(−2.39)	(−2.27)	(−2.50)	(−2.38)

	Momentum	ST Profit	Distress	Uncertainty	ST Avg
	Without Controlling for ΔILQ				
Anomaly	0.055^a	0.011^a	0.008^a	0.006^c	0.043^a
(t-stat)	(12.61)	(5.40)	(3.73)	(1.70)	(7.86)
Ln(Size)	-0.172^a	-0.082^b	-0.085^a	-0.079^a	-0.215^a
(t-stat)	(−5.64)	(−2.57)	(−2.78)	(−2.70)	(−7.32)
	Controlling for ΔILQ				
Anomaly	0.035^a	0.007^a	0.006^a	0.005	0.027^a
(t-stat)	(7.68)	(3.78)	(3.30)	(1.61)	(4.96)
ΔILQ	-0.146^a	-0.181^a	-0.182^a	-0.182^a	-0.173^a
(t-stat)	(−9.22)	(−12.28)	(−12.32)	(−12.14)	(−10.99)
Ln(Size)	-0.155^a	-0.101^a	-0.111^a	-0.107^a	-0.186^a
(t-stat)	(−5.51)	(−3.42)	(−3.90)	(−3.61)	(−6.43)

Panel B: Δ#Inst as Dependent Variable

	Value	Investment	Financing	Quality	Efficiency	Intangible	LT Profit	LT Avg
	Without Controlling for ΔILQ							
Anomaly	-0.408^a	-0.172^a	-0.257^a	-0.021^b	0.084^a	-0.088^a	0.105^a	-0.301^a
(t-stat)	(−12.69)	(−9.78)	(−11.60)	(−2.15)	(3.28)	(−4.29)	(5.01)	(−6.43)
Ln(Size)	-2.082^a	-1.338^c	−0.833	−1.066	−0.905	-1.338^b	−0.972	-1.428^b
(t-stat)	(−3.36)	(−1.96)	(−1.21)	(−1.58)	(−1.46)	(−2.13)	(−1.49)	(−2.32)
	Controlling for ΔILQ							
Anomaly	-0.182^a	−0.008	-0.105^a	0.026^a	0.074^a	0.008	0.071^a	−0.024
(t-stat)	(−8.12)	(−0.50)	(−7.90)	(2.78)	(5.00)	(0.68)	(5.78)	(−0.84)
ΔILQ	-1.622^a	-1.714^a	-1.664^a	-1.718^a	-1.703^a	-1.745^a	-1.701^a	-1.703^a
(t-stat)	(−13.59)	(−14.04)	(−13.60)	(−14.08)	(−14.70)	(−13.50)	(−14.66)	(−14.04)
Ln(Size)	-2.185^a	-1.800^a	-1.670^b	-1.822^a	-1.662^a	-1.606^b	-1.731^a	-1.782^a
(t-stat)	(−3.45)	(−2.75)	(−2.52)	(−2.78)	(−2.64)	(−2.46)	(−2.68)	(−2.84)

	Momentum	ST Profit	Distress	Uncertainty	ST Avg
			Without Controlling for ΔILQ		
Anomaly	0.400^a	0.108^a	0.061^a	0.009	0.318^a
(t-stat)	(28.48)	(11.67)	(7.91)	(0.86)	(18.77)
Ln(Size)	-1.165^a	-0.613^a	-0.578^b	-0.334	-1.533^a
(t-stat)	(-5.99)	(-2.79)	(-2.51)	(-1.52)	(-6.45)
			Controlling for ΔILQ		
Anomaly	0.295^a	0.082^a	0.049^a	0.000	0.220^a
(t-stat)	(28.57)	(10.92)	(8.81)	(0.05)	(15.48)
ΔILQ	-0.759^a	-1.079^a	-1.087^a	-1.090^a	-1.012^a
(t-stat)	(-16.78)	(-19.37)	(-19.57)	(-19.39)	(-18.19)
Ln(Size)	-1.070^a	-0.721^a	-0.705^a	-0.474^b	-1.327^a
(t-stat)	(-5.70)	(-3.61)	(-3.42)	(-2.39)	(-6.19)

Table 10. Trading on Market Anomalies by Institutions with Different Liquidity Preferences

This table reports the institutional trading measure Δ%Inst on the 11 anomaly category portfolios by institutions with different liquidity preferences. Institutions ranked in the top and bottom terciles of equity portfolio size are defined as large and small institutions respectively, and those in the top and bottom terciles of the weighted average illiquidity (ILQ) of their equity portfolios are defined as institutions with illiquid and liquid portfolios respectively. Institutional trading is measured over 6 quarters for long-horizon anomalies and over 2 quarters for short-horizon anomalies. We report the differences in the average institutional trading Δ%Inst (reported in percentage points) between the long legs and short legs for the 11 anomaly categories. LT Avg and ST Avg are the averages across 7 long-horizon categories and across 4 short-horizon categories, respectively. Panels A to D are for the four types of institutions separately. The *t*-statistics are computed using the Newey-West standard errors. *a*, *b*, and *c* denote significance at 1%, 5%, and 10% respectively.

Panel A: Large Institutions

	Value	Investment	Financing	Quality	Efficiency	Intangible	LT Profit	LT Avg
L-S	-1.80^a	-0.47^a	-1.82^a	-0.07	0.12	-1.01^a	0.38^b	-0.67^a
(*t*-stat)	(−11.72)	(−4.40)	(−9.06)	(−0.73)	(1.21)	(−6.04)	(2.36)	(−7.84)

	Momentum	ST Profit	Distress	Uncertainty	ST Avg
L-S	1.95^a	0.44^a	0.33^a	0.30^c	0.75^a
(*t*-stat)	(12.24)	(5.71)	(2.88)	(1.80)	(6.77)

Panel B: Small Institutions

	Value	Investment	Financing	Quality	Efficiency	Intangible	LT Profit	LT Avg
L-S	0.02	0.00	−0.02	0.01	0.01	0.05^c	−0.01	0.01
(*t*-stat)	(0.71)	(0.15)	(−0.78)	(0.52)	(0.31)	(1.86)	(−0.90)	(0.54)

	Momentum	ST Profit	Distress	Uncertainty	ST Avg
L-S	−0.03	−0.01	-0.03^a	-0.03^b	-0.02^b
(*t*-stat)	(−1.35)	(−0.76)	(−3.02)	(−2.45)	(−2.36)

Panel C: Institutions with Liquid Portfolios

	Value	Investment	Financing	Quality	Efficiency	Intangible	LT Profit	LT Avg
L-S	-0.56^a	-0.28^a	-0.40^a	0.00	−0.02	-0.49^a	0.04	-0.24^a
(*t*-stat)	(−7.85)	(−5.85)	(−5.66)	(−0.07)	(−0.49)	(−7.03)	(0.93)	(−7.51)

	Momentum	ST Profit	Distress	Uncertainty	ST Avg
L-S	0.42^a	0.13^a	0.12^a	0.21^a	0.22^a
(*t*-stat)	(8.28)	(5.19)	(3.84)	(5.04)	(6.89)

Panel D: Institutions with Illiquid Portfolios

	Value	Investment	Financing	Quality	Efficiency	Intangible	LT Profit	LT Avg
L-S	0.36^{a}	0.39^{a}	-0.11	-0.09	0.15^{b}	0.90^{a}	0.16	0.25^{a}
(t-stat)	(2.85)	(4.24)	(-0.90)	(-1.05)	(2.18)	(8.78)	(1.52)	(4.24)

	Momentum	ST Profit	Distress	Uncertainty	ST Avg
L-S	-0.07	-0.08^{c}	-0.10^{b}	-0.32^{a}	-0.14^{a}
(t-stat)	(-0.73)	(-1.96)	(-2.26)	(-4.71)	(-2.77)

Table 11. Institutional Trading on Market Anomalies: Exogenous Liquidity Shocks Around the Minimum Tick Size Changes of 1997 and 2001

This table reports changes in liquidity and in institutional trading around the two minimum tick size change events in 1997 and 2001. The treatment periods are the year of 1997 and the first half of 2001 for the two events respectively and the corresponding pre-treatment periods are the year 1996 and the first half of 2000 respectively. Technology stocks are excluded from the analysis on the 2001 event to avoid the confounding effect of tech bubble burst. Illiquidity is measured by the value-weighted percentage effective spread. Institutional trading is measured by Δ%Inst, the change in the fraction of shares held by institutions. Both effective spread and institutional trading are reported in percentage points. Panel A reports the effective spreads and institutional trading during the pre-treatment and treatment periods, averaged across all stocks as well as for stocks with high and low liquidity shocks. Stocks with high (low) liquidity shocks are those with above (below) median reduction in effective spread from the pre-treatment to the treatment period. Panel B reports the effective spreads and institutional trading for the long and short legs of the aggregate long-horizon anomaly portfolio and the aggregate short-horizon anomaly portfolio, during the pre-treatment and treatment periods of the two events respectively. Panel C reports the liquidity change and institutional trading for the stocks with high and low liquidity shocks separately, in the long and short legs of the aggregate anomaly portfolio, during the pre-treatment and treatment periods of the two events. To ensure a parallel-trend requirement, we identify stocks with high and low liquidity shocks in each leg of the portfolio using a double-sorting procedure based on both the pre-treatment trend of institutional trading and the treatment-period change in effective spread. *a*, *b*, and *c* denote significance at 1%, 5%, and 10% respectively.

Panel A: Effective Spread and Institutional Trading Around Tick Size Changes

	Effective Spread (%)			Δ%Inst (%)		
	Pre-treatment Period	Treatment Period	Difference	Pre-treatment Period	Treatment Period	Difference
			Panel A1: the 1997 event			
All Stocks	18.26	14.73	-3.53^a	-0.10	4.81	4.91^a
Stocks with High Liquidity Shock	25.28	17.27	-8.01^a	0.45	6.67	6.22^a
Stocks with Low Liquidity Shock	11.24	12.19	0.95^a	-0.64	2.95	3.59^a
High - Low	14.04^a	5.07^a	-8.97^a	1.09^a	3.71^a	2.63^a
			Panel A2: the 2001 event			
All Stocks	12.25	10.09	-2.16^a	0.77	1.82	1.04^a
Stocks with High Liquidity Shock	15.72	10.69	-5.03^a	1.16	3.03	1.87^a
Stocks with Low Liquidity Shock	8.78	9.48	0.70^a	0.38	0.60	0.22
High - Low	6.94^a	1.21^a	-5.74^a	0.78^c	2.43^a	1.65^a

Panel B: Institutional Trading on Anomalies Around Tick Size Changes

	Percentage Effective Spread (%)			Δ%Inst (%)		
	Pre-treatment Period	Treatment Period	Difference	Pre-treatment Period	Treatment Period	Difference
	Panel B1: the 1997 event					
	Long-Horizon Anomaly					
Short	17.45	13.87	-3.58[a]	1.42	4.09	2.67[a]
Long	20.08	16.29	-3.79[a]	-1.38	5.33	6.71[a]
Long-Short	2.63[a]	2.42[a]	-0.21[a]	-2.80[a]	1.24[a]	4.04[a]
	Short-Horizon Anomaly					
Short	20.88	17.47	-3.42[a]	-0.33	3.79	4.12[a]
Long	14.93	11.48	-3.45[a]	0.44	5.35	4.92[a]
Long-Short	-5.95[a]	-5.99[a]	-0.04	0.76[a]	1.56[a]	0.80[a]
	Panel B2: the 2001 event					
	Long-Horizon Anomaly					
Short	11.4	9.61	-1.79[a]	0.75	1.64	0.90[a]
Long	13.44	11.04	-2.40[a]	0.59	2.08	1.48[a]
Long-Short	2.04[a]	1.43[a]	-0.61[a]	-0.15[c]	0.43[a]	0.59[a]
	Short-Horizon Anomaly					
Short	13.71	11.91	-1.80[a]	0.55	1.72	1.17[a]
Long	10.19	7.92	-2.27[a]	1.07	1.98	0.91[a]
Long-Short	-3.52[a]	-3.99[a]	-0.47[a]	0.51[a]	0.26[a]	-0.26

Panel C: DiD Analysis: Institutional Trading on Anomalies Around Tick Size Changes

	Effective Spread (%)			Δ%Inst (%)		Change in Δ%Inst From Previous Period	
	Pre-treatment Period	Treatment Period	Difference	Pre-treatment Period	Treatment Period	Pre-treatment Period	Treatment Period
				Panel C1: the 1997 event			
				Long-Horizon Anomaly Category			
Short Leg							
High Shock (Treated)	23.98	16.08	-7.90^{a}	1.95	6.12	-3.19^{a}	4.17^{a}
Low Shock (Control)	11.02	11.70	0.67^{a}	0.89	2.09	-3.14^{a}	1.19^{a}
Treated-Control	12.96^{a}	4.39^{c}	-8.57^{a}	1.06^{a}	4.03^{a}	0.04	2.98^{a}
Long Leg							
High Shock (Treated)	27.67	18.97	-8.7^{a}	-1.66	7.15	-4.45^{a}	8.81^{a}
Low Shock (Control)	12.61	13.66	1.05^{a}	-1.11	3.53	-4.51^{a}	4.64^{a}
Treated-Control	15.06^{a}	5.31^{c}	-9.75^{a}	-0.55^{a}	3.62^{a}	0.06	4.17^{a}
				Short-Horizon Anomaly Category			
Short Leg							
High Shock (Treated)	27.35	18.87	-8.48^{a}	-0.14	5.78	-4.00^{a}	5.92^{a}
Low Shock (Control)	14.51	16.08	1.58^{a}	-0.52	1.82	-4.35^{a}	2.34^{a}
Treated-Control	12.84^{a}	2.79	-10.05^{a}	0.38	3.96^{a}	0.35	3.58^{a}
Long Leg							
High Shock (Treated)	21.27	14.10	-7.18^{a}	0.60	7.23	-3.73^{a}	6.63^{a}
Low Shock (Control)	8.68	8.90	0.22^{a}	0.27	3.51	-3.81^{a}	3.23^{a}
Treated-Control	12.60^{a}	5.20^{b}	-7.40^{a}	0.33	3.72^{a}	0.08	3.40^{a}

	Effective Spread			Δ%Inst		Change in Δ%Inst From Previous Period	
Period	Pre-treatment Period	Treatment Period	Difference	Pre-treatment Period	Treatment Period	Pre-treatment Period	Treatment Period
	Panel C2: the 2001 event						
	Long-Horizon Anomaly Category						
Short Leg							
High Shock (Treated)	14.21	9.75	-4.46[a]	0.63	2.71	-2.69[a]	2.08[a]
Low Shock (Control)	8.64	9.47	0.83[a]	0.86	0.59	-3.1[a]	-0.27
Treated-Control	5.57[b]	0.29	-5.29[a]	-0.23	2.12[a]	0.41	2.35[a]
Long Leg							
High Shock (Treated)	17.16	11.67	-5.5[a]	0.27	3.28	-0.60[c]	3.01[a]
Low Shock (Control)	9.77	10.42	0.65[a]	0.91	0.89	-0.68[a]	-0.02
Treated-Control	7.39[a]	1.25	-6.14[a]	-0.64[a]	2.39[a]	0.08	3.03[a]
	Short-Horizon Anomaly Category						
Short Leg							
High Shock (Treated)	16.44	11.34	-5.10[a]	0.12	2.64	-1.23[a]	2.52[a]
Low Shock (Control)	11.03	12.47	1.45[a]	0.98	0.82	-1.80[a]	-0.16
Treated-Control	5.41	-1.13	-6.55[a]	-0.86[a]	1.82[a]	0.57	2.68[a]
Long Leg							
High Shock (Treated)	13.76	9.17	-4.59[a]	0.97	3.34	-1.69[a]	2.37[a]
Low Shock (Control)	6.67	6.68	0.01	1.16	0.65	-2.05[a]	-0.52[b]
Treated-Control	7.09[a]	2.49	-4.60[a]	-0.19	2.69[a]	0.36	2.89[a]

Table 12. Returns to Anomaly Portfolios: Adjusted for Liquidity Change Premium

This table reports liquidity change premium and returns to anomaly portfolio after adjustment for liquidity change premium. Panel A reports return differences between the top and bottom decile portfolios sorted on illiquidity (ILQ) and illiquidity change (ΔILQ). In each quarter we sort stocks into equal-weighted decile portfolios based on ILQ or ΔILQ, which is measured over both 2 quarters and 6 quarters. We calculate the average return differences between the top and bottom deciles during each of the subsequent 8 quarters after portfolio formation. Panel B reports liquidity-adjusted quarterly returns to 11 anomaly category portfolios. The liquidity adjusted return of an anomaly portfolio is the quarterly return to the portfolio in excess of the liquidity change premium. The liquidity change premium is the average quarterly return to the same liquidity change (ΔILQ) decile. Liquidity change is measured over 6 quarters when evaluating long-horizon anomalies and over 2 quarters when evaluating short-horizon anomalies. In each quarter we compute the liquidity-adjusted returns to the long-short portfolios during each of the 8 quarters after portfolio formation, and then average them over anomalies in the same category. All returns are expressed in percentage points. LT Avg and ST Avg are the averages across 7 long-horizon categories and 4 short-horizon categories respectively. *a*, *b*, and *c* denote significance at 1%, 5%, and 10% respectively, for the t-statistics (not tabulated) of adjusted-return differences.

Panel A: Liquidity Premium and Liquidity Change Premium (%)

Qtr	ILQ	ΔILQ over 2 qtrs	ΔILQ over 6 qtrs
1	0.61	0.31	1.22^b
2	0.57	1.04^c	1.19^b
3	0.44	1.42^a	1.13^b
4	0.33	1.59^a	0.88^c
5	0.05	1.01^b	0.69
6	0.12	0.60	0.77^c
7	0.08	0.76	0.65
8	−0.02	0.78^c	0.21

Panel B: Returns to Anomaly Portfolios: Adjusted for Liquidity Change Premium (%)

Qtr	Value	Investment	Financing	Quality	Efficiency	Intangible	LT Profit	LT Avg
1	0.36	0.53^{a}	0.82^{a}	0.69^{a}	0.96^{a}	1.28^{a}	1.38^{a}	0.86^{a}
2	0.37	0.43^{a}	0.69^{a}	0.49^{a}	0.85^{a}	1.17^{a}	1.21^{a}	0.74^{a}
3	0.32	0.35^{b}	0.63^{b}	0.40^{a}	0.76^{a}	1.21^{a}	1.14^{a}	0.69^{a}
4	0.26	0.26^{c}	0.59^{b}	0.26^{b}	0.67^{a}	1.15^{a}	1.07^{a}	0.61^{a}
5	0.24	0.21	0.59^{b}	0.24^{c}	0.69^{a}	1.27^{a}	1.08^{a}	0.62^{a}
6	0.24	0.24	0.49^{b}	0.24^{b}	0.63^{a}	1.23^{a}	0.97^{a}	0.58^{a}
7	0.21	0.25	0.44^{c}	0.19	0.56^{a}	1.22^{a}	0.96^{a}	0.55^{a}
8	0.11	0.23	0.42^{c}	0.22^{b}	0.56^{a}	1.02^{a}	0.93^{a}	0.50^{a}

Qtr	Momentum	ST Profit	Distress	Uncertainty	ST Avg
1	1.29^{a}	1.45^{a}	0.98^{a}	0.95^{b}	1.17^{a}
2	0.84^{a}	1.04^{a}	0.89^{a}	0.77^{b}	0.88^{a}
3	0.39^{c}	0.45^{b}	0.77^{a}	0.49	0.52^{b}
4	-0.03	0.22	0.48^{c}	0.28	0.24

Table 13. Magnitude of Market Anomalies Conditional on Institutional Trading

This table reports the quarterly returns of 11 anomaly category portfolios conditional on the directions of institutional trading as well as the liquidity-driven component and the non-liquidity component of institutional trading. Institutional trading is measured over 6 quarters for long-horizon anomalies and over 2 quarters for short-horizon anomalies. For each anomaly portfolio we identify a long-short subportfolio on which institutional trading (or its component) is in the wrong direction ("LL-SH"), and a long-short subportfolio on which institutions trade in the right direction ("LH-SL"). "Wrong - Right" ((LL-SH)-(LH-SL)) is the return difference between the wrong and right subportfolios. To summarize return patterns over multiple holding horizons, we follow the Jegadeesh and Titman (1993) approach to combine portfolios from different formation quarters into a single non-overlapping portfolio. We choose a total holding period of 4 quarters for long-horizon anomalies and 2 quarters for short-horizon anomalies. LT Avg and ST Avg are the averages across 7 long-horizon categories and across 4 short-horizon categories respectively. Panels A, B, and C are for the results conditional on institutional trading and its liquidity-driven and non-liquidity components, respectively. In Panel D, we report the liquidity-adjusted subportfolio returns conditional on institutional trading, where the liquidity-adjusted return is the stock return in excess of the average return of the liquidity-change decile the stock belongs to. *a*, *b*, and *c* denote significance at 1%, 5%, and 10% respectively.

Panel A: Anomaly Portfolio Returns (%) Conditional on Institutional Trading $\Delta\%$Inst

	Value	Investment	Financing	Quality	Efficiency	Intangible	LT Profit	LT Avg
LH-SL (Right)	-0.02	0.13	0.61^c	0.21	0.42	1.04^a	1.06^a	0.49^b
t-stat	(-0.07)	(0.48)	(1.91)	(0.79)	(1.41)	(2.85)	(2.71)	(2.18)
LL-SH (Wrong)	0.88^b	1.22^a	1.40^a	1.21^a	1.46^a	1.86^a	1.90^a	1.42^a
t-stat	(1.94)	(4.01)	(3.18)	(4.00)	(4.87)	(4.86)	(4.87)	(4.59)
Wrong-Right	0.90^b	1.09^b	0.79^c	1.00^b	1.04^b	0.82^c	0.84^c	0.93^b
t-stat	(2.22)	(2.46)	(1.84)	(2.10)	(2.38)	(1.70)	(1.80)	(2.13)

	Momentum	ST Profit	Distress	Uncertainty	ST Avg
LH-SL (Right)	1.30^a	1.52^a	1.40^a	1.52^a	1.43^a
t-stat	(3.01)	(4.33)	(3.40)	(3.35)	(3.95)
LL-SH (Wrong)	0.95^a	1.00^a	0.87^b	0.55	0.84^b
t-stat	(2.60)	(3.14)	(2.21)	(1.02)	(2.45)
Wrong-Right	-0.35	-0.51	-0.53	-0.97^b	-0.59
t-stat	(-0.86)	(-1.06)	(-1.14)	(-2.18)	(-1.34)

Panel B: Anomaly Portfolio Returns (%) Conditional on Liquidity-Driven Institutional Trading $\Delta\%\text{Inst}_{LIQ}$

	Value	Investment	Financing	Quality	Efficiency	Intangible	LT Profit	LT Avg
LH-SL (Right)	−0.14	−0.44	0.38	−0.33	0.19	0.65	0.54	0.12
t-stat	(−0.50)	(−1.41)	(1.20)	(−1.07)	(0.51)	(1.49)	(1.30)	(0.44)
LL-SH (Wrong)	1.19^{a}	1.28^{a}	1.53^{a}	1.25^{a}	1.89^{a}	2.19^{a}	2.46^{a}	1.68^{a}
t-stat	(2.52)	(3.66)	(3.26)	(3.64)	(5.19)	(5.55)	(5.70)	(4.68)
Wrong-Right	1.33^{b}	1.73^{a}	1.15^{b}	1.58^{a}	1.70^{a}	1.54^{b}	1.93^{a}	1.56^{a}
t-stat	(2.46)	(2.95)	(2.09)	(2.63)	(2.80)	(2.44)	(3.16)	(2.72)

	Momentum	ST Profit	Distress	Uncertainty	ST Avg
LH-SL (Right)	1.18^{b}	1.51^{a}	1.36^{a}	1.40^{a}	1.36^{a}
t-stat	(2.34)	(3.28)	(2.75)	(2.52)	(2.91)
LL-SH (Wrong)	1.36^{a}	1.21^{a}	1.08^{b}	0.74	1.10^{a}
t-stat	(4.54)	(2.94)	(2.42)	(1.31)	(2.85)
Wrong-Right	0.18	−0.30	−0.29	−0.67	−0.27
t-stat	(0.32)	(−0.40)	(−0.41)	(−1.02)	(−0.41)

Panel C: Anomaly Portfolio Returns (%) Conditional on Non-liquidity Institutional Trading $\Delta\%\text{Inst}_{NLQ}$

	Value	Investment	Financing	Quality	Efficiency	Intangible	LT Profit	LT Avg
LH-SL (Right)	0.23	0.36	0.82^{b}	0.37	0.63^{b}	1.23^{a}	1.24^{a}	0.70^{a}
t-stat	(0.67)	(1.42)	(2.43)	(1.59)	(2.30)	(3.51)	(3.29)	(3.11)
LL-SH (Wrong)	0.82^{b}	1.03^{a}	1.30^{a}	1.02^{a}	1.23^{a}	1.59^{a}	1.63^{a}	1.23^{a}
t-stat	(1.94)	(3.97)	(3.19)	(3.91)	(4.52)	(4.44)	(4.44)	(4.60)
Wrong-Right	0.60	0.67^{c}	0.48	0.65	0.60	0.36	0.39	0.53
t-stat	(1.63)	(1.76)	(1.26)	(1.62)	(1.59)	(0.86)	(0.97)	(1.43)

	Momentum	ST Profit	Distress	Uncertainty	ST Avg
LH-SL (Right)	1.33^{a}	1.54^{a}	1.31^{a}	1.33^{a}	1.38^{a}
t-stat	(3.38)	(5.06)	(3.49)	(3.02)	(4.27)
LL-SH (Wrong)	1.00^{a}	1.07^{a}	0.92^{b}	0.54	0.88^{a}
t-stat	(2.51)	(3.56)	(2.36)	(1.00)	(2.52)
Wrong-Right	−0.33	−0.47	−0.39	-0.79^{b}	−0.50
t-stat	(−0.92)	(−1.18)	(−1.02)	(−2.14)	(−1.35)

Panel D: Liquidity-adjusted Anomaly Portfolio Returns (%) Conditional on Institutional Trading Δ%Inst

	Value	Investment	Financing	Quality	Efficiency	Intangible	LT Profit	LT Avg
LH-SL (Right)	0.00	0.31	0.72^{b}	0.36	0.77^{a}	1.14^{a}	1.39^{a}	0.67^{a}
(t-stat)	(0.01)	(1.12)	(2.16)	(1.31)	(2.59)	(3.01)	(3.46)	(2.66)
LL-SH (Wrong)	0.43	0.88^{a}	0.97^{a}	0.85^{a}	1.21^{a}	1.45^{a}	1.67^{a}	1.06^{a}
(t-stat)	(1.26)	(4.09)	(2.98)	(3.71)	(4.08)	(4.54)	(4.42)	(4.56)
Wrong-Right	0.43	0.57	0.25	0.49	0.43	0.31	0.28	0.39
(t-stat)	(1.17)	(1.55)	(0.72)	(1.22)	(1.21)	(0.75)	(0.76)	(1.10)

	Momentum	ST Profit	Distress	Uncertainty	ST Avg
LH-SL (Right)	1.28^{a}	1.49^{a}	1.37^{a}	1.47^{a}	1.40^{a}
(t-stat)	(3.96)	(4.85)	(3.01)	(3.72)	(4.38)
LL-SH (Wrong)	0.81^{b}	0.89^{a}	0.77^{c}	0.40	0.72^{b}
(t-stat)	(2.39)	(2.60)	(1.91)	(0.85)	(2.20)
Wrong-Right	−0.48	−0.60	−0.60	-1.07^{a}	-0.69^{c}
(t-stat)	(−1.18)	(−1.36)	(−1.45)	(−2.64)	(−1.69)

Internet Appendix

I.1 Mapping Individual Anomalies in Existing Literature into Anomaly Categories

To show that the 11 categories of anomalies are representative of the large number of individual anomalies documented in existing studies, we map the anomalies examined by Green, Hand, and Zhang (2017) into the 11 anomaly categories in the list below. We use the notations for the anomaly variables in Table 1 of Green, Hand, and Zhang (2017). In addition to the 11 anomaly categories, we also include the variables in the liquidity category and a category for variables that cannot be classified into either the 11 anomaly categories or the liquidity category. The number of anomalies included in each category is in the parentheses. As the list shows, out of the 102 anomaly variables examined by their study, 76 belong to the 11 categories covered by this study. Among the remaining 26, 10 are measures of liquidity, leaving only 16 anomaly variables uncovered.

- Value (12): bm, bm_ia, cfp, cfp_ia, ps, dy, ep, fgr5yr, sgr, sp, mom1m, mom36m
- Investment (8): agr, chempia, cinvest, pchcapx_ia, grcapx, grltnoa, hire, invest
- Financing and payouts (6): chchsho, divi, divo, egr, IPO, lgr
- Quality (3): absacc, acc, pctacc
- Efficiency (8): cashpr, chatoia, pchsale_pchinvt, pchsale_pchrect, pchsaleinv, salecash, saleinv, salerec
- Long-term profitability (1): gma
- Momentum (9): chfeps, chmom, ear, indmom, mom12m, mom6m, nincr, rsup, sue
- Short-term profitability (8): chmia, pchmg_pchsale, ms, operprof, roeq, roic, sfe, roaq
- Distress and leverage (7): cashdebt, currat, lev, secured, securedind, quick, tang
- Uncertainty (9): beta, betasq, disp, idiovol, maxret, retvol, roavol, stdacc, stdcf
- Liquidity (10): baspread, pricedelay, dolvol, ill, size, mve_ia, std_dolvol, std_turn, turn, zerotrade
- Not in above categories (16): aeavol, age, cash, chinv, chanalyst, chtx, convind, depr, pchcurrat, pchdepr, pchquick, herf, nanalyst, sin, realestate, tb

Further, among the 452 anomalies in Hou, Xue, and Zhang (2020), 346 fall into their classifications of momentum, value, investing, financing, profitability, and intangibles. The remaining 106 in their category of "trading frictions" include 39 variables that belong to our category of Uncertainty (e.g., total and idiosyncratic volatility, betas, max returns, and total and idiosyncratic skewness), as well as 51 measures of liquidity (e.g., size, turnover, price, zero-trading days, liquidity beta and liquidity-risk beta).

In a recent study, Jensen, Kelly, and Pedersen (2021) identify 13 clusters out of 153 anomalies based on residual return correlations of the anomaly portfolios. Nine of their 13 anomaly clusters can be mapped by nature into our anomaly categories in a direct way (their cluster name followed by our category in parentheses): Accruals (Quality), Debt Issuance (Financing), Investment (Investment), Low risk (Uncertainty), Momentum (Momentum), Profit Growth (Growth), Profitability (Short-term profitability), Quality (Quality), and Value (Value). In addition, their Size cluster can be viewed as a liquidity anomaly category. The three clusters with no direct mapping to our anomaly categories are Leverage, Seasonality, and Skewness. Nonetheless, a closer look at the individual anomalies in these remaining three clusters suggests that some of the anomalies further belong to our 11 anomaly categories. For brevity we do not provide a complete list of their mapping.

I.2 Return Horizons, Institutional Trading, and Liquidity Characteristics of Individual Anomalies

In this part we provide results on the return-predictive horizons and liquidity characteristics of the 24 individual anomalies, as well as institutional trading patterns on these individual anomalies.

Table A1 reports the return-predictive horizon of individual anomalies. This table is constructed in a way similar to Table 1, which reports the return-predictive horizon of the 11 anomaly categories. The return-predictive horizons of individual anomalies in Table A1 are largely consistent with those at the category level (Table 1). They are also consistent with those reported by Daniel, Hirshleifer, and Sun (2020).

Table A2 reports institutional trading on individual anomalies. This table is constructed in a way similar to Table 2, and the results based on individual anomalies are also similar to those reported for the anomaly categories in Table 2. With a few exceptions, the net institutional trading (labeled as "L-S" in the table) is negative for most of the long-horizon anomalies, and positive for most of the short-horizon anomalies.

Table A3 reports the liquidity characteristics of individual anomalies. This table is constructed in a way similar to Table 3, and the results are consistent with those in Table 3. That is, for long-horizon anomalies, the long legs tend to be more illiquid and have worsening liquidity, relative to the short legs. By contrast, for short-horizon anomalies, the long legs tend to be more liquid and have improving liquidity relative to the short legs.

I.3 Return Impact of Anomaly Portfolios and Portfolios Sorted by Institutional Ownership and Trading

In this part of analysis we provide an alternative way to present the magnitude of the liquidity characteristics of anomaly portfolios. Following the existing literature (e.g., Acharya and Pedersen, 2005), We convert the raw Amihud illiquidity ratio into a return impact measure, which can be interpreted as the impact on absolute stock return per $1 million of trading. Specifically, return impact is the Amihud illiquidity ratio (measured over 6 quarters for long-horizon anomalies and 2 quarters for short-horizon anomalies) times 1,000,000, and further multiplied by a trend-adjustment factor P. P is the ratio of the total market cap of all CRSP stocks at the quarter of portfolio formation to the total market cap at June 2018. The total market cap is obtained from the CRSP monthly stock index (MSI) dataset. This factor is used to adjust for the time trend in the Amihud illiquidity ratio.

We replace the cross-sectional percentile rank of illiquidity and its change in Table 3 with the level and change in return impact. To control for the outliers in the Amihud illiquidity ratio, we winsorize it at the top and bottom one percentiles. Further, within each long leg and short leg of an anomaly portfolio, we take the median instead of mean of return impact across stocks.

Table A4 shows that the long legs of long-horizon anomalies tend to have significantly higher return impact than the short legs. This suggests that the long legs are more illiquid. Further, the change in return impact for the long legs of the long-horizon anomalies tends to be positive (with some exceptions) while that for the short legs is negative. This suggests that the long legs have deteriorating liquidity while the short legs have improving liquidity. For the short-horizon anomalies, the patterns in return impact and its change are opposite to those for the long-horizon anomalies. These results are qualitatively similar to those reported in Table 3 of the paper, which are based on the cross-sectional ranking of the illiquidity ratio.

I.4 Institutional Trading Over Six Quarters on Short-horizon Anomalies

Note that we measure institutional trading on short-horizon anomalies over a 2-quarter period. We do so because the return predictive power of these anomaly variables is typically short-lived. This is different from Edelen et al. (2016), who examine 6-quarter institutional trading for all anomalies. To ensure that our different conclusion on institutional trading for short-horizon anomalies is not driven by the choice of a short-term trading measure, in Table A5 we repeat the analysis of Table 2 for short-horizon anomalies using institutional trading over 6 quarters. The results show that using either Δ%Inst or Δ#Inst (both over 6 quarters) as the institutional trading measure, institutional investors tend to trade in the right direction of short-horizon anomalies, confirming the result reported in Table 2.

Table A1. Return-predictive Horizons of Individual Anomalies

This table reports quarterly returns to long-short portfolios based on 24 individual anomalies. The individual anomalies are described in the Appendix of the paper. Stocks are sorted quarterly into equal-weighted terciles using each of the 24 individual anomaly variables. The long (short) leg of an anomaly portfolio is the tercile predicted to have high (low) returns. The table reports the time series averages of the return differences between the long and short legs during the subsequent 8 quarters for long-horizon anomalies and during the subsequent 4 quarters for short-horizon anomalies. Panels A and B report the results for the long-horizon and short-horizon anomalies respectively. Returns are reported in percentage points. *a*, *b*, and *c* denote significance at 1%, 5%, and 10% respectively.

Panel A: Long-Horizon Anomalies															
	BP	EP	SG	CAPX	AI	AG	NS	XFIN	ACC	DACC	ATTO	NOA	RD	SGA	GP
1	1.37^b	1.04^b	0.84^b	0.87^a	0.70^a	1.52^a	1.52^a	1.85^a	0.84^a	1.04^a	1.24^a	1.33^a	1.79^a	2.13^a	1.78^a
2	1.27^b	1.07^b	0.57	0.57^b	0.46^b	1.15^a	1.27^a	1.63^a	0.59^b	0.69^a	1.16^a	1.08^a	1.45^a	1.82^a	1.57^a
3	1.27^b	0.98^b	0.53	0.48^c	0.32	1.06^a	1.26^a	1.42^a	0.55^b	0.60^a	1.02^b	0.97^a	1.35^a	1.71^a	1.41^a
4	1.11^b	0.87^b	0.38	0.36	0.13	0.79^b	1.08^a	1.30^a	0.47^b	0.41^a	0.97^b	0.81^b	1.11^b	1.58^a	1.29^a
5	1.06^b	0.75^c	0.30	0.42	0.02	0.81^b	1.02^a	1.26^a	0.39^c	0.32^b	0.89^b	0.89^a	1.25^a	1.63^a	1.19^a
6	0.94^c	0.64	0.34	0.36	0.09	0.71^b	0.96^b	1.12^a	0.37^c	0.33^b	0.79^b	0.80^a	1.18^b	1.47^a	1.10^a
7	0.95^c	0.55	0.27	0.33	0.11	0.62^c	0.79^b	1.01^a	0.20	0.29^b	0.68^c	0.73^b	1.16^b	1.41^a	1.08^a
8	0.77	0.42	0.20	0.31	0.12	0.45	0.69^c	0.89^b	0.23	0.37^a	0.61	0.65^b	0.96^b	1.27^a	0.98^a

Short-Horizon Anomalies									
	MOM	SUE	FRV	ROE	GM	OSCORE	CHS	IVOL	DISP
1	1.77^a	1.81^a	1.56^a	2.50^a	0.85^b	0.50^c	1.93^a	1.62^b	0.89^b
2	0.71	0.81^a	1.06^a	1.69^a	0.68^b	0.59^b	1.62^a	1.37^c	0.63^c
3	−0.07	0.25	0.30	0.77	0.46	0.51^c	1.43^a	1.28^c	0.12
4	−0.77	−0.22	−0.13	0.45	0.31	0.58^b	0.90^b	1.07	−0.13

Table A2. Institutional Trading on Individual Anomalies

This table reports institutional trading on the 24 individual-anomaly portfolios. Institutional trading Δ%Inst is the change in percentage of shares held by institutions, measured over 6 quarters for long-horizon anomalies and over 2 quarters for short-horizon anomalies. In each quarter, we first calculate the average institutional trading for the long leg and short leg of an individual anomaly portfolio, and the difference in institutional trading between the two legs (L-S). We then average them over time. Panels A and B report the results for the long-horizon and short-horizon anomalies respectively. Δ%Inst is reported in percentage points. The t-statistics for the differences between the long and short legs are computed using the Newey-West standard errors. a, b, and c denote significance at 1%, 5%, and 10% respectively.

Panel A: Long-Horizon Anomalies

	BP	EP	SG	CAPX	AI	AG	NS	XFIN	ACC	DACC	ATTO	NOA	RD	SGA	GP
Short	3.60	3.15	3.66	2.61	2.51	3.59	3.74	3.41	2.94	2.95	2.66	2.95	2.91	3.04	2.58
Long	1.74	2.50	2.16	2.96	2.93	2.30	2.04	2.31	2.84	2.94	3.00	3.08	2.50	2.23	2.98
L-S	-1.86^a	-0.65^a	-1.50^a	0.35^a	0.41^a	-1.28^a	-1.70^a	-1.10^a	-0.10	-0.01	0.34	0.13	-0.41^b	-0.81^a	0.40^b
t-stat	(-7.37)	(-3.79)	(-7.30)	(2.51)	(3.14)	(-6.61)	(-8.21)	(-6.23)	(-0.63)	(-0.10)	(1.67)	(0.88)	(-1.98)	(-3.29)	(2.37)

Panel B: Short-Horizon Anomalies

	MOM	SUE	FRV	ROE	GM	OSCORE	CHS	IVOL	DISP
Short	-0.37	0.27	-0.02	0.78	0.90	1.32	0.35	1.02	0.62
Long	2.56	1.34	2.14	1.34	1.20	0.77	1.41	0.65	1.49
L-S	2.93^a	1.07^a	2.16^a	0.56^a	0.30^a	-0.55^a	1.07^a	-0.37^b	0.86^a
t-stat	(12.57)	(9.46)	(9.73)	(3.93)	(4.03)	(-5.98)	(5.64)	(-1.99)	(4.30)

Table A3. Liquidity Characteristics of Individual Anomalies

This table reports the illiquidity level and change of 24 individual-anomaly portfolios. We measure stock illiquidity (ILQ) by the cross-sectional percentile rank of the Amihud illiquidity ratio. Illiquidity change ΔILQ is the change of ILQ over 6 quarters for long-horizon anomalies and over 2 quarters for short-horizon anomalies. In each quarter we first calculate the average ILQ and ΔILQ for the long and short legs of individual anomalies, and the difference in ILQ and ΔILQ between the long and short legs (L-S). We then average them over time. Panels A1 and A2 report the level and change in illiquidity for the long-horizon anomalies. Panels B1 and B2 report the level and change in illiquidity for the short-horizon anomalies. The t-statistics for the differences between the long and short legs are computed using the Newey-West standard errors. a, b, and c denote significance at 1%, 5%, and 10% respectively.

Panel A1: ILQ for Long-Horizon Anomalies															
	BP	EP	SG	CAPX	AI	AG	NS	XFIN	ACC	DACC	ATTO	NOA	RD	SGA	GP
Short	39.13	44.20	45.59	44.60	49.55	45.03	46.11	49.12	51.81	50.50	44.60	50.93	43.37	40.14	48.52
Long	60.37	53.83	54.32	56.14	53.15	54.94	47.56	48.34	50.50	47.94	55.35	50.64	51.56	62.61	49.45
L-S	21.24^a	9.62^a	8.73^a	11.54^a	3.60^a	9.91^a	1.45^a	-0.78^a	-1.30^a	-2.57^a	10.74^a	-0.29^a	8.19^a	22.47^a	0.93^a
t-stat	(25.47)	(7.57)	(14.60)	(13.79)	(6.26)	(14.07)	(0.93)	(−0.87)	(−2.85)	(−6.00)	(17.12)	(−0.44)	(11.17)	(36.25)	(1.42)

Panel A2: ΔILQ for Long-Horizon Anomalies															
	BP	EP	SG	CAPX	AI	AG	NS	XFIN	ACC	DACC	ATTO	NOA	RD	SGA	GP
Short	−4.00	−1.97	−4.73	−1.56	−1.91	−4.57	−4.63	−3.15	−1.97	−1.12	−0.41	−2.07	−2.28	−2.86	−0.35
Long	2.10	−0.61	2.35	−0.10	0.64	1.99	1.27	0.18	−0.28	−0.85	−1.41	−0.42	1.27	1.59	−1.33
L-S	6.10^a	1.36^a	7.09^a	1.45^a	2.56^a	6.56^a	5.90^a	3.33^a	1.69^a	0.27^a	-1.00^a	1.65^a	3.55^a	4.45^a	-0.99^a
t-stat	(19.28)	(3.90)	(25.13)	(8.24)	(14.68)	(20.47)	(15.40)	(11.66)	(9.61)	(1.41)	(−2.79)	(6.36)	(11.71)	(10.30)	(−3.57)

Panel B1: ILQ for Short-Horizon Anomalies									
	MOM	SUE	FRV	ROE	GM	OSCORE	CHS	IVOL	DISP
Short	51.99	51.25	48.77	55.95	53.52	58.78	60.30	59.46	47.34
Long	47.74	44.77	40.79	43.42	44.00	42.01	41.63	39.65	33.61
L-S	-4.24^a	-6.48^a	-7.98^a	-12.53^a	-9.52^a	-16.77^a	-18.67^a	-19.81^a	-13.73^a
t-stat	(−4.37)	(−16.77)	(−22.35)	(−21.34)	(−30.49)	(−29.89)	(−26.15)	(−15.96)	(−20.94)

Panel B2: ΔILQ for Short-Horizon Anomalies									
	MOM	SUE	FRV	ROE	GM	OSCORE	CHS	IVOL	DISP
Short	3.30	1.39	2.04	0.45	−0.13	−0.98	1.18	−0.35	0.81
Long	−4.73	−1.83	−2.57	−1.24	−0.60	0.10	−1.42	−0.42	−1.27
L-S	-8.02^a	-3.22^a	-4.61^a	-1.69^a	-0.47^a	1.08^a	-2.60^a	-0.08^a	-2.07^a
t-stat	(−31.29)	(−19.29)	(−21.65)	(−8.83)	(−4.54)	(8.89)	(−10.68)	(−0.23)	(−8.13)

Table A4. Level and Change in Return Impact of Anomaly Portfolios

This table reports the level and change in return impact by $1 million of trading, for the 11 anomaly category portfolios. The return impact is expressed in percentage points and is the impact on absolute stock return by $1 million (in June 2018 dollar) of trading. Specifically, it is the Amihud illiquidity ratio multiplied by 1,000,000, and further multiplied by a trend-adjustment factor P, which is the ratio of the total market cap in CRSP at the time of portfolio ranking to the total market cap in June 2018. The Amihud illiquidity ratio is winsorized at the top and bottom one percentiles. Change in return impact is measured over 6 quarters for long-horizon anomalies and over 2 quarters for short-horizon anomalies. In each quarter we first calculate the cross sectional median levels and median changes of return impact for the long and short legs of individual anomalies, and the difference in them between the long and short legs (L-S). The table reports the time-series averages of the long-short differences in the level and change of return impact over anomalies in the same category. LT Avg and ST Avg are the averages across 7 long-horizon anomaly categories and 4 short-horizon anomaly categories respectively. Panels A and B report the level and change of return impact respectively. The t-statistics are computed using the Newey-West standard errors. a, b, and c denote significance at 1%, 5%, and 10% respectively.

Panel A: Return Impact

	Value	Investment	Financing	Quality	Efficiency	Intangible	LT Profit	LT Avg
Short	0.5872	0.6690	0.8362	1.1257	0.7967	0.4144	0.6368	0.7241
Long	1.7019	1.4924	0.7352	0.8932	1.3867	2.3498	0.9438	1.3573
L-S	1.1147^a	0.8225^a	-0.1011^a	-0.2316^a	0.5900^a	1.9353^a	0.3060^a	0.6341^a
(t-stat)	(5.84)	(6.86)	(−1.78)	(−4.84)	(7.76)	(7.18)	(7.03)	(7.04)

	Momentum	ST Profit	Distress	Uncertainty	ST Avg
Short	0.8105	1.2351	1.9996	1.7423	1.4473
Long	0.4310	0.4347	0.3529	0.1820	0.3501
L-S	-0.3795^a	-0.8004^a	-1.6477^a	-1.5604^a	-1.0972^a
(t-stat)	(−6.61)	(−7.99)	(−7.20)	(−6.28)	(−7.07)

Panel B: Change in Return Impact

	Value	Investment	Financing	Quality	Efficiency	Intangible	LT Profit	LT Avg
Short	-0.0570	-0.0542	-0.0992	-0.0368	-0.0303	-0.0230	-0.0046	-0.0432
Long	0.0377	0.0202	0.0028	-0.0055	-0.0276	0.0662	-0.0303	0.0092
L-S	0.0947^a	0.0735^a	0.1020^a	0.0312^a	0.0028^a	0.0891^a	-0.0257^a	0.0524^a
(t-stat)	(4.02)	(6.17)	(5.08)	(4.31)	(0.27)	(2.92)	(-3.25)	(4.66)

	Momentum	ST Profit	Distress	Uncertainty	ST Avg
Short	0.0662	0.0303	0.0505	0.0469	0.0487
Long	-0.0561	-0.0046	-0.0028	-0.0037	-0.0165
L-S	-0.1222^a	-0.0340^a	-0.0533^a	-0.0515^a	-0.0652^a
(t-stat)	(-8.05)	(-3.85)	(-2.85)	(-2.21)	(-4.26)

Table A5. Institutional Trading on Short-Horizon Market Anomalies over 6 quarters

This table reports institutional trading on the 4 short-horizon anomaly category portfolios over 6 quarters. The institutional trading measures are the change in percentage of shares held by institutions (Δ%Inst, reported in Panel A) and the size-adjusted change in number of institutional owners (Δ#Inst, reported in Panel B). In each panel, we report the total institutional trading, as well as the liquidity-driven and non-liquidity components of institutional trading. The liquidity-driven component of institutional trading on a stock (Δ%Inst$_{LIQ}$ and Δ#Inst$_{LIQ}$) is the average institutional trading measure across all stocks in the same liquidity change (ΔILQ) decile. The non-liquidity component of institutional trading (Δ%Inst$_{NLQ}$ and Δ#Inst$_{NLQ}$) is the institutional trading measure in excess of the liquidity-driven component. Institutional trading and its components are measured over 6 quarters. In each quarter, we first calculate the average institutional trading for the long leg and short leg of an individual anomaly portfolio, and the difference in institutional trading between the two legs (L-S). We then average them across anomalies within the same category, and average over time. ST Avg is the average across 4 short-horizon categories. Institutional trading measures are reported in percentage points. The t-statistics are computed using the Newey-West standard errors. a, b, and c denote significance at 1%, 5%, and 10% respectively.

Panel A: Δ%Inst and Its Components

	Momentum	ST Profit	Distress	Uncertainty	ST Avg
			Δ%Inst		
Short	1.38	2.17	2.21	2.35	2.03
Long	4.29	3.21	2.97	2.88	3.34
L-S	2.91^a	1.05^a	0.76^a	0.53	1.31^a
t-stat	(8.65)	(5.73)	(2.99)	(1.67)	(5.39)
			Liquidity-driven Δ%Inst$_{LIQ}$		
Short	2.59	2.54	2.63	2.81	2.64
Long	3.00	2.94	2.80	2.69	2.86
L-S	0.41^a	0.41^a	0.17^b	−0.12	0.22^a
t-stat	(6.96)	(7.22)	(2.14)	(−0.96)	(3.21)
			Non-Liquidity Δ%Inst$_{NLQ}$		
Short	−1.21	−0.37	−0.42	−0.46	−0.62
Long	1.29	0.27	0.17	0.19	0.48
L-S	2.50^a	0.64^a	0.59^a	0.65^b	1.10^a
t-stat	(7.65)	(3.94)	(2.69)	(2.39)	(4.95)

Panel B: Δ#Inst and Its Components

	Momentum	ST Profit	Distress	Uncertainty	ST Avg
			Δ#Inst		
Short	7.86	14.19	16.37	18.59	14.25
Long	36.10	26.41	23.44	21.66	26.90
L-S	28.25^a	12.22^a	7.07^a	3.07^a	12.65^a
t-stat	(17.62)	(13.25)	(7.70)	(2.83)	(13.50)
			Liquidity-driven Δ#Inst$_{LIQ}$		
Short	18.65	18.26	18.89	19.99	18.95
Long	23.04	22.54	21.36	21.06	22.00
L-S	4.39^a	4.29^a	2.47^a	1.07	3.05^a
t-stat	(7.11)	(8.02)	(5.02)	(1.37)	(5.58)
			Non-Liquidity Δ#Inst$_{NLQ}$		
Short	−10.80	−4.07	−2.52	−1.40	−4.70
Long	13.06	3.87	2.08	0.60	4.90
L-S	23.86^a	7.94^a	4.60^a	2.00^b	9.60^a
t-stat	(20.17)	(12.43)	(6.23)	(2.15)	(14.40)