Liquidity Characteristics of Market Anomalies and Institutional Trading

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Abstract

This study examines the liquidity characteristics of market anomalies and how liquidity affects institutional trading on anomalies. We find that long-short portfolios based on market anomalies have pervasive liquidity exposure. For long-horizon anomalies, the long legs of the portfolios are less liquid and have deteriorating liquidity relative to the short legs. Short-horizon anomaly portfolios exhibit an opposite pattern. Consistent with such liquidity characteristics and institutional liquidity preference, aggregate institutional trades appear to be in the right direction of short-horizon anomalies and in the wrong direction of long-horizon anomalies. Perverse institutional trading on long-horizon anomalies disappears after controlling for liquidity. We further find that liquidity-driven and non-liquidity components of institutional trades have different impact on market mispricing.

I. Introduction

Existing empirical studies have presented an intrigue regarding the impact of institutional investors on market efficiency, especially in correcting mispricing in the form of market anomalies. On the one hand, many studies show that market anomalies are weaker among stocks with higher institutional ownership or more active institutional trading.[1] On the other hand, several recent papers point out 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. The evidence reported by Edelen, Ince, and Kadlec (2016) is even more puzzling. They find that institutions often trade in the wrong direction of market anomalies, i.e., buying stocks predicted by anomalies to have low returns, and selling stocks predicted to have high returns. Further, when institutional investors trade in the wrong direction of an anomaly, the magnitude of the anomaly often gets exacerbated. Such findings suggest that the price impact of institutional trading could well be a cause of stock mispricing.

This study shows that liquidity goes a long way in explaining both the puzzling pattern of institutional trading on anomalies and the impact of institutional trading on market efficiency. We find that the liquidity characteristics of anomaly-based portfolios are heterogenous, depending on the return-predictive horizons of anomalies. Such liquidity characteristics, combined with institutional investors' liquidity preference, cause the aggregate institutional trades to be in the wrong direction of some anomalies and in the right direction of other anomalies. The non-liquidity-driven component of institutional trades appears to be either uncorrelated with or in the right direction of anomalies. We further find that the perverse impact of institutional trading on the magnitude of market anomalies is also due to the liquidity-driven institutional trades.

The market anomalies in our study are in 11 broad categories that cover a large proportion of individual anomalies documented by researchers. Consistent with existing studies (e.g., Daniel, Hirshleifer, and Sun, 2020), these anomalies can be classified into two groups based

[1]See, e.g., Bartov, Radhakrishnan, and Krinsky, 2000; Ali, Hwang, and Trombley, 2003; Collins, Gong and Haribar, 2003; Nagel, 2005; Jiang, Yao, and Xu, 2009; Lam and Wei, 2011.

on their return-predictive horizons. Seven categories of anomaly variables, including value, investment, financing, quality, efficiency, intangible investments, and gross profitability, predict stock returns at relatively long horizons, e.g., 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, e.g., within one year.

We find that how institutions trade on an anomaly is related to the return predictive horizon of the anomaly. Institutions tend to be wrong on the long-horizon anomalies, but right on the short-horizon anomalies. Specifically, we measure net institutional trading on an anomaly as the difference in institutional trading between the long leg and the short leg of the anomaly portfolio. The net institutional trading is significantly negative for five out of seven long-horizon categories, and significantly positive for all the four short-horizon categories. Such a horizon-dependent, heterogeneous pattern of institutional trading on anomalies adds to the intrigue already documented in existing studies.

What may drive institutional investors to trade in the right direction of one set of anomalies but in the opposite direction of another set? We find that liquidity characteristics of the anomalies offer an intuitive and powerful clue. Across anomalies, the return-predictive horizon is pervasively related to the level and change of liquidity at the long and short legs of anomaly portfolios. For long-horizon anomalies, stocks in the long legs tend to be illiquid and with deteriorating liquidity, while the short legs tend to be liquid and with improving liquidity. For short-horizon anomalies, the liquidity pattern is reversed – both the level and change of liquidity are higher for stocks in the long legs than those in the short legs. Thus, even if institutions do not intentionally pursue any market anomaly but merely follow a liquidity preference, they might appear to trade correctly on the short-horizon anomalies and incorrectly on the long-horizon anomalies.

Due to their large portfolio size and the concern for trading cost, institutions tend to hold liquid stocks. Such an institutional liquidity preference has been well documented in the existing literature (e.g., Gompers and Metrick, 2001). In this study, we find that the liquidity preference translates into two patterns of institutional trading. First, because most institutions are long-only, the stocks they sell must be those they already hold; thus the stocks institutions bought and sold are similarly liquid. Second, to maintain liquid positions, institutions tend to sell stocks that have become less illiquid and buy stocks that have become more liquid.

To see the extent to which liquidity preference drives institutional investors' trading behavior on anomalies, we decompose institutional trading into a liquidity-driven component and a non-liquidity component. Averaged across the long-horizon anomalies, the net liquidity-driven institutional trading is significantly negative, while the net non-liquidity component is statistically insignificant. Therefore, 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 suggests that institutions' tendency to trade on short-horizon anomalies is not completely due to liquidity.

Having shown that liquidity is important for understanding the institutional trading patterns 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 may 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 – a positive return difference between stocks with deteriorating liquidity and those with improving liquidity. During this period, the liquidity change premium fully explains the magnitude of the value anomaly. However, anomaly portfolio returns to the other 10 categories remain significant after controlling for the liquidity change premium. Thus, 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, an observation by Edelen et al. (2016) that implicates institutional investors on market mispricing. We separate the long-short portfolio of an anomaly into two subportfolios – one on which institutions trade in the right direction, and another on which institutions trade in the wrong direction. Our analysis confirms that for long-horizon anomalies, the abnormal returns to the subporfolios where institutional trading is in the wrong direction is 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 component of institutional trading, while the direction of non-liquidity component of 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 opposite institutional trading directions. These findings combined suggest that liquidity is behind the perverse price impact of institutional trading that aggravates stock mispricing.

The main contribution of this study is to document pervasive liquidity exposure of portfolios formed on market anomalies and relate such liquidity exposure to institutional trading patterns on anomalies. Relative to Edelen et al. (2016), we cover a more inclusive set of anomalies, and find that the direction of institutional trading on anomalies is heterogeneous, depending on the return-predictive horizon of anomalies. More importantly, we show that the perverse institutional trading on long-horizon anomalies, and their resulting impact on market mispricing, are driven by institutional liquidity preference.

Empirical studies on mutual funds have also documented rich patterns of fund trading on anomalies. Grinblatt, Titman, and Wermers (1995) and Carhart (1997) find that mutual funds chase stock price momentum. Ali, Chen, Yao, and Yu (2006 and 2020) find that few funds exploit the accruals anomaly, but many funds trade on the post earnings announcement drift, and they do so more aggressively than trading on price momentum. Wermers, Yao, and Zhao (2012) find that stock selection information revealed by fund holdings is positively correlated with momentum anomalies but not highly related to value (except for a negative relation with the book-to-market ratio anomaly), investment, or quality anomalies. A recent study by Lattau, Ludvigson, and Manoel (2018) further confirms that mutual funds do not significantly exploit many well-known anomalies. However researchers have not been able to offer a consistent explanation for these heterogenous trading patterns. Our study adds to the literature by highlighting the role of liquidity in explaining the institutional trading patterns.

Several recent studies provide evidence that speaks to the possible reasons for the perverse pattern of institutional trading on anomalies. Akbas, Amstrong, Socescu, and Sub-

[2] For short-horizon anomalies, we do not find significant difference in the magnitude of anomalies between the right and wrong directions of institutional trading.

rahmanyam (2015) point out that fund flows may 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 on an anomaly in the right direction when the anomaly becomes well-known. Engelberg, McLean, and Pontiff (2020) find that analyst price targets and recommendations contradict anomalies, which may influence the trades of institutions who follow analysts' advices. Ince and Kadlec (2019) find that performance of institutional investors has declined over time, mainly because they increasingly trade with more sophisticated and informed counterparties such as firms and corporate insiders. A recent study by McLean, Pontiff, and Reilly (2020) examines the trades of nine types of market participants on market anomalies. They show that 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, the explanation provided by our study is unique in that it explains the heterogeneity of institutional trading direction related to the return-predictive horizon of an anomaly.

The rest of the paper is organized as follows. Section II describes the 11 categories of anomalies, data samples, and empirical methodologies. Section III presents the empirical results on the impact of institutions' liquidity preference on how institutions trade on market anomalies. Section IV further examines the extent to which liquidity premium explains the abnormal returns to anomaly portfolios and the effect of institutional trading on the magnitude of market anomalies. Section V concludes.

II. Data, Sample, and Variables

II.A. Market Anomalies

Existing studies have documented several hundred market anomalies; e.g., Green, Hand, and Zhang (2013 and 2017), Harvey, Liu, and Zhu (2016), McLean and Pontiff (2016), and Hou, Xue, and Zhang (2020). 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 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 Lakonoshok, 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 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 existing studies; e.g., Wei, Wermers, and Yao (2015), Daniel, Hirshleifer, and Sun (2020), and Hou, Xue, and Zhang (2020). The anomaly categories and the 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 individual anomaly variables. As we show subsequently, the first 7 categories (Value, Investment, Financing, Quality, Efficiency, Intangible, and LT Profitability) have long return-predictive horizons and the remaining 4 categories (Momentum, ST Profitability, Distress, and Uncertainty) have short return-predictive horizons. These 11 categories cover a large proportion of individual anomalies examined by existing studies. For example, out of the 102 anomalies analyzed by Green, Hand, and Zhang (2017), 76 belong to the 11 categories above. Among the 26 that cannot be classified into the 11 categories, 10 are measures of liquidity.[3] Further, among the 452 anomalies studied by Hou, Xue, and Zhang (2020), 346 fall into the categories of momentum, value, investing, financing, profitability, and intangibles. The remaining 106 in the category of "trading frictions" include 39 variables that belong to our Uncertainty category (e.g., total and idiosyncratic volatility, betas, max returns, and total and idiosyncratic skewness), and 51 measures of liquidity (e.g., size, turnover, price, zero-trading days, liquidity beta and liquidity-risk beta).

The anomaly categories in this study include and extend those in Edelen et al. (2016) and Lewellen (2011). Edelen et al. (2016) examine seven individual anomalies, including five long-horizon ones – book to market (Value), investment to asset (investment), equity and debt issuance and repurchase (financing), gross profit (long-term profitability), and net operating assets (efficiency), and two short-horizon ones – price momentum (momentum), and O-score (distress). Relative to theirs, we additionally include anomalies in the quality, intangible, short-term profitability, and uncertainty categories. Lewellen (2011) studies 11 anomalies, including five in the long-horizon categories – book to market and long-run reversal (value), share issuance (financing), asset growth (investment), and accruals (quality), and six in the short-horizon categories – price momentum (momentum), return on assets (short-term profitability), volatility and beta (uncertainty), and two anomalies related to liquidity per se – size and turnover. Relative to his, we additionally include anomalies in the

[3]In Internet Appendix, we provide further details on how the 102 anomalies of Green, Hand, and Zhang (2017) map into these anomaly categories.

efficiency, intangible, long-horizon profitability, and distress categories.

II.B. Data and Anomaly Portfolios

The data for constructing anomaly variables are from CRSP, Compustat, and IBES. Quarterly institutional holdings are from the 13F data of Refinitiv (formerly Thomson-Reuters).

The stocks eligible for inclusion in anomaly portfolios are selected in the following way. We start with all common stocks (share code 10 or 11) in the CRSP database, and exclude financial firms (4-digit SIC codes between 6000 and 6999). We also exclude firms 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, portfolios formed from June of year t to March of year t+1 are based on financial statements reported for the fiscal year that ends in calendar year t-1. This procedure follows Fama and French (1996) and allows a minimum of six-month lag relative to the fiscal year end for accounting information to be available. 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, following the existing literature (e.g., Green, Hand, and Zhang, 2017) we assume that data become available two 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 the highest returns, and the short leg is the tercile portfolio predicted to have the lowest returns. This procedure roughly follows Edelen et al. (2016), who define the long and short legs as the top and bottom 30% of stocks ranked by an anomaly variable.

II.C. Liquidity Measures

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

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

where r_t is the daily stock return, S_t is the daily number of shares traded, and P_t is the daily closing price. T is the total number of trading days during the measurement period. ILLIQ is estimated quarterly using the daily data over previous 12 months.

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, in early sample years, trading volume for NASDAQ is reported differently than that for NYSE and AMEX. To account for this reporting difference, we follow existing studies (e.g., Lee and Swaminathan 2000) to perform ranking separately among NYSE/AMEX stocks and among NASDAQ stocks. The resulting ranked illiquidity measure is denoted as ILQ, which takes value between 1 and 100. A higher value of ILQ indicates 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 quarter t-5 to quarter t (the portfolio formation quarter). For short-horizon anomalies, ΔILQ is the change in ILQ from quarter t-1 to quarter t. A positive value of ΔILQ indicates deteriorating liquidity.

In a later part of the paper we discuss the analysis based on alternative measures of liquidity.

II.D. Institutional Holding and Trading

We measure institutional trading by the change in the percentage of shares outstanding of the stock held by institutions. The percentage of shares held by institutions, %Inst, is the total number of shares held by institutions divided by the total shares outstanding of the stock. Correspondingly, institutional trading, Δ%Inst, is the change in %Inst measured over past 6 quarters (from quarter t-5 to quarter t, the portfolio formation quarter) for long-horizon anomalies and over past 2 quarters (from quarter t-1 to quarter t) for short-horizon anomalies. To alleviate the influence of outliers on statistical inference, we winsorize institutional trading at the 0.5 and 99.5 percentiles across all stocks in each quarter.

The measure Δ%Inst follows Edelen et al. (2016), who also employ a second measure based on the change in the number of institutions holding a stock. We discuss the robustness of the results based on the second measure in a later part of the paper.

III. Empirical Evidence: Liquidity Characteristics and Institutional Trading

III.A. Return-Predictive Horizons of Anomalies

The sample period of our analysis throughout the paper is from 1980 to 2018.

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.B., we form equal-weighted long-short anomaly portfolios at the end of each calendar quarter. The long leg is the tercile portfolio predicted to have the highest returns and the short leg is the tercile portfolio predicted to have the lowest returns. Returns to individual anomaly portfolios are further averaged within a category to obtain the category-level anomaly portfolio return. Table 1 reports 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 returns for 8 quarters after portfolio formation on the long-horizon categories (to be defined below) and 4 quarters on short-horizon categories.

The table reveals substantial heterogeneity in the return-predictive horizon of the 11 anomaly categories. Returns to the long-short hedge portfolios of 7 categories – Value, Investment, Financing, Quality, Efficiency, Intangible, and Long-term Profitability – are sig-

[4] At the beginning of each holding quarter the portfolios are rebalanced to keep equal weights. If a stock drops out of sample (due to delisting or stock price dropping below \$5) at the beginning of a holding quarter, it is removed from the portfolio and the remaining stocks in the portfolio are re-weighted 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), when the CRSP delisting return is missing, we replace it with -30% if delisting is performance-related, and zero otherwise.

nificantly positive at horizons beyond 4 quarters. By contrast, returns to the long-short portfolios of 3 categories – Momentum, Short-term profitability, and Uncertainty, are only significant for the less than four quarters after portfolio formation. The returns to the long-short portfolio of the Distress category is significant for four quarters, but becomes insignificant afterwards (untabulated). Based on these patterns, we classify the first 7 categories as long-horizon anomalies and the remaining 4 as short-horizon anomalies.[5,6]

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

III.B. Institutional Trading on Anomalies

We now examine institutional trading on anomalies. We measure institutional trading on an individual stock using $\Delta\%\text{Inst}$, as introduced in Section II.D.. In each quarter, we calculate the averages of $\Delta\%\text{Inst}$ 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,

[5]We have also extended the analysis to the period of 1963-2018. During this longer sample period, all the seven long-horizon anomaly categories significantly predict returns for at least 12 quarters, while the return predictive power of the short-horizon anomaly categories tends to be limited to within one year. An exception is the short-term profitability category, whose return-predictive power is insignificant by quarter 4 but regains significance for quarters 5 and 6 before becoming insignificant again.

[6]Interestingly, profitability belongs to both the long-horizon and short-horizon categories. We note that the single anomaly variable in the long-horizon profitability category, gross profitability, may 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 the gross profitability measure is related to selling, general, and administrative (SGA) expenses, an anomaly in the Intangible category. Hou, Xue, and Zhang (2020) point out that via its denominator, the gross profitability measure is related to asset growth, an anomaly in the Investment category.

estimate the time series averages and the corresponding t-statistics at the category level. Institutional trading is measured over 6 quarters for long-horizon anomalies and 2 quarters for short-horizon anomalies. To take into account the serial correlations of institutional trading measures, when we calculate the time series t-statistics, the standard errors are estimated using the Newey-West (1987) procedure with a lag of 8 quarters.[7]

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. Judged by the sign and t-statistic of net institutional trading, institutions are in the wrong direction of 5 out of 7 long-horizon categories, and significantly so for the categories of Value, Investment, Financing, and Intangible. Further, they are in the right direction of all 4 short-horizon categories, and significantly so for the categories of Momentum, ST Profitability, and Distress. Averaged over the 7 long-horizon anomaly categories, the net institutional trading is significantly negative (-0.63% with a t-stat of -6.75). Averaged over the 4 short-horizon categories, the net institutional trading is significantly positive (0.75% with a t-stat of 5.97).

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 tend to be more likely on the wrong side of the long-horizon anomalies and on the right side of short-horizon anomalies. In the next set of analysis, we link such institutional trading patterns to the liquidity characteristics of anomalies and the liquidity preference of institutional investors.

III.C. Liquidity Characteristics of Market Anomalies

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, percentile rank of Amihud illiquidity ratio) and liquidity change (ΔILQ) for the stocks in the long leg and short leg of an anomaly, and calculate the difference between the two legs. Liquidity change is measured over 6 quarters for long-horizon anomalies and 2 quarters for short-horizon anomalies. We then average the liquidity level and change across anomalies in

[7]Throughout the paper, we systematically use the Newey-West standard errors with a lag of 8 quarters when calculating the t-statistics for institutional trading, liquidity, and liquidity change.

the same category, and take the time series averages.

Table A and B of Table 3 report the liquidity level and change respectively for the 11 anomaly categories. The distinction between long-horizon and short-horizon anomalies is clear. For long-horizon anomalies, the long legs tend to consist of stocks that are less liquid and with deteriorating liquidity, relative to the short legs. Specifically, the long-short difference in ILQ is positive for 6 out of 7 categories (with the exception of Quality). Further, the long-short difference in ΔILQ is positive for 6 out of 7 categories (with the exception of LT Profitability). For the 4 short-horizon categories, the long legs of anomaly portfolios all have significantly lower ILQ and significantly lower ΔILQ than the short legs.

Evidence in existing studies has hinted toward liquidity patterns of anomalies but has not 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 positive exposure to liquidity risk while momentum anomalies have negative exposure to liquidity risk. Akbas, Amstrong, Sorescu, 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 5 anomalies (Return on assets, Oscore, Gross profitability, Net stock issues, and Composite equity issues) and insignificant correlations for 6 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.D. Institutional Preference for Liquidity

Due to their large portfolio size and the associated concern for trading cost, 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 part of analysis, we document institutional liquidity preference in both their holdings and trades.

Panel A of Table 4 reports the average liquidity and liquidity change for stock deciles sorted by the institutional holding measure %Inst. Liquidity change is measured over both

6 quarters and 2 quarters. Across %Inst decile ranks, the illiquidity level ILQ decreases monotonically from 76.30 for the bottom decile to 30.31 for top decile. The liquidity change measure ΔILQ, over both 2 quarters and 6 quarters, also declines with institutional holding ranks. This suggests that institutions tend to hold liquid stocks and stocks with improving liquidity. However, the magnitude of the difference in liquidity change between the top and bottom institutional holding deciles is much smaller than the difference in liquidity level.

Panel B of the table reports the average liquidity and liquidity change for stock deciles sorted by institutional trading, which is measured over both 2 quarters and 6 quarters. The institutional trading measure Δ%Inst has an inverse U-shaped relation with ILQ. That is, stocks with large institutional purchases and those with large institutional sales are both liquid. This is consistent with the notion that a majority of the institutions are long-only and the stocks they sell must be from what they hold, which tend to be liquid. Perhaps more novel in this panel is the monotonically negative relation between Δ%Inst and ΔILQ. This suggests that institutions tend to buy stocks with improving liquidity and sell stocks with deteriorating liquidity. This is consistent with the institutional preference for maintaining liquid stock holdings – 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 their trading on market anomalies. We examine this issue next.

III.E. 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 component, and examine the magnitude of each component in the long-short anomaly portfolios. The liquidity-driven component of institutional trading on a stock, denoted $\Delta\%\text{Inst}_{LIQ}$, is simply the average institutional trading (Δ%Inst) on all stocks in the same ΔILQ decile during the same period. And 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, $\Delta\%\text{Inst}_{NLQ} = \Delta\% Inst - \Delta\%\text{Inst}_{LIQ}$. For long-horizon anomalies, institutional trading and liquidity change are consistently measured over 6 quarters. For short-horizon anomalies, institutional trading and liquidity change are consistently measured over 2 quarters. In each quarter, we average the liquidity-driven and non-liquidity components of institutional trading over the long leg and short leg of each individual anomaly and calculate the long-short difference, and then average them over anomalies within the same category. Finally, we average these statistics over time and report them in Table 5.

Panel A of Table 5 shows that based on $\Delta\%\text{Inst}_{LIQ}$, averaged over the 11 categories, the net liquidity-driven institutional trading (i.e., the long-short difference in $\Delta\%\text{Inst}_{LIQ}$) is significantly negative, at -0.33 (t=-7.37). Therefore, liquidity preference tends to cause institutions to trade in the wrong direction of anomalies. However, the patterns are different between long-horizon and short-horizon anomalies. Among the long-horizon anomalies, the net liquidity-driven institutional trading is significantly negative for Value, Investment, Financing, Quality, and Intangible categories (although insignificantly negative for Efficiency, and significantly positive for LT Profitability). Among the 4 short-horizon categories, Momentum and ST Profitability have significantly positive long-short difference in $\Delta\%\text{Inst}_{LIQ}$, while the statistics for the other 2 categories are insignificant.

Panel B of Table 5 shows that based on $\Delta\%\text{Inst}_{NLQ}$, the net non-liquidity institutional trading (i.e., the long-short difference in $\Delta\%\text{Inst}_{NLQ}$), averaged over 11 categories, is significantly positive (0.22 with a t-statistic of 3.35). Thus, after controlling for liquidity preference, institutions tend to trade in the right direction of anomalies. Further, averaged over the 7 long-horizon categories, the net non-liquidity institutional trading is insignificantly positive. Thus, the intriguingly perverse pattern of institutional trading on long-horizon anomalies is mainly due to liquidity. Among the long-horizon anomalies, the net non-liquidity institutional trading is either insignificantly or even significantly positive for Investment, Quality, Efficiency, Intangible, and LT Profitability. Only Value and Financing have significantly negative net non-liquidity institutional trading. On the other hand, net non-liquidity institutional trading is significantly positive for all 4 short-horizon categories.

The key conclusion from this part of the analysis is that liquidity explains why institutional trading tends to be in the wrong direction of market anomalies. The direction of the non-liquidity component of institutional trading, which should be more related to institutions' intention to explore mispricing, does not contradicts long-horizon anomalies while remaining consistent with short-horizon anomalies.

III.F. Trading by Institutions with Different Liquidity Preferences

In this part, we use an alternative approach to demonstrate the relation between institutional investors' liquidity preference and their trading on anomalies. Instead of examining the aggregate institutional trading, we classify institutions into groups based on their liquidity preference, and analyze the trading behavior of each group. We consider two proxies for institutional liquidity preference. The first is the size of their equity holdings, based on the idea that institutions with large stock portfolios are likely sensitive to liquidity due to the high price impact of their trading. The second measure is the illiquidity of an institution's stock holdings, based on a 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 ILQ (i.e., cross-sectional percentile rank of the Amihud ratio) of stocks it holds. In each quarter, we classify institutional investors into terciles based on each of the two 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.

In Table 6, we report the net institutional trading Δ%Inst for each type of institutions on the 11 categories of anomalies. Panel A shows that large institutions' net trading is significantly negative on long-horizon anomalies and significantly positive on short-horizon anomalies. By contrast, Panel B shows that small institutions' net trading on long-horizon anomalies is insignificantly positive (although their net trading on short-horizon anomalies is significantly negative). Such contrasts are consistent with the difference in liquidity preferences between large and small institutions.

The results in Panels C and D, based on institutions with different levels of portfolio liquidity, are largely consistent those in Panels A and B. The results show that institutions with liquid portfolios trade significantly in the opposite direction of long-horizon anomalies. By contrast, the pattern is very different for institutions with illiquid portfolio – their net trading on long-horizon anomalies is significantly positive. On short-horizon anomalies, net trading by institutions with liquid portfolios is significantly positive, while net trading by institutions with illiquid portfolios is significantly negative.

III.G. Robustness

In this part we briefly discuss variations of the analysis we have performed to check the robustness of the findings. The details of the analysis are provided 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, we report the liquidity characteristics of long-horizon and short-horizon anomalies using five alternative liquidity measures. The patterns are largely consistent with those based on the Amihud illiquidity ratio.

Third, we repeat the key analyses using the second measure of institutional trading of Edelen et al. (2016), which is based on the size-adjusted change in number of institutional owners. We note that due to an issue with its denominator, this measure exhibits a somewhat counter-intuitive relation with the level of liquidity. Nonetheless, its relations with liquidity change and with the long-horizon and short-horizon anomalies, are all consistent with those based on the the main measure in the paper. We also obtain consistent results based on the second measure when we examine the directions of liquidity-driven and non-liquidity components of institutional trading on market anomalies.

Fourth, we find that measuring institutional trading over six quarters does not substantially change our key inferences regarding institutional trading on short-horizon anomalies.

Finally, we perform Fama-MacBeth regressions to verify our key results based on sorted portfolios, including the institutional trading patterns on long-horizon and short-horizon anomalies, with and without controlling for liquidity change.

IV. Further Analysis

Having documented the relations among liquidity, institutional trading, and anomalies, we move next to explore two issues related to the magnitude of the anomalies. First, given the liquidity characteristics of the anomaly portfolios, we examine whether abnormal anomaly returns can be explained by the premium associated with liquidity or liquidity change. Second, given the wrong direction of institutional trading on long-horizon anomalies, we examine how institutional trading affects the magnitude of market mispricing and to what extend liquidity may explain such effects.

IV.A. Liquidity Premium and Market Anomalies

Institutional preference for liquidity may give rise to liquidity premium, i.e., higher return to illiquid stocks. Given that the long legs and short legs of anomaly portfolios have substantially different liquidity characteristics, it is natural to question the extent to which returns of anomaly portfolios are reincarnations of the liquidity premium.

To address this question, we first report a pattern for liquidity premium. In Table 7, we report the return difference between the top and bottom decile portfolios (equal-weighted) sorted by the level of illiquidity (measured by ILQ). The table shows that this measure of liquidity premium is insignificant in the 8 quarters after portfolio ranking. That is, the premium associated illiquidity has disappeared during the sample period we study.[8]

Interestingly, we find a significant long-horizon phenomenon of liquidity change premium. As the same table shows, the return difference between the top and bottom decile portfolios sorted by the two-quarter change of illiquidity (ΔILQ), is significantly positive for 6 quarters after portfolio ranking, and that for portfolios sorted by the six-quarter change of illiquidity is significantly positive for 7 quarters after portfolio ranking, with the exception for the initial one or two quarters after portfolio ranking.[9]

Given the above findings, we further examine whether the return premium associated

[8] When we perform analysis on an earlier period of 1963-1979, we find that the top-bottom return difference for ILQ-sorted portfolios is significant at least 8 after portfolio ranking. Therefore, in early years the liquidity premium is much stronger and is a long-horizon phenomenon.

[9] We also find that, in untabulated analysis, the liquidity change premium is even more stronger as a long-horizon phenomenon during early years of 1963-1979.

with liquidity change affects the magnitude of market anomalies. For each stock in each quarter, we calculate its liquidity-adjusted return as the quarterly stock return in excess of the return to a liquidity benchmark, where the liquidity benchmark return is the average return to stocks in the same decile of liquidity change. The liquidity change is measured over 6 quarters when evaluating long-horizon anomalies and 2 quarters when evaluating short-horizon anomalies. We then calculate the average liquidity-adjusted return for the long leg and short-leg of an individual anomaly, and further average them over anomalies in the same category.

Table 8 reports the results of the liquidity-adjusted long-short return difference for the 11 anomaly-category portfolios. The long-short return difference to the value anomaly portfolio, after liquidity adjustment, is no longer significant at any horizon. That is, the value anomaly appears to be mainly driven by the liquidity change premium during the sample period. The magnitude of other anomalies also appears to be somewhat reduced by the adjustment for liquidity change, but to a much lesser extent. The average adjusted-return difference across 7 long-horizon categories remains significant over 8 quarters and the average across 4 short-horizon categories remains significant during the first three quarters. These patterns are quite similar to those in Table 1.

Therefore, although the long legs 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 liquidity change premium.

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

A further issue we examine is the impact of institutional trading on stock mispricing. Edelen et al. (2016) examine the relation between the direction of institutional trading and the magnitude of market anomalies. They find that when institutional trading is in the wrong direction of anomalies, the magnitude of anomalies tends to be higher. Given our findings on how liquidity drives institutional trading, the relevant questions are, first, whether institutional trading has different impact on the magnitude of long-horizon and short-horizon anomalies, and second, whether the liquidity-driven and the non-liquidity components of institutional trading have different impact on the magnitude of anomalies. These questions go to the core issue of the effect of institutional investors on market efficiency.

We first follow the procedure of Edelen et al. (2016) 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 6 quarters when evaluating long-horizon anomalies and over 2 quarters when evaluating short-horizon anomalies. 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 "Long+Low (LL)"), and the short leg of this subportfolio consists of the short-leg stocks in the top quintile of institutional trading ("Short + High (SH)"). 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 ("Long+High (LH)"), and the short leg of this subportfolio consists of the short-leg stocks in the bottom quintile of institutional trading ("Short+Low (SL)").

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 initial portfolio ranking (with quarterly rebalancing). In each quarter t, there are K such portfolios, formed during quarter 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 have a time series of non-overlapping quarterly returns, based on which we further compute the average returns. We set K=6 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. After obtaining the time series of returns, we further estimate the alphas of various subportfolios based on CAPM. The magnitude of portfolio alpha summarizes the magnitude of mispricing relative to CAPM.

Panel A of Table 9 reports the alphas to the anomaly subportfolios on which institutions trade in the wrong and right directions. For long-horizon anomalies, we find a pattern consistent with that reported by Edelen et al. (2016). The magnitude of the anomalies, as measured by the long-short alpha 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 7 long-horizon categories, the alpha difference between the two subportfolios (labeled "Wrong - Right", i.e., (LL-SH) - (LH-SL)) is 1.35%, significantly positive. However, for the four short-horizon anomaly categories and averaged over the four categories, the alpha differences between the "wrong" and "right" subportfolios are all statistically insignificant.

To see if the patterns are different for liquidity-driven trading and non-liquidity trading, we further construct subportfolios on which the liquidity-driven component and the non-liquidity component are in the wrong and right directions, and repeat the analysis of Panel A on these subportfolios. Panel B of Table 9 shows that when institutions' liquidity-driven trades are in the wrong direction, the magnitude of anomalies tends to be larger, for both long-horizon and short-horizon anomalies (although the statistical significance is weaker for short-horizon anomalies).

Further, Panel C of the table shows the results of analysis on institutions' non-liquidity trades. Out of 11 anomaly categories, the alpha difference between the "wrong" subportfolio and the "right" subportfolio of non-liquidity institutional trading is significantly positive for only one category – Investments. The alpha differences are insignificant when averaged over long-horizon anomalies and short-horizon anomalies. Thus, non-liquidity institutional trading does not impact the magnitude of mispricing.

Panel D of the table reports further results that highlight the effect of liquidity change premium on the relation between institutional trading direction and the magnitude of market anomalies. We compute the liquidity-adjusted returns of anomaly subportfolios – i.e. the long-short anomaly portfolios conditional on institutional trading direction, as reported in Panel A of the table. We then compute the CAPM alphas on the liquidity-adjusted returns. The panel shows that the alpha differences for the liquidity-adjusted returns, labeled "Wrong-Right", become all insignificant across the 7 long-horizon anomalies. Thus, despite the inability of the liquidity change premium to explain the average magnitude of the anomalies, it fully explains the difference in the magnitude of long-horizon anomalies attributable to the direction of institutional trading. Meanwhile, there is no significant relation between the liquidity-adjusted magnitude of short-horizon anomalies and the institutional trading direction.

To sum up, the results reported in Table 9 suggest that wrong-directional institutional trades aggravate long-horizon anomalies, which is because of liquidity-driven trades and is closely related to the liquidity change premium. By contrast, the magnitude of short-horizon anomalies tends to be not affected by the direction of institutional trading.

V. Conclusions

In this study, we document pervasive patterns of liquidity exposure for anomaly portfolios. For long-horizon anomalies, stocks in the long legs of the anomaly portfolios are typically more illiquid and have deteriorating liquidity, relative to stocks in the short legs. For the short-horizon signals, the liquidity exposure tends to exhibit an opposite pattern. We show that these liquidity characteristics go a long way in explaining the perverse pattern of institutional trading on long-horizon anomalies. We further show that the liquidity-driven and non-liquidity components of institutional trading have different implications on market efficiency. The liquidity-driven institutional trades seem to exacerbate mispricing associated with long-horizon anomalies, while the non-liquidity institutional trades do not substantially impact the magnitude of anomalies.

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 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 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_{t-1} is capital expenditure (item CPAX) scaled by sales (item SALE) during the fiscal year-end in year *t-1*. 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): Change in the natural log of the split-adjusted shares outstanding from June of last year to June of this year. NS is set to missing if it is zero. The data are from CRSP monthly 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. Operating Accruals (ACC): (ΔCA - ΔCASH - ΔCL - ΔSTD - ΔTP - DEP)/ATA, 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 ATA is the two-year average 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. 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. 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. 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): Analyst average EPS forecast for the currently unreported fiscal year FY1 during month t, in excess of the average EPS forecast for the same fiscal year made during month t-3, divided by stock price at the time the average forecast of month t 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 SALE) minus Cost of Goods Sold (item COGS), then divided by Sales (item SALE). The data are from Compustat annual 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 contemporaneous Fama-French 3 factors (available from July 1963) and three lags of daily returns to CRSP value-weighted index. The regression is performed using daily returns in each month t with a minimum of 15 observations. The data are from CRSP daily files.

24. Analyst forecast dispersion (DISP): Standard deviation of analyst EPS forecasts for the unreported fiscal year FY1, divided by the absolute value of the average analyst EPS forecast for the same fiscal year, measured in month t. The data are from IBES.

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Table 1. Return-predictive Horizons of Market Anomalies

This table reports returns to 11 anomaly category portfolios. Stocks are sorted quarterly into equal-weighted terciles using each of the 24 individual anomaly variables. The long leg of an anomaly portfolio is the tercile predicted to have high returns and the short leg is the tercile predicted to have low returns. We compute the average 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, ST Avg, and ALL Avg are the long-short return differences averaged across 7 long-horizon anomaly categories, 4 short-horizon anomaly categories, and all 11 anomaly 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 statistical significance at 1%, 5%, and 10% respectively, for the t-statistics (not tabulated) of return differences. The sample period for all the tables is from 1980 to 2018.

Qtr	Value	Investment	Financing	Quality	Efficiency	Intangible	LT Profit
1	1.07^b	1.03^a	1.68^a	0.96^a	1.28^a	1.96^a	1.77^a
2	0.97^b	0.73^a	1.43^a	0.67^a	1.12^a	1.63^a	1.56^a
3	0.93^b	0.62^a	1.34^a	0.59^a	1.00^a	1.54^a	1.40^a
4	0.79^b	0.42^b	1.17^a	0.44^a	0.89^a	1.34^a	1.28^a
5	0.70^c	0.42^b	1.13^a	0.34^b	0.90^a	1.43^a	1.18^a
6	0.64	0.39^b	1.04^a	0.32^b	0.79^a	1.33^a	1.10^a
7	0.59	0.35^c	0.90^b	0.24^c	0.71^a	1.28^a	1.07^a
8	0.46	0.29	0.79^b	0.30^b	0.62^a	1.10^a	0.97^a
	Momentum	ST Profit	Distress	Uncertainty	LT Avg	ST Avg	ALL Avg
1	1.73^a	1.73^a	1.18^a	1.14^b	1.39^a	1.44^a	1.41^a
2	0.86^a	1.19^a	1.01^a	0.90^c	1.16^a	0.99^a	1.10^a
3	0.17	0.58^b	0.90^a	0.62	1.06^a	0.57^b	0.88^a
4	−0.38	0.25	0.62^b	0.42	0.90^a	0.23	0.66^a

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, ST Avg, and ALL Avg are the long-short differences in institutional trading averaged across 7 long-horizon anomaly categories, 4 short-horizon anomaly categories, and all 11 anomaly 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 statistical significance at 1%, 5%, and 10% respectively.

	Value	Investment	Financing	Quality	Efficiency	Intangible	LT Profit
Short	4.01	3.28	4.15	3.30	3.15	3.36	2.89
Long	2.21	2.84	2.28	3.20	3.34	2.58	3.29
L-S	-1.80^a	-0.44^a	-1.88^a	-0.10	0.19	-0.78^a	0.40^b
t-stat	(−10.92)	(−3.82)	(−9.57)	(−1.00)	(1.51)	(−4.28)	(2.18)
	Momentum	**ST Profit**	**Distress**	**Uncertainty**	**LT Avg**	**ST Avg**	**ALL Avg**
Short	−0.05	0.79	0.81	0.79	3.45	0.59	2.36
Long	1.99	1.23	1.08	1.05	2.82	1.33	2.26
L-S	2.04^a	0.44^a	0.27^b	0.26	-0.63^a	0.75^a	-0.11
t-stat	(11.46)	(4.95)	(2.24)	(1.47)	(−6.75)	(5.97)	(−1.38)

Table 3. Liquidity Characteristics of Anomaly Portfolios

This table reports the illiquidity level and change of 11 anomaly category portfolios. We measure stock illiquidity (ILQ) by the cross-sectional percentile rank (with value between 0 and 100) of 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, ST Avg, and ALL Avg are the liquidity level and change measures averaged across 7 long-horizon anomaly categories, 4 short-horizon anomaly categories, and all 11 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 statistical significance at 1%, 5%, and 10% respectively. Panel A reports the level of illiquidity ILQ and Panel B reports the change of illiquidity ΔILQ.

Panel A: ILQ

	Value	Investment	Financing	Quality	Efficiency	Intangible	LT Profit
Short	42.68	46.38	47.47	50.97	47.71	41.50	48.55
Long	56.26	54.38	47.81	48.76	52.59	57.04	49.14
L-S	13.58^a	8.00^a	0.34	-2.21^a	4.87^a	15.54^a	0.59
t-stat	(17.13)	(15.15)	(0.28)	(−7.00)	(9.45)	(24.15)	(0.90)

	Momentum	ST Profit	Distress	Uncertainty	LT Avg	ST Avg	ALL Avg
Short	49.29	54.80	59.44	53.08	46.47	54.15	49.26
Long	45.92	43.26	41.86	36.65	52.28	41.92	48.51
L-S	-3.36^a	-11.54^a	-17.59^a	-16.44^a	5.82^a	-12.23^a	-0.75^c
t-stat	(−7.29)	(−28.75)	(−38.75)	(−21.14)	(12.13)	(−30.95)	(−1.79)

Panel B: ΔILLIQ

	Value	Investment	Financing	Quality	Efficiency	Intangible	LT Profit
Short	−3.14	−1.97	−3.26	−0.98	−0.95	−2.30	−0.33
Long	1.38	0.69	0.74	−0.65	−0.76	1.51	−1.09
L-S	4.52^a	2.66^a	4.01^a	0.34^b	0.19	3.81^a	-0.75^b
t-stat	(13.85)	(13.70)	(12.29)	(2.42)	(0.97)	(11.64)	(−2.63)

	Momentum	ST Profit	Distress	Uncertainty	LT Avg	ST Avg	ALL Avg
Short	1.42	0.10	−0.16	−0.06	−1.85	0.33	−1.06
Long	−2.32	−0.99	−0.59	−0.73	0.26	−1.15	−0.25
L-S	-3.74^a	-1.09^a	-0.43^a	-0.67^a	2.11^a	-1.48^a	0.80^a
t-stat	(−24.29)	(−11.00)	(−3.14)	(−3.05)	(10.25)	(−10.95)	(5.65)

Table 4. Liquidity Characteristics of Institutional Holding and Trading

This table reports the illiquidity level of and change of stock portfolios sorted by institutional holding and trading. We measure stock illiquidity (ILQ) by the cross-sectional percentile rank (with value between 0 and 100) of 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 report the average level and change in illiquidity (ILQ, ΔILQ over 2 quarters, and *Delta*ILQ over 6 quarters) for stock deciles sorted by institutional holding %Inst. Panel B report 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 compute 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 statistical significance at 1%, 5%, and 10% respectively.

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

	by %Inst		
	ILQ	ΔILQ 2-Qtr	ΔILQ 6-Qtr
Low	76.02	−0.58	0.19
2	70.83	−0.36	0.29
3	63.32	−0.37	0.23
4	54.60	−0.33	0.01
5	48.82	−0.35	−0.17
6	44.29	−0.34	−0.57
7	40.71	−0.34	−0.61
8	36.45	−0.36	−0.81
9	33.30	−0.45	−1.19
High	30.31	−0.73	−2.08
H-L	-45.71^{a}	−0.15	-2.26^{a}
t-stat	(−26.61)	(−1.15)	(−6.95)

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

	by 2-Qtr Δ%Inst		by 6-Qtr Δ%Inst	
	ILQ	ΔILQ 2-Qtr	ILQ	ΔILQ 6-Qtr
Low	44.03	0.04	46.39	2.58
2	46.48	0.30	48.81	1.91
3	49.60	0.25	52.22	1.13
4	55.51	0.17	53.93	0.84
5	55.99	0.06	51.12	0.50
6	51.61	−0.01	48.96	0.23
7	49.57	−0.23	48.27	−0.34
8	48.31	−0.63	48.16	−1.26
9	46.96	−1.41	47.31	−3.65
High	48.04	−3.22	45.01	−9.72
H-L	4.02^a	-3.26^a	−1.38	-12.30^a
t-stat	(5.16)	(−18.21)	(−1.44)	(−18.87)

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. LT Avg, ST Avg, and ALL Avg are the institutional trading measures averaged across 7 long-horizon anomaly categories, 4 short-horizon anomaly categories, and all 11 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 statistical 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
Short	3.76	3.40	3.95	3.17	3.15	3.40	2.95
Long	2.38	2.68	2.44	3.06	3.09	2.54	3.09
L-S	-1.38^a	-0.72^a	-1.51^a	-0.11^a	−0.05	-0.86^a	0.14^c
t-stat	(−11.82)	(−10.24)	(−10.22)	(−2.81)	(−1.04)	(−7.73)	(1.74)
	Momentum	**ST Profit**	**Distress**	**Uncertainty**	**LT Avg**	**ST Avg**	**ALL Avg**
Short	0.67	0.92	0.98	1.00	3.40	0.89	2.45
Long	1.33	1.06	0.98	0.96	2.75	1.08	2.12
L-S	0.66^a	0.15^a	−0.01	−0.04	-0.64^a	0.19^a	-0.33^a
t-stat	(12.60)	(6.21)	(−0.18)	(−0.76)	(−9.03)	(5.63)	(−7.37)

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

	Value	Investment	Financing	Quality	Efficiency	Intangible	LT Profit
Short	0.25	−0.12	0.20	0.13	0.00	−0.04	−0.07
Long	−0.17	0.16	−0.16	0.15	0.25	0.05	0.20
L-S	-0.43^a	0.28^a	-0.37^a	0.02	0.25^b	0.09	0.26
t-stat	(−3.76)	(2.72)	(−3.22)	(0.16)	(2.33)	(0.57)	(1.63)
	Momentum	**ST Profit**	**Distress**	**Uncertainty**	**LT Avg**	**ST Avg**	**ALL Avg**
Short	−0.73	−0.12	−0.17	−0.21	0.05	−0.31	−0.08
Long	0.65	0.16	0.10	0.09	0.07	0.25	0.14
L-S	1.38^a	0.29^a	0.27^b	0.30^b	0.01	0.56^a	0.22^a
t-stat	(8.33)	(3.69)	(2.61)	(1.98)	(0.22)	(4.87)	(3.35)

Table 6. Trading on Market Anomalies by Institutions with Different Liquidity Preferences

This table reports trading on the 11 anomaly category portfolios by institutions with different liquidity preferences. In each quarter we classify institutional investors into terciles by the size of their equity portfolios, and label those in the top and bottom terciles as large institutions and small institutions respectively. We also classify institutional investors by the weighted average ILQ (cross-sectional percentile rank of Amihud illiquidity ratio) of their stock holdings, and label those in the top and bottom terciles as institutions with illiquid portfolios and institutions with liquid portfolios respectively. The institutional trading measure is the change in percentage of shares held by institutions (Δ%Inst), within each of the above institutional types. Institutional trading is measured over 6 quarters for long-horizon anomalies and over 2 quarters for short-horizon anomalies. In each quarter, we first calculate the difference (L-S) in average institutional trading, within an institutional type, between the long leg and short leg of an individual anomaly portfolio. We then average them across anomalies within the same category, and average over time. LT Avg, ST Avg, and ALL Avg are the long-short differences averaged across 7 long-horizon anomaly categories, 4 short-horizon anomaly categories, and all 11 anomaly categories respectively. Panel A, B, C, and D are for large institutions, small institutions, institutions with liquid portfolios, and institutions with illiquid portfolios, 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 statistical significance at 1%, 5%, and 10% respectively.

Panel A: Large Institutions

	Value	Investment	Financing	Quality	Efficiency	Intangible	LT Profit
L-S	-1.80^a	-0.47^a	-1.82^a	-0.07	0.12	-1.01^a	0.38^b
t-stat	(-11.72)	(-4.40)	(-9.06)	(-0.73)	(1.21)	(-6.04)	(2.36)
	Momentum	ST Profit	Distress	Uncertainty	LT Avg	ST Avg	ALL Avg
L-S	1.95^a	0.44^a	0.33^a	0.30^c	-0.67^a	0.75^a	-0.13^b
t-stat	(12.24)	(5.71)	(2.88)	(1.80)	(-7.84)	(6.77)	(-2.02)

Panel B: Small Institutions

	Value	Investment	Financing	Quality	Efficiency	Intangible	LT Profit
L-S	0.02	0.00	-0.02	0.01	0.01	0.05^c	-0.01
t-stat	(0.71)	(0.15)	(-0.78)	(0.52)	(0.31)	(1.86)	(-0.90)
	Momentum	ST Profit	Distress	Uncertainty	LT Avg	ST Avg	ALL Avg
L-S	-0.03	-0.01	-0.03^a	-0.03^b	0.01	-0.02^b	0.00
t-stat	(-1.35)	(-0.76)	(-3.02)	(-2.45)	(0.54)	(-2.36)	(-0.55)

Panel C: Institutions with Liquid Portfolios

	Value	Investment	Financing	Quality	Efficiency	Intangible	LT Profit
L-S	-0.56^a	-0.28^a	-0.40^a	0.00	-0.02	-0.49^a	0.04
t-stat	(-7.85)	(-5.85)	(-5.66)	(-0.07)	(-0.49)	(-7.03)	(0.93)
	Momentum	ST Profit	Distress	Uncertainty	LT Avg	ST Avg	ALL Avg
L-S	0.42^a	0.13^a	0.12^a	0.21^a	-0.24^a	0.22^a	-0.06^b
t-stat	(8.28)	(5.19)	(3.84)	(5.04)	(-7.51)	(6.89)	(-2.61)

Panel D: Institutions with Illiquid Portfolios

	Value	Investment	Financing	Quality	Efficiency	Intangible	LT Profit
L-S	0.36^a	0.39^a	-0.11	-0.09	0.15^b	0.90^a	0.16
t-stat	(2.85)	(4.24)	(-0.90)	(-1.05)	(2.18)	(8.78)	(1.52)
	Momentum	ST Profit	Distress	Uncertainty	LT Avg	ST Avg	ALL Avg
L-S	-0.07	-0.08^c	-0.10^b	-0.32^a	0.25^a	-0.14^a	0.10^b
t-stat	(-0.73)	(-1.96)	(-2.26)	(-4.71)	(4.24)	(-2.77)	(2.49)

Table 7. Liquidity Premium and Liquidity Change Premium

This table 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. Returns are expressed in percentage points. *a*, *b*, and *c* denote statistical significance at 1%, 5%, and 10% respectively, for the t-statistics (not tabulated) of return differences.

Qtr	ILQ	ΔILQ over 2 qtrs	ΔILQ over 6 qtrs
1	0.66	−0.20	0.87
2	0.90	0.85	1.27^b
3	0.82	1.27^b	1.30^b
4	0.65	1.45^a	0.87^c
5	0.38	1.05^b	0.90^b
6	0.33	0.95^b	0.92^b
7	0.26	0.70	0.79^c
8	0.00	0.53	0.61

Table 8. Returns to Anomaly Portfolios: Adjusted for Liquidity Change Premium

This table reports liquidity-adjusted returns to 11 anomaly category portfolios. The liquidity adjusted return of an anomaly portfolio is the return to the portfolio in excess of the liquidity change premium. The liquidity change premium is the average 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 difference in liquidity adjusted returns for an individual anomaly during each of the 8 quarters after portfolio formation, and then average them over anomalies in the same category. Liquidity-adjusted returns are expressed in percentage points. LT Avg, ST Avg, and ALL Avg are the long-short adjusted-return differences averaged across 7 long-horizon anomaly categories, 4 short-horizon anomaly categories, and all 11 anomaly categories respectively. *a*, *b*, and *c* denote statistical significance at 1%, 5%, and 10% respectively, for the t-statistics (not tabulated) of adjusted-return differences.

Qtr	Value	Investment	Financing	Quality	Efficiency	Intangible	LT Profit
1	0.50	0.68^a	1.00^a	0.79^a	1.05^a	1.41^a	1.44^a
2	0.46	0.48^a	0.78^a	0.51^a	0.94^a	1.22^a	1.27^a
3	0.41	0.39^b	0.73^a	0.43^a	0.87^a	1.24^a	1.18^a
4	0.36	0.32^c	0.69^b	0.28^c	0.77^a	1.13^a	1.10^a
5	0.25	0.26	0.66^b	0.24^c	0.74^a	1.22^a	1.05^a
6	0.23	0.29^c	0.52^b	0.26^b	0.65^a	1.21^a	0.95^a
7	0.24	0.28	0.44^c	0.24^c	0.58^a	1.21^a	0.90^a
8	0.15	0.24	0.42	0.26^b	0.55^a	1.06^a	0.90^a
	Momentum	ST Profit	Distress	Uncertainty	LT Avg	ST Avg	ALL Avg
1	1.45^a	1.46^a	0.97^a	0.89^b	0.98^a	1.19^a	1.03^a
2	0.98^a	1.10^a	0.87^a	0.76^b	0.81^a	0.93^a	0.80^a
3	0.44^b	0.49^b	0.72^b	0.45	0.75^a	0.53^b	0.62^a
4	−0.05	0.19	0.45^c	0.29	0.66^a	0.22	0.46^a
5	0.23	0.54^a	0.27	0.39	0.63^a	0.36^c	0.49^a
6	0.18	0.38^c	0.15	0.29	0.59^a	0.25	0.44^a
7	0.07	0.13	0.21	0.20	0.55^a	0.15	0.39^a
8	−0.04	0.29	0.19	−0.03	0.51^a	0.11	0.36^a

Table 9. Market Anomalies Conditional on Institutional Trading $\Delta\%$Inst

This table reports the CAPM alphas of 11 anomaly category portfolios conditional on the directions of institutional trading and the directions of the liquidity-driven component and the non-liquidity component of institutional trading. Institutional trading is measured by change in the percentage of shares held by institutions $\Delta\%$Inst. The liquidity-driven component of institutional trading on a stock is the average institutional trading measure across all stocks in the same liquidity change (ΔILQ) decile. The non-liquidity component of institutional trading is the institutional trading measure in excess of the liquidity-driven component. Institutional trading and liquidity change are measured over 6 quarters for long-horizon anomalies and over 2 quarters for short-horizon anomalies. For each anomaly portfolio we identify a subportfolio on which institutional trading (or its component) is in the wrong direction ("LL-SH"). The long leg of this subportfolio consists of the long-leg stocks in the bottom quintile of institutional trading ("LL"), and the short leg of this subportfolio consists of the short-leg stocks in the top quintile of institutional trading ("SH"). Similarly, we identify an anomaly subportfolio on which institutions trade in the right direction ("LH-SL"). The long leg of this subportfolio consists of the long-leg stocks in the top quintile of institutional trading ("LH"), and the short leg of this subportfolio consists of the short-leg stocks in the bottom quintile of institutional trading ("SL"). 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. In each quarter we compute the CAPM alphas to these subportfolios for an anomaly, and then average them over anomalies in the same category. "Wrong - Right" ((LL-SH)-(LH-SL)) is the alpha difference between the wrong and right subportfolios. LT Avg, ST Avg, and ALL Avg are the alphas of the average anomaly portfolios across 7 long-horizon categories, 4 short-horizon categories, and all 11 anomaly categories respectively. *a*, *b*, and *c* denote statistical significance at 1%, 5%, and 10% respectively, for the t-statistics of alpha differences. Panel 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 CAPM alphas for 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 it belongs to.

Panel A: Conditional on Institutional Trading Δ%Inst

	Value	Investment	Financing	Quality	Efficiency	Intangible	LT Profit
Short+Low (SL)	-0.30	-0.28	-0.70	-0.01	-0.42	-0.64^c	-0.56
Long+High (LH)	0.07	-0.15	0.41	0.07	-0.19	0.15	0.20
LH-SL (Right)	0.36	0.13	1.11^a	0.08	0.23	0.79^c	0.77^c
t-stat	(0.97)	(0.42)	(3.48)	(0.23)	(0.74)	(1.94)	(1.77)
Short+High (SH)	-0.96^b	-0.99^b	-1.23^a	-0.88^b	-1.06^a	-1.25^a	-1.12^a
Long+Low (LL)	0.72	0.65	0.96^b	0.59	0.66	0.84	0.97^b
LL-SH (Wrong)	1.69^a	1.64^a	2.20^a	1.48^a	1.72^a	2.09^a	2.09^a
t-stat	(3.08)	(4.28)	(4.57)	(4.47)	(4.31)	(4.24)	(4.28)
Wrong-Right	1.32^a	1.51^a	1.09^b	1.40^b	1.49^a	1.30^b	1.32^b
t-stat	(2.96)	(2.83)	(2.31)	(2.49)	(2.92)	(2.53)	(2.47)

	Momentum	ST Profit	Distress	Uncertainty	LT Avg	ST Avg	ALL Avg
Short+Low (SL)	-1.12^b	-1.31^a	-1.46^a	-1.73^a	-0.42	-1.40^a	-0.74^c
Long+High (LH)	0.12	0.14	0.11	0.39	0.08	0.19	0.15
LH-SL (Right)	1.24^a	1.45^a	1.57^a	2.12^a	0.50^c	1.59^a	0.89^a
t-stat	(2.94)	(4.24)	(3.55)	(5.13)	(1.88)	(4.55)	(3.76)
Short+High (SH)	-1.16^b	-1.18^a	-1.22^a	-1.09^b	-1.07^a	-1.16^a	-1.07^a
Long+Low (LL)	0.11	0.13	0.29	0.50^c	0.77	0.26	0.60
LL-SH (Wrong)	1.27^a	1.31^a	1.51^a	1.59^a	1.84^a	1.42^a	1.67^a
t-stat	(3.36)	(3.85)	(4.42)	(4.11)	(4.64)	(5.22)	(5.74)
Wrong-Right	0.04	-0.14	-0.06	-0.52	1.35^a	-0.17	0.77^c
t-stat	(0.09)	(-0.29)	(-0.13)	(-1.25)	(2.71)	(-0.40)	(1.96)

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

	Value	Investment	Financing	Quality	Efficiency	Intangible	LT Profit
Short+Low (SL)	0.14	0.16	−0.04	0.34	0.05	−0.25	−0.04
Long+High (LH)	0.20	−0.35	0.65^c	−0.26	−0.24	0.00	0.05
LH-SL (Right)	0.06	−0.51	0.69^c	−0.60	−0.29	0.26	0.09
t-stat	(0.14)	(−1.27)	(1.68)	(−1.42)	(−0.71)	(0.63)	(0.21)
Short+High (SH)	-1.31^a	-1.15^a	-1.73^a	-0.99^b	-1.41^a	-1.42^a	-1.57^a
Long+Low (LL)	0.72	0.63	0.83	0.84	0.70	1.01	1.13^b
LL-SH (Wrong)	2.03^a	1.78^a	2.56^a	1.83^a	2.11^a	2.43^a	2.69^a
t-stat	(3.72)	(3.96)	(4.70)	(4.06)	(4.38)	(4.43)	(4.76)
Wrong-Right	1.96^a	2.29^a	1.87^a	2.42^a	2.40^a	2.17^a	2.61^a
t-stat	(2.92)	(3.01)	(2.68)	(2.98)	(3.06)	(3.03)	(3.39)

	Momentum	ST Profit	Distress	Uncertainty	LT Avg	ST Avg	ALL Avg
Short+Low (SL)	−0.74	-0.95^b	-0.83^c	-1.12^b	0.05	-0.91^c	−0.28
Long+High (LH)	−0.10	−0.06	0.05	0.48	0.01	0.09	0.07
LH-SL (Right)	0.64	0.88^b	0.89^c	1.59^a	−0.04	1.00^b	0.35
t-stat	(1.23)	(1.98)	(1.96)	(3.45)	(−0.13)	(2.29)	(1.08)
Short+High (SH)	-1.85^a	-1.73^a	-1.72^a	-1.60^a	-1.37^a	-1.72^a	-1.44^a
Long+Low (LL)	0.66^c	0.55	0.57	0.59^c	0.83	0.59	0.77^c
LL-SH (Wrong)	2.51^a	2.28^a	2.29^a	2.19^a	2.20^a	2.32^a	2.21^a
t-stat	(6.43)	(4.65)	(4.32)	(4.26)	(4.66)	(5.25)	(5.69)
Wrong-Right	1.87^b	1.39^c	1.40^c	0.60	2.25^a	1.31^c	1.86^a
t-stat	(2.51)	(1.73)	(1.80)	(0.83)	(3.07)	(1.74)	(2.92)

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

	Value	Investment	Financing	Quality	Efficiency	Intangible	LT Profit
Short+Low (SL)	-0.64	-0.56	-1.09^b	-0.29	-0.73^c	-0.90^b	-0.85^b
Long+High (LH)	0.15	0.01	0.46	0.22	-0.04	0.27	0.31
LH-SL (Right)	0.79^c	0.57^c	1.55^a	0.52^c	0.70^b	1.17^a	1.15^a
t-stat	(1.93)	(1.93)	(4.27)	(1.94)	(2.40)	(2.79)	(2.75)
Short+High (SH)	-0.81^b	-0.82^b	-1.07^b	-0.72	-0.87^b	-1.05^a	-0.87^b
Long+Low (LL)	0.69	0.45	0.97^b	0.40	0.44	0.61	0.80^c
LL-SH (Wrong)	1.51^a	1.27^a	2.04^a	1.12^a	1.32^a	1.67^a	1.67^a
t-stat	(3.01)	(4.20)	(4.78)	(4.08)	(3.92)	(4.07)	(3.83)
Wrong-Right	0.72^c	0.70^c	0.49	0.60	0.62	0.50	0.51
t-stat	(1.81)	(1.75)	(1.35)	(1.42)	(1.57)	(1.10)	(1.18)

	Momentum	ST Profit	Distress	Uncertainty	LT Avg	ST Avg	ALL Avg
Short+Low (SL)	-1.18^b	-1.39^a	-1.52^a	-1.74^a	-0.72^c	-1.46^a	-0.96^b
Long+High (LH)	0.16	0.18	0.15	0.39	0.20	0.22	0.24
LH-SL (Right)	1.34^a	1.56^a	1.67^a	2.13^a	0.92^a	1.68^a	1.19^a
t-stat	(3.40)	(4.76)	(3.64)	(5.15)	(3.37)	(4.89)	(4.86)
Short+High (SH)	-1.06^b	-1.12^b	-1.11^b	-1.04^b	-0.89^b	-1.08^b	-0.92^b
Long+Low (LL)	0.01	0.05	0.27	0.49^c	0.63	0.20	0.49
LL-SH (Wrong)	1.07^b	1.16^a	1.38^a	1.53^a	1.51^a	1.29^a	1.41^a
t-stat	(2.50)	(3.37)	(4.46)	(3.82)	(4.68)	(4.38)	(5.50)
Wrong-Right	-0.26	-0.40	-0.30	-0.60	0.59	-0.39	0.22
t-stat	(-0.58)	(-0.88)	(-0.69)	(-1.46)	(1.50)	(-0.91)	(0.62)

Panel D: Liquidity-adjusted Anomaly Magnitude, Conditional on Institutional Trading Δ%Inst

	Value	Investment	Financing	Quality	Efficiency	Intangible	LT Profit
Short+Low (SL)	-1.52^a	-1.57^a	-1.98^a	-1.22^a	-1.77^a	-1.86^a	-1.93^a
Long+High (LH)	-1.01^a	-1.05^a	-0.63^a	-0.77^a	-0.95^a	-0.75^b	-0.61^b
LH-SL (Right)	0.51	0.52^c	1.35^a	0.46^c	0.82^a	1.11^a	1.32^a
t-stat	(1.37)	(1.81)	(4.31)	(1.73)	(2.85)	(2.71)	(3.19)
Short+High (SH)	-1.62^a	-1.77^a	-1.87^a	-1.60^a	-1.86^a	-1.95^a	-1.94^a
Long+Low (LL)	-0.65^a	-0.66^a	-0.39^c	-0.65^a	-0.59^a	-0.50^b	-0.31
LL-SH (Wrong)	0.97^b	1.11^a	1.49^a	0.95^a	1.27^a	1.45^a	1.63^a
t-stat	(2.31)	(4.07)	(4.39)	(3.75)	(3.82)	(4.18)	(3.95)
Wrong-Right	0.46	0.58	0.13	0.49	0.45	0.34	0.31
t-stat	(1.21)	(1.57)	(0.39)	(1.23)	(1.24)	(0.85)	(0.82)
	Momentum	ST Profit	Distress	Uncertainty	LT Avg	ST Avg	ALL Avg
Short+Low (SL)	-2.16^a	-2.29^a	-2.41^a	-2.66^a	-1.69^a	-2.38^a	-1.99^a
Long+High (LH)	-0.64^a	-0.69^a	-0.75^a	-0.58^a	-0.82^a	-0.66^a	-0.81^a
LH-SL (Right)	1.51^a	1.60^a	1.66^a	2.08^a	0.87^a	1.72^a	1.17^a
t-stat	(4.70)	(5.09)	(3.79)	(5.66)	(3.38)	(5.41)	(5.26)
Short+High (SH)	-2.08^a	-1.99^a	-2.01^a	-1.82^a	-1.80^a	-1.97^a	-1.92^a
Long+Low (LL)	-0.86^a	-0.91^a	-0.80^a	-0.66^a	-0.54^a	-0.81^a	-0.69^a
LL-SH (Wrong)	1.22^a	1.08^a	1.21^a	1.16^a	1.26^a	1.17^a	1.22^a
t-stat	(4.03)	(3.34)	(3.92)	(3.41)	(4.59)	(4.65)	(5.65)
Wrong-Right	-0.29	-0.52	-0.45	-0.92^b	0.40	-0.55	0.05
t-stat	(-0.72)	(-1.19)	(-1.12)	(-2.35)	(1.10)	(-1.37)	(0.15)

Internet Appendix

I.1 Mapping 102 Individual Anomalies of Green, Hand, and Zhang (2017) 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 103 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 et al. (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, 76 belong to the 11 categories covered by this study. Among the remaining 26, 10 are measures of liquidity.

- 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, nanlyst, sin, realestate, tb

I.2 Evidence on 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. These results are largely consistent with those for the anomaly categories reported in the paper.

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) tends to be negative for most of the anomalies in long-horizon group, and tends to be positive for most of the anomalies in the short-horizon group.

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, the long legs of anomalies in the long-horizon group tend to be more illiquid and have worsening liquidity, relative to the short legs. By contrast, the long legs of short-horizon anomalies tend to be more liquid and have improving liquidity relative to the short legs.

I.3 Alternative Liquidity Measures

Liquidity is a multi-faceted concept and multiple liquidity measures are available in the existing 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 cost, 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 the daily frequency, ILLIQ is most strongly correlated with the price impact measure based on the intra-day data.

Nonetheless, to ensure the robustness of inference, we also perform analysis using five alternative liquidity measures. Details of these liquidity measures are provided below. They are constructed using the CRSP daily data on a 12-month rolling window up to the end of the portfolio formation period.

1. Dollar turnover (DTO): daily dollar trading volume (shares traded times closing price) as a percentage of total shares outstanding, averaged over the rolling window of 12 months.

2. Roll's (1984) effective spread (ROLL): the first-order autocovariance of the change in daily log price over a rolling window of 12 months, following Hasbrouck (2009). When the autocovariance is negative, ROLL is set to missing.

3. Gibbs estimate of Roll's (1984) effective spread (GIBBS): the Gibbs sampler estimate of the effective spread, estimated using daily data over the rolling window of 12 months, following Hasbrouck (2004; 2009).

4. Hou and Moskowitz (2003) measure of delayed stock return response to market (DELAY): $1 - R^2(0)/R^2(4)$, where $R^2(0)$ is the R-square of regressing weekly stock returns onto contemporaneous weekly market returns, and $R^2(4)$ is the R-square of regressing weekly stock returns onto contemporaneous and 4 lags of weekly market returns.

Market returns are the value-weighted CRSP index returns. Weekly returns are measured from previous Wednesday close to current Wendnesday close. Regressions are performed using weekly returns during the rolling window of 12 months.

5. Lo and MacKinlay (1988) 5-day vs. 1-day variance ratio (VAR5): the variance of 5-day overlapping log return divided by 5 times the variance of one-day log return, over a rolling window of 12 months.

All the above liquidity measures are cross-sectionally ranked into percentiles at the end of each portfolio formation quarter. We adjust the direction of the ranking such that a higher ranking indicates higher illiquidity. Due to different ways of reporting trading volume by stock exchanges, for the measure that involves trading volume, DTO, the cross-sectional ranking is performed separately for NYSE/AMEX stocks and NASDAQ stocks.

We use these five alternative liquidity measures to replace ILQ, and 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 A4. The patterns for both the level and change of liquidity in Table A4 are largely consistent with those in Table 3.

I.3 Results Based on An Alternative Institutional Trading Measure

We have also performed 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 marketcap decile. The corresponding institutional trading measure, Δ#Inst, is the change in the number of institutions holding the stock over 6 quarters for long-horizon anomalies or 2 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. Again, we winsorize the measure at the 0.5 and 99.5 percentiles to alleviate the influence of outliers.

As Edelen et al. (2016) point out, between the two institutional trading measures, Δ#Inst may be more informative in reflecting institutional investors' belief about a stock. However, we notice that the scaling factor of $\#Inst$, i.e., the average number of institutions holding stocks in the same marketcap decile, could sometimes be very low for small-cap stocks. As we shall see below, this may sometimes result in undesirable distributional properties of $\#Inst$. Nonetheless, we find that the key patterns of institutional trading on anomalies based on this measure are consistent with those those based on the first measure %Inst.

In Table A5, we report the the liquidity characteristics of institutional holding and trading using $\#Inst$. This table is constructed in a way similar to Table 4, but with somewhat different results. Panel A of Table A5 shows that #Inst appears to be negatively correlated with ILQ; however the relation is not monotonic. ILQ for the top #Inst decile, at 51.31, is higher than all but the bottom two deciles. This non-monotonicity can be attributed to the denominator effect mentioned above, i.e., the adjustment for market cap in the measure of #Inst, which results in a high proportion of small stocks in the top #Inst decile. Small stocks tend to have few institutional owners, hence a low denominator for #Inst. For a reasonable dispersion in the numerator, i.e., the number of institutional owners on such stocks, the ratio as measured by #Inst could be either very high or very low. That is, small stocks may be over-represented in both the bottom and top #Inst deciles. Since small stocks on average have low liquidity, their presence may cause the average ILQ for the two extreme deciles to be both high. Further, note that #Inst is positively related to change of illiquidity, ΔILQ, a pattern opposite to that for %Inst. However again the economic magnitude of this relation is small, regardless of its direction.

Panel B of Table A5 shows that institutional trading measures $\Delta\#$Inst, over both 2 quarters and 6 quarters, have a U-shaped relation with ILQ. Stocks in both the bottom decile and the top decile of $\Delta\#$Inst appear to be more illiquid, relative to stocks in the middle ranks. This is opposite of the pattern for $\Delta\%$Inst reported in Table 4. Again, this counter-intuitive pattern appears to be related to the size adjustment in constructing $\Delta\#$Inst. Small stocks tend to have a low denominator to $\Delta\#$Inst. Thus, with a reasonable dispersion in the numerator, change of number of institutions holding a stock, small stocks tend to have either very high or very low $\Delta\#$Inst, causing them to show up disproportionally in both the top and bottom $\Delta\#$Inst deciles.

Nonetheless, the table shows that $\Delta\#$Inst has a relatively monotonic and negative relation with liquidity change ΔILQ, consistent with the pattern for $\Delta\%$Inst in Table 4. This particular relation is key to understanding the institutional trading patterns on anomalies.

Table A6 reports institutional trading on anomalies, based $\Delta\#$Inst as well as its liquidity-driven and non-liquidity components. The liquidity-driven component $\Delta\#\text{Inst}_{LIQ}$ is simply the average institutional trading ($\Delta\#$Inst) on all stocks in the same ΔILQ decile during the same period. And 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, $\Delta\#\text{Inst}_{NLQ} = \Delta\#Inst - \Delta\#\text{Inst}_{LIQ}$. For long-horizon anomalies, institutional trading and liquidity change are consistently measured over 6 quarters. For short-horizon anomalies, institutional trading and liquidity change are consistently measured over 2 quarters. The table is constructed in a way similar to Table 2 and Table 5. And the results in this table are largely consistent with those based on $\Delta\%$Inst. That is, 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 significantly related to long-horizon anomalies, but remains significantly positively related to short-horizon anomalies.

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, based on the finding that 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 these anomalies is not driven by the choice of a short-term trading measure, in Table A7 we repeat the analysis of Table 2 for short-horizon anomalies using institutional trading over 6 quarters. The results show that using either $\Delta\%$Inst or $\Delta\#$Inst (both over 6 quarters), institutional investors tend to trade in the right direction of short-horizon anomalies, confirming that reported in Table 2.

I.5 Regression Analysis

We have mainly relied on a sorted portfolio approach and have focused 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 be more inclusive in our analysis, we perform Fama-MacBeth regression analysis on the entire cross section of stocks.

Specifically, we perform cross-sectional regressions to check the relation between institutional trading and anomalies. The dependent variable is the institutional trading measure, either Δ%Inst or Δ#Inst. The main explanatory variable is the the cross-sectional percentile rank of an anomaly category. To obtain this variable, we first obtain the cross-sectional percentile ranks based on an 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 the liquidity change ΔILQ. We also include the log market cap (Ln(Size)) as an additional control.

The results, tabulated in Table A8, 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 are consistent with those based on sorted portfolios, i.e. Tables 2 and 5.

Table A1. Return-predictive Horizons of Individual Anomalies

This table reports returns to long-short portfolios based on 24 individual anomalies. Stocks are sorted quarterly into equal-weighted terciles using each of the 24 individual anomaly variables. The long leg of an anomaly portfolio is the tercile predicted to have high returns and the short leg is the tercile predicted to have 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. Returns are expressed in percentage points. *a*, *b*, and *c* denote statistical significance at 1%, 5%, and 10% respectively, for the t-statistics (not tabulated) of return differences.

	Long-Horizon Anomalies														
	BP	EP	SG	CAPX	AI	AG	NS	XFIN	ACC	DACC	ATTO	NOA	GP	RD	SGA
1	1.36^b	1.04^b	0.83^b	0.86^a	0.70^a	1.51^a	1.52^a	1.83^a	0.84^a	1.08^a	1.22^a	1.33^a	1.77^a	1.80^a	2.12^a
2	1.26^b	1.07^b	0.57^c	0.58^b	0.46^b	1.14^a	1.25^a	1.61^a	0.60^a	0.73^a	1.15^a	1.09^a	1.56^a	1.44^a	1.81^a
3	1.27^b	0.98^b	0.54	0.49^c	0.32	1.05^a	1.26^a	1.41^a	0.55^a	0.63^a	1.02^b	0.97^a	1.40^a	1.37^a	1.71^a
4	1.11^b	0.87^b	0.38	0.36	0.13	0.78^b	1.07^a	1.28^a	0.46^b	0.41^a	0.97^b	0.81^b	1.28^a	1.11^b	1.58^a
5	1.05^b	0.76^c	0.29	0.43^c	0.03	0.80^b	1.02^a	1.25^a	0.38^c	0.30^b	0.89^b	0.90^a	1.18^a	1.24^a	1.63^a
6	0.94^c	0.63	0.34	0.36	0.09	0.71^b	0.96^b	1.12^a	0.36^c	0.28^b	0.80^b	0.79^a	1.10^a	1.19^b	1.47^a
7	0.95^c	0.56	0.26	0.34	0.11	0.62^c	0.79^b	1.01^a	0.20	0.27^c	0.68^c	0.73^b	1.07^a	1.15^b	1.41^a
8	0.78	0.42	0.17	0.31	0.12	0.44	0.70^c	0.88^b	0.23	0.36^b	0.60	0.64^b	0.97^a	0.95^b	1.26^a

	Short-Horizon Anomalies								
	MOM	SUE	FRV	ROE	GM	OSCORE	CHS	IVOL	DISP
1	1.77^a	1.86^a	1.56^a	2.63^a	0.83^b	0.49^c	1.87^a	1.47^b	0.81^b
2	0.71	0.82^a	1.06^a	1.69^a	0.68^b	0.58^b	1.44^a	1.22^c	0.57
3	−0.07	0.28	0.30	0.68	0.47	0.51^c	1.29^a	1.12	0.12
4	−0.78	−0.23	−0.13	0.23	0.27	0.55^b	0.69^c	0.94	−0.11

Table A2: Institutional Trading on Individual Anomalies

This table reports institutional trading measures on the 24 individual-anomaly portfolios. The institutional trading 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. 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 statistical significance at 1%, 5%, and 10% respectively.

	Long-Horizon Anomalies														
	BP	EP	SG	CAPX	AI	AG	NS	XFIN	ACC	DACC	ATTO	NOA	GP	RD	SGA
Short	4.18	3.60	4.25	3.01	2.59	4.24	4.32	3.98	3.34	3.25	2.98	3.32	2.89	3.20	3.52
Long	1.82	2.59	2.21	3.17	2.94	2.40	2.13	2.43	3.10	3.30	3.21	3.47	3.29	2.84	2.33
L-S	-2.36^a	-1.01^a	-2.04^a	0.17	0.35^a	-1.84^a	-2.19^a	-1.56^a	−0.24	0.05	0.23	0.15	0.40^b	-0.36^c	-1.19^a
t-stat	(−9.73)	(−5.76)	(−10.17)	(1.24)	(2.66)	(−9.81)	(−10.02)	(−8.29)	(−1.63)	(0.46)	(1.05)	(1.06)	(2.18)	(−1.78)	(−4.85)

	Short-Horizon Anomalies								
	MOM	SUE	FRV	ROE	GM	OSCORE	CHS	IVOL	DISP
Short	−0.37	0.26	−0.04	0.71	0.88	1.30	0.32	0.98	0.60
Long	2.53	1.33	2.10	1.30	1.16	0.76	1.40	0.65	1.45
L-S	2.91^a	1.07^a	2.14^a	0.59^a	0.28^a	-0.53^a	1.07^a	-0.34^c	0.85^a
t-stat	(12.59)	(9.44)	(9.80)	(4.17)	(3.82)	(−5.91)	(5.68)	(−1.80)	(4.39)

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 (with value between 0 and 100) of 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. 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 statistical significance at 1%, 5%, and 10% respectively.

ILQ for Long-Horizon Anomalies															
	BP	EP	SG	CAPX	AI	AG	NS	XFIN	ACC	DACC	ATTO	NOA	GP	RD	SGA
Short	39.05	43.77	45.22	44.74	49.33	45.07	45.91	49.03	51.52	50.41	44.69	50.74	48.55	42.87	40.13
Long	60.50	53.90	54.37	55.68	52.68	54.77	47.51	48.11	50.13	47.39	54.90	50.27	49.14	51.63	62.45
L-S	21.46^a	10.14^a	9.15^a	10.95^a	3.35^a	9.70^a	1.60	−0.92	-1.39^a	-3.03^a	10.21^a	−0.46	0.59	8.76^a	22.32^a
t-stat	(25.33)	(8.24)	(15.18)	(14.50)	(6.27)	(13.45)	(1.08)	(−1.00)	(−3.17)	(−7.90)	(16.80)	(−0.80)	(0.90)	(12.32)	(34.80)
ΔILQ for Long-Horizon Anomalies															
	BP	EP	SG	CAPX	AI	AG	NS	XFIN	ACC	DACC	ATTO	NOA	GP	RD	SGA
Short	−3.64	−1.85	−3.93	−1.00	−1.17	−3.73	−4.04	−2.49	−1.30	−0.67	−0.36	−1.55	−0.33	−2.06	−2.55
Long	2.06	−0.26	2.32	−0.23	0.46	1.84	1.33	0.16	−0.40	−0.89	−1.13	−0.40	−1.09	1.38	1.63
L-S	5.71^a	1.60^a	6.25^a	0.78^a	1.63^a	5.57^a	5.36^a	2.65^a	0.90^a	−0.22	-0.77^b	1.15^a	-0.75^b	3.45^a	4.18^a
t-stat	(14.88)	(3.87)	(23.19)	(4.11)	(10.03)	(16.68)	(14.34)	(8.64)	(5.24)	(−1.15)	(−2.10)	(4.22)	(−2.63)	(11.00)	(8.89)

ILQ for Short-Horizon Anomalies									
	MOM	SUE	FRV	ROE	GM	OSCORE	CHS	IVOL	DISP
Short	50.08	50.33	47.45	56.15	53.44	59.33	59.55	59.50	46.66
Long	50.30	45.61	41.87	42.42	44.10	41.65	42.07	39.53	33.77
L-S	0.22	-4.72^a	-5.59^a	-13.73^a	-9.34^a	-17.69^a	-17.48^a	-19.98^a	-12.89^a
t-stat	(0.22)	(−11.67)	(−15.11)	(−20.63)	(−30.94)	(−33.10)	(−23.99)	(−16.06)	(−19.25)
ΔILQ for Short-Horizon Anomalies									
	MOM	SUE	FRV	ROE	GM	OSCORE	CHS	IVOL	DISP
Short	2.23	0.85	1.18	0.41	−0.20	−0.87	0.56	−0.57	0.46
Long	−3.54	−1.54	−1.87	−1.32	−0.65	−0.14	−1.03	−0.29	−1.16
L-S	-5.77^a	-2.39^a	-3.05^a	-1.73^a	-0.45^a	0.73^a	-1.59^a	0.28	-1.62^a
t-stat	(−27.53)	(−17.91)	(−19.03)	(−10.48)	(−5.00)	(7.57)	(−7.87)	(0.96)	(−7.56)

Table A4. Liquidity Characteristics of Anomaly Portfolios Under Alternative Liquidity Measures

This table reports the illiquidity level and change of 11 anomaly category portfolios using alternative liquidity measures. The five alternative liquidity measures include dollar trading volume (DTO), Roll's effective spread (Roll), Gibbs sample estimate of the effective spread (Gibbs), Delayed return response to market (Delay), and 5-to-1 daily return variance ratio (VAR5). There measures are cross-sectionally ranked into percentiles, with a higher ranking indicating higher illiquidity. Measures of illiquidity change (liquidity measures preceded by Δ) is the change of illiquidity ranking 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 over anomalies in the same category. LT Avg, ST Avg, and ALL Avg are the liquidity level and change measures averaged across 7 long-horizon anomaly categories, 4 short-horizon anomaly categories, and all 11 anomaly categories respectively. The t-statistics are computed using the Newey-West standard errors. a, b, and c denote statistical significance at 1%, 5%, and 10% respectively. Panel A and B report the level and change of illiquidity respectively.

Panel A: Difference in Illiquidity Level ILQ Between Long and Short Legs

	Value	Investment	Financing	Quality	Efficiency	Intangible	LT Profit
DTO	15.21^{a}	9.23^{a}	6.69^{a}	0.91^{c}	0.49	11.83^{a}	-3.93^{a}
Roll	4.49^{a}	3.62^{a}	0.81^{b}	0.27	0.95^{a}	6.32^{a}	-0.19
Gibbs	3.60^{a}	4.79^{a}	-2.87^{a}	-0.92^{a}	3.25^{a}	10.91^{a}	0.69
Delay	5.55^{a}	3.84^{a}	0.75	-0.22	2.01^{a}	7.30^{a}	0.26
VAR5	5.13^{a}	3.51^{a}	2.59^{a}	0.58^{c}	-0.45	3.90^{a}	-1.45^{b}

	Momentum	ST Profit	Distress	Uncertainty	LT Avg	ST Avg	ALL Avg
DTO	-5.70^{a}	-11.06^{a}	-11.55^{a}	-5.06^{a}	5.77^{a}	-7.85^{a}	0.86^{b}
Roll	-2.79^{a}	-3.51^{a}	-6.36^{a}	-9.16^{a}	2.32^{a}	-5.71^{a}	-0.48^{b}
Gibbs	-3.92^{a}	-5.91^{a}	-15.91^{a}	-23.47^{a}	2.77^{a}	-13.12^{a}	-2.69^{a}
Delay	-2.89^{a}	-5.78^{a}	-8.85^{a}	-8.66^{a}	2.78^{a}	-6.51^{a}	-0.51
VAR5	-1.78^{a}	-1.49^{a}	-3.93^{a}	-5.23^{a}	1.97^{a}	-3.57^{a}	0.10

Panel B: Difference in Illiquidity Change ΔILQ Between Long and Short Legs

	Value	Investment	Financing	Quality	Efficiency	Intangible	LT Profit
ΔDTO	2.90^{a}	1.14^{a}	0.60	-1.01^{a}	-0.47	2.46^{a}	-0.92^{c}
ΔRoll	0.48	0.66^{a}	0.17	0.07	0.00	0.64^{c}	0.12
ΔGibbs	1.44^{a}	0.88^{a}	0.93^{b}	-0.04	-0.63^{c}	1.02^{a}	-0.90^{b}
ΔDelay	1.89^{a}	0.61^{b}	1.42^{a}	-0.42^{c}	-0.38	1.25^{a}	-0.55
ΔVAR5	0.22	0.93^{a}	-0.14	0.17	-0.12	0.34	0.07

	Momentum	ST Profit	Distress	Uncertainty	LT Avg	ST Avg	ALL Avg
ΔDTO	-7.20^{a}	-1.58^{a}	-0.50^{b}	0.29	0.67^{b}	-2.26^{a}	-0.38^{b}
ΔRoll	-2.91^{a}	-0.55^{a}	-0.60^{a}	-0.95^{a}	0.31	-1.30^{a}	-0.26^{b}
ΔGibbs	-3.95^{a}	-0.79^{a}	-0.70^{a}	-1.04^{a}	0.39^{b}	-1.69^{a}	-0.35^{b}
ΔDelay	-2.81^{a}	-0.85^{a}	0.25	-0.83^{b}	0.55^{b}	-1.05^{a}	-0.03
ΔVAR5	-2.27^{a}	-0.35^{c}	-0.47^{b}	-0.93^{a}	0.21	-1.09^{a}	-0.25

Table A5. Liquidity Characteristics of Institutional Holding and Trading, Based on #Inst and Δ#Inst

This table reports the illiquidity level of and change of stock portfolios sorted by alternative measures of institutional holding and trading. Institutional holding is measured by the size-adjusted number of institutional owners (#Inst). Institutional trading is measured by the size-adjusted change in number of institutional owners (Δ#Inst), over both 2 quarters and 6 quarters. We measure stock illiquidity (ILQ) by the cross-sectional percentile rank (with value between 0 and 100) of Amihud illiquidity ratio. Illiquidity change ΔILQ is the change of ILQ, over both 2 quarters and 6 quarters. Panel A report the average level and change in illiquidity (ILQ, ΔILQ over 2 quarters, and *Delta*ILQ over 6 quarters) for stock deciles sorted by institutional holding #Inst. Panel B report 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 compute 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 statistical significance at 1%, 5%, and 10% respectively.

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

	by #Inst		
	ILQ	ΔILQ 2-Qtr	ΔILQ 6-Qtr
Low	70.06	−0.78	−0.46
2	55.66	−1.02	−1.53
3	49.39	−0.94	−1.66
4	47.71	−0.75	−1.31
5	45.40	−0.69	−1.26
6	44.86	−0.48	−0.95
7	43.60	−0.35	−0.58
8	43.42	−0.22	−0.37
9	44.97	0.08	0.27
High	51.31	0.77	1.90
H-L	-18.75^a	1.56^a	2.36^a
t-stat	(−12.27)	(8.9)	(7.92)

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

	by 2-Qtr Δ#Inst		by 6-Qtr Δ#Inst	
	ILQ	ΔILQ 2-Qtr	ILQ	ΔILQ 6-Qtr
Low	56.46	1.42	58.42	7.19
2	48.91	0.98	50.54	4.67
3	43.33	0.61	48.48	2.80
4	46.52	0.34	43.92	1.75
5	42.23	0.09	43.86	0.76
6	41.27	−0.17	44.01	−0.40
7	44.24	−0.61	46.63	−1.68
8	47.87	−1.25	48.21	−3.81
9	53.09	−2.23	50.77	−7.41
High	60.13	−4.25	52.65	−14.80
H-L	3.67[a]	−5.67[a]	−5.77[a]	−21.99[a]
t-stat	(3.16)	(−20.14)	(−3.15)	(−23.49)

Table A6. 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. The alternative measure is the size-adjusted change in number of institutional owners, Δ#Inst. It is measured over 6 quarters for long-horizon anomalies and over 2 quarters for short-horizon anomalies. The institutional trading measure 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 statistical significance at 1%, 5%, and 10% respectively.

Panel A: Institutional Trading, Δ#Inst

	Value	Investment	Financing	Quality	Efficiency	Intangible	LT Profit
Short	29.83	25.41	30.41	23.82	21.79	24.73	18.26
Long	15.48	19.26	16.57	22.83	24.76	18.13	25.53
L-S	-14.35^a	-6.15^a	-13.84^a	-0.99^c	2.97^b	-6.60^a	7.27^a
t-stat	(−10.22)	(−7.72)	(−11.42)	(−1.97)	(2.30)	(−5.62)	(4.89)
	Momentum	ST Profit	Distress	Uncertainty	LT Avg	ST Avg	ALL Avg
Short	−0.92	4.44	5.42	5.36	24.89	3.58	16.88
Long	14.43	8.76	7.64	6.90	20.36	9.43	16.34
L-S	15.35^a	4.32^a	2.22^a	1.54^a	-4.53^a	5.86^a	−0.54
t-stat	(25.01)	(12.26)	(6.34)	(3.12)	(−5.48)	(15.87)	(−1.02)

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

	Value	Investment	Financing	Quality	Efficiency	Intangible	LT Profit
Short	27.27	24.63	27.94	22.89	22.40	24.65	20.71
Long	17.12	19.14	18.08	21.81	22.60	17.90	22.92
L-S	-10.14^a	-5.49^a	-9.87^a	-1.08^a	0.19	-6.75^a	2.21^b
t-stat	(−11.48)	(−11.30)	(−10.88)	(−3.84)	(0.31)	(−9.19)	(2.54)
	Momentum	ST Profit	Distress	Uncertainty	LT Avg	ST Avg	ALL Avg
Short	4.33	5.92	6.27	6.17	24.36	5.67	17.36
Long	8.84	7.20	6.72	6.78	19.94	7.38	15.27
L-S	4.51^a	1.27^a	0.45^a	0.60^b	-4.42^a	1.71^a	-2.09^a
t-stat	(14.85)	(9.54)	(2.90)	(2.42)	(−8.25)	(9.36)	(−6.01)

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

	Value	Investment	Financing	Quality	Efficiency	Intangible	LT Profit
Short	2.56	0.78	2.46	0.93	−0.61	0.09	−2.45
Long	−1.64	0.12	−1.51	1.02	2.17	0.23	2.61
L-S	-4.21^a	−0.66	-3.97^a	0.09	2.78^a	0.14	5.06^a
t-stat	(−5.68)	(−1.06)	(−6.98)	(0.20)	(3.76)	(0.18)	(6.33)
	Momentum	**ST Profit**	**Distress**	**Uncertainty**	**LT Avg**	**ST Avg**	**ALL Avg**
Short	−5.25	−1.48	−0.85	−0.82	0.54	−2.10	−0.47
Long	5.59	1.56	0.92	0.13	0.43	2.05	1.07
L-S	10.84^a	3.04^a	1.77^a	0.94^b	−0.11	4.15^a	1.55^a
t-stat	(27.58)	(11.04)	(6.40)	(2.57)	(−0.25)	(15.48)	(5.89)

Table A7. Institutional Trading on Short-Horizon Market Anomalies over 6 quarters

This table reports institutional trading measures on the 4 short-horizon anomaly category portfolios over previous 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 ($\Delta\%\text{Inst}_{LIQ}$ and $\Delta\#\text{Inst}_{LIQ}$) is the average institutional trading measure across all stocks in the same liquidity change (ΔILQ) decile. The non-liquidity component of institutional trading ($\Delta\%\text{Inst}_{NLQ}$ and $\Delta\#\text{Inst}_{NLQ}$) 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 long-short difference in institutional trading averaged across 4 short-horizon anomaly categories. 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 statistical significance at 1%, 5%, and 10% respectively.

Panel A: Δ%Inst

	Momentum	ST Profit	Distress	Uncertainty	ST Avg
			Δ%Inst		
Short	1.61	2.43	2.46	2.69	2.30
Long	4.64	3.58	3.26	3.19	3.67
L-S	3.03^{a}	1.15^{a}	0.80^{a}	0.50	1.37^{a}
t-stat	(8.51)	(5.94)	(2.96)	(1.47)	(5.17)
			Liquidity-driven $\Delta\%\text{Inst}_{LIQ}$		
Short	2.64	2.76	2.89	3.09	2.84
Long	3.56	3.29	3.07	2.99	3.23
L-S	0.92^{a}	0.53^{a}	0.18^{c}	-0.10	0.39^{a}
t-stat	(12.04)	(7.71)	(1.90)	(-0.66)	(4.76)
			Non-Liquidity $\Delta\%\text{Inst}_{NLQ}$		
Short	-1.03	-0.33	-0.42	-0.39	-0.54
Long	1.07	0.29	0.20	0.20	0.44
L-S	2.11^{a}	0.61^{a}	0.62^{a}	0.60^{b}	0.98^{a}
t-stat	(6.35)	(3.78)	(2.78)	(2.17)	(4.30)

Panel B: Δ#Inst

	Momentum	ST Profit	Distress	Uncertainty	ST Avg
	Δ#Inst				
Short	8.91	15.43	17.71	19.75	15.45
Long	37.90	28.02	24.69	23.12	28.43
L-S	29.00^a	12.59^a	6.97^a	3.36^a	12.98^a
t-stat	(16.87)	(12.97)	(7.49)	(2.81)	(12.63)
	Liquidity-driven Δ#Inst$_{LIQ}$				
Short	18.10	19.14	19.99	21.03	19.56
Long	26.53	24.28	22.64	22.56	24.00
L-S	8.44^a	5.14^a	2.65^a	1.53	4.44^a
t-stat	(10.16)	(9.07)	(4.37)	(1.64)	(6.77)
	Non-Liquidity Δ#Inst$_{NLQ}$				
Short	−9.19	−3.71	−2.28	−1.28	−4.11
Long	11.37	3.74	2.05	0.55	4.43
L-S	20.56^a	7.44^a	4.33^a	1.83^b	8.54^a
t-stat	(19.72)	(11.79)	(6.73)	(2.26)	(13.88)

Table A8. Fama-MacBeth Regressions: 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. 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. "LT Avg" and "ST Avg" are the results where the main explanatory variable is the average anomaly ranks across long-horizon and short-horizon anomalies, respectively. The t-statistics, reported in parentheses, are computed using the Newey-West (1987) standard errors. The regression include an intercept, which is not tabulated. *a*, *b*, and *c* denote statistical 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	-0.057^a	-0.018^a	-0.038^a	-0.004^c	0.004	-0.017^a	0.006^b	-0.057^a
	(−11.29)	(−5.53)	(−10.55)	(−1.77)	(1.12)	(−5.54)	(2.13)	(−7.20)
Ln(Size)	-0.190^a	−0.072	0.010	−0.050	−0.043	-0.123^c	−0.045	−0.110
	(−2.78)	(−1.04)	(0.16)	(−0.73)	(−0.64)	(−1.72)	(−0.66)	(−1.60)
				Controlling for ΔILQ				
Anomaly	-0.020^a	0.003	-0.012^a	0.000	0.004	−0.001	0.003	-0.010^c
	(−5.18)	(1.17)	(−4.85)	(0.09)	(1.39)	(−0.19)	(1.48)	(−1.74)
ΔILQ	-0.262^a	-0.271^a	-0.265^a	-0.271^a	-0.270^a	-0.275^a	-0.270^a	-0.268^a
	(−14.17)	(−14.40)	(−14.42)	(−14.39)	(−14.29)	(−14.21)	(−14.26)	(−14.26)
Ln(Size)	-0.246^a	-0.201^a	-0.188^a	-0.208^a	-0.199^a	-0.203^a	-0.202^a	-0.212^a
	(−3.79)	(−3.15)	(−3.06)	(−3.35)	(−3.17)	(−3.06)	(−3.22)	(−3.31)

	Momentum	ST Profit	Distress	Uncertainty	ST Avg
	Without Controlling for ΔILQ				
Anomaly	0.054^a	0.011^a	0.008^a	0.006^c	0.043^a
	(12.57)	(5.58)	(3.80)	(1.75)	(7.97)
Ln(Size)	-0.169^a	-0.081^b	-0.085^a	-0.078^a	-0.213^a
	(−5.62)	(−2.60)	(−2.83)	(−2.73)	(−7.34)
	Controlling for ΔILQ				
Anomaly	0.044^a	0.008^a	0.007^a	0.006^c	0.033^a
	(9.46)	(4.08)	(3.67)	(1.84)	(6.16)
ΔILQ	-0.120^a	-0.173^a	-0.174^a	-0.173^a	-0.160^a
	(−7.38)	(−11.84)	(−11.95)	(−11.76)	(−10.06)
Ln(Size)	-0.160^a	-0.092^a	-0.103^a	-0.100^a	-0.197^a
	(−5.73)	(−3.14)	(−3.66)	(−3.38)	(−6.83)

Panel B: Δ#Inst as Dependent Variable

	Value	Investment	Financing	Quality	Efficiency	Intangible	LT Profit	LT Avg
	Without Controlling for ΔILQ							
Anomaly	-0.431^a	-0.201^a	-0.285^a	-0.033^a	0.072^a	-0.103^a	0.103^a	-0.360^a
	(−13.47)	(−9.88)	(−12.28)	(−3.02)	(2.78)	(−4.89)	(4.67)	(−7.40)
Ln(Size)	-1.966^a	-1.233^c	−0.647	−0.946	−0.830	-1.277^b	−0.874	-1.360^b
	(−3.32)	(−1.86)	(−0.96)	(−1.44)	(−1.35)	(−2.08)	(−1.37)	(−2.26)
	Controlling for ΔILQ							
Anomaly	-0.182^a	-0.056^a	-0.121^a	−0.003	0.055^a	−0.002	0.071^a	-0.079^a
	(−7.89)	(−2.88)	(−7.98)	(−0.26)	(4.72)	(−0.18)	(6.26)	(−2.83)
ΔILQ	-1.931^a	-1.987^a	-1.959^a	-1.996^a	-1.988^a	-2.025^a	-1.987^a	-1.984^a
	(−17.32)	(−17.51)	(−17.32)	(−17.62)	(−18.12)	(−16.98)	(−18.09)	(−17.58)
Ln(Size)	-2.491^a	-2.229^a	-2.036^a	-2.163^a	-2.074^a	-2.026^a	-2.102^a	-2.222^a
	(−4.12)	(−3.54)	(−3.22)	(−3.50)	(−3.44)	(−3.20)	(−3.44)	(−3.63)

	Momentum	ST Profit	Distress	Uncertainty	ST Avg
	Without Controlling for ΔILQ				
Anomaly	0.402^{a}	0.110^{a}	0.061^{a}	0.008	0.320^{a}
	(27.06)	(11.41)	(7.83)	(0.71)	(17.99)
Ln(Size)	-1.175^{a}	-0.630^{a}	-0.588^{b}	-0.338	-1.542^{a}
	(-5.92)	(-2.82)	(-2.53)	(-1.53)	(-6.39)
	Controlling for ΔILQ				
Anomaly	0.355^{a}	0.087^{a}	0.052^{a}	0.001	0.261^{a}
	(28.74)	(11.30)	(9.24)	(0.11)	(18.94)
ΔILQ	-0.487^{a}	-0.937^{a}	-0.955^{a}	-0.952^{a}	-0.840^{a}
	(-16.26)	(-18.66)	(-19.18)	(-18.55)	(-19.08)
Ln(Size)	-1.126^{a}	-0.674^{a}	-0.659^{a}	-0.414^{b}	-1.411^{a}
	(-5.81)	(-3.23)	(-3.08)	(-2.07)	(-6.39)