Liquidity Characteristics of Market Anomalies and Institutional Trading

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Abstract

The long and short legs of stock portfolios formed on market anomalies typically have different liquidity characteristics. For anomalies with long return-predictive horizons, the long legs of the anomaly portfolios tend to be less liquid and have deteriorating liquidity relative to the short legs. Short-horizon anomaly portfolios exhibit an opposite pattern. We show that liquidity characteristics go a long way in explaining how institutional investors trade on anomalies. Consistent with institutional investors' 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. The perverse pattern of 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.

In this study, we examine the liquidity characteristics of market anomalies and how liquidity affects institutional trading on anomalies. We find that the long and short legs of anomaly portfolios typically have different liquidity characteristics. Such liquidity characteristics, combined with institutional preference for liquidity, go a long way in explaining how institutions trade on anomalies. Further, we find that the liquidity-driven trades and non-liquidity-driven trades by institutions are related to mispricing in very different ways.

We examine market anomalies in 11 broad categories that cover a large proportion of individual anomalies documented in existing studies. Consistent with the finding of Daniel, Hirshleifer, and Sun, (2019), these anomalies can be classified into two groups based on their return-predictive horizons. Seven categories of anomalies, including value, investment, financing, quality, efficiency, intangible investments, and gross profitability, predict stock returns at relatively long horizons, e.g., beyond one year. Anomalies in the other four categories, including momentum, short-term profitability, distress, and uncertainty, predict

[1] See, e.g., Alangar, Bathala, and Rao, 1999; 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; Shu, 2013.

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.[2] For example, based on change in percentage of shares held by institutions, net institutional trading is in the wrong direction of five out of seven long-horizon categories – value, investment, financing, quality, and intangible anomalies, and in the right direction of all the four short-horizon categories – momentum, short-term profitability, distress, and uncertainty.[3] 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 direct 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 the 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.

The liquidity preference of institutional investors has been well documented in the existing literature (e.g., Gompers and Metrick, 2001). Due to their large portfolio size and the concern for trading cost, institutions tend to hold liquid stocks. In this study, we show that such a liquidity preference translates into two patterns on institutional trading. First, because most institutions are long-only investors, the stocks they sell must be those they already

[2]Following Edelen Ince, and Kadlec (2016), 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, where institutional trading is measured by either the change in percentage of shares held by institutions or in the number of institutional owners.

[3]Averaged over the 11 anomaly categories, net institutional trading difference between the long and short legs of anomaly portfolios is insignificantly negative. That is, although institutions tend to be on the wrong side of the anomalies, they are not significantly wrong.

hold. Thus the stocks institutions bought and the stocks they sold are similarly liquid. Second, when stock liquidity changes substantially over time, to maintain liquid positions, institutions tend to be net sellers of stocks that have become less liquid and net buyers on stocks that have become more liquid.

To see the extent to which the above-described liquidity preference drives the institutional investors' trading behavior on anomalies, we decompose institutional trading into a liquidity-driven component and a non-liquidity component. We find that averaged over all anomalies, the net liquidity-driven component of institutional trading is significantly negative while the net non-liquidity component is significantly positive. Thus, at the aggregate level, the perverse institutional trading on anomalies, if any, is mainly driven by liquidity, and the part of institutional trading not driven by liquidity does appear to be in the right direction of anomalies. 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. Further, averaged across the long-horizon anomalies, the net liquidity-driven institutional trading is significantly negative, while the net non-liquidity component is statistically insignificant. This suggests that liquidity is the key factor that causes institutional trading to be on the wrong side of long-horizon anomalies.

Having shown that liquidity is important for understanding the institutional trading pattern on anomalies, we further address two issues regarding 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, liquidity premium under its conventional measure – the return difference between illiquid and liquid stocks – has largely disappeared. 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 returns to the long-short value anomaly portfolio. 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 – potentially driven by the institutional liquidity preference – does not completely explain the returns to anomaly portfolios.

Second, we re-examine whether market anomalies are aggravated by institutions' tendency to trade in the wrong direction of anomalies, an observation by Edelen et al. (2016) that implicates institutional investors on market mispricing. We follow Edelen et al. to 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 their finding on long-horizon anomalies. For these 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. Further, we find that liquidity-driven institutional trading, when in the wrong direction, tends to significantly exacerbate the magnitude of long-horizon anomalies. But the direction of non-liquidity component of institutional trading is not significantly related to the magnitude of these anomalies. Thus, liquidity appears to be responsible for institutional price impact that aggravates market inefficiency.

The pattern is different for short-horizon anomalies. Based on change in percentage of institutional ownership, the direction of institutional trading does not cause a significant difference in the magnitude of these anomalies. Based on change in the number of institutional investors, we find that short-horizon anomalies are stronger when institutional trading is in the right direction, an effect mainly driven by the non-liquidity component of institutional trading. This suggests that hen trading on short-horizon anomalies, institutions may have stock selection skills and they pick more mispriced stocks to trade on.

The main contribution of this study is to document pervasive liquidity characteristics of market anomalies and show that such liquidity characteristics, combined with institutional preference for liquidity, are important for understanding how institutions trade on anomalies. Our findings are different from Edelen et al. (2016) in several dimensions. First, we cover a broader set of anomalies and find that institutions do not significantly trade in the wrong direction of anomalies on aggregate. Second, our analysis reveals that the direction of institutional trading on anomalies is heterogeneous and depends on the return-predictive horizon. Third, liquidity characteristics are important for understanding how institutions trade on long- vs short-horizon anomalies. Finally, institutions' liquidity-driven trades on long-horizon anomalies intensify mispricing, while their (non-liquidity) trades on short-horizon anomalies appear to exhibit stock-selection skills.

A few existing studies, mostly in the mutual fund literature, have also examined the direction of institutional trading on anomalies. Grinblatt, Titman, and Wermers (1995) and Carhart (1997) find that funds chase stock price momentum. Ali, Chen, Yao, and Yu (2006 and 2020) find that few mutual 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 mutual 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. These findings combined provide a rich picture of how mutual funds trade on anomalies. Our study adds to this literature by highlighting the role of liquidity in explaining the heterogenous 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 Subrahmanyam (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 it gets broadly publicized. 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. Relative to these effects, the explanation provided by our study, i.e., the liquidity characteristics of anomalies, is unique in that it helps explain the heterogenous patterns of institutional trading related to the horizons of anomalies.

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 concludes.

II. Data, Sample, and Variables

II.A. Market Anomalies

Existing studies have reported and analyzed several hundreds of individual market anomalies; e.g., Green, Hand, and Zhang (2013 and 2017); Harvey, Liu, and Zhu (2016), Pontiff and McLean (2016); Hou, Xue, and Zhang (2018). It is a challenge if we were to analyze institutional trading on all individual anomalies and tabulate all the results. However, despite the large number, many anomalies are related to each other conceptually and economically, and they 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 referred to as the value anomaly (e.g., Fama and French 1996), while price momentum, standardized unexpected earnings, and earnings announcement window returns are collectively known 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 2018).

The approach of this study is to focus on the relatively small number of, but broadly representative, anomaly categories. Specifically, we include 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 classifications of individual anomalies have been used in several existing studies; e.g., Wei, Wermers, and Yao (2015), and Daniel, Hirshleifer, and Sun (2019). 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)

Appendix A provides further details on the construction of these individual anomalies. As we show subsequently, the first 7 categories (Value, Investment, Financing, Quality, Efficiency, Intangible, and LT Profitability) have long return-predictive horizons and the last 4 categories (Momentum, ST Profitability, Distress, and Uncertainty) have short return-predictive horizons.

It is worth mentioning that 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. In Appendix B, we provide further details on how the 102 anomalies of Green, Hand, and Zhang (2017) map into the anomaly categories of this study.

Also note that the categories of anomalies in this study include and extend those in Edelen et al. (2016). They 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). They do not examine anomalies in the quality, intangible, short-term profitability, or uncertainty categories. In addition, 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. He does not examine anomalies in the efficiency, intangible, long-horizon profitability, or distress categories.

II.B. Data and Anomaly Portfolios

We use data from CRSP, Compustat, and IBES to construct anomaly variables. Quarterly institutional holdings are obtained from the 13F institutional holding dataset by Thomson-Reuters. The sample period for our analysis on institutional holdings and trades are for the period of 1980-2018. For the liquidity characteristics and return predictive horizons of anomalies, we go back to include earlier years and cover the period of 1963-2018.

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. Then, following existing studies (e.g., Fama and French 2008), we 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 constructed from Compustat annual data, portfolios formed from June of year t to March of year t+1 are based on data for financial statements reported for the fiscal year that ends in calendar year t-1. This procedure follows Fama and French (1996) and essentially allows a minimum of six-month lag for accounting information to be available after the fiscal year end. For anomalies constructed from Compustat quarterly data, we use the earnings reporting dates reported by Compustat to determine when the financial statement data are available. If the earnings reporting date is missing, we follow the existing literature (e.g., Green, Hand, and Zhang, 2017) and assume that the data are 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 of an anomaly portfolio is the tercile portfolio predicted to have the lowest returns. This procedure roughly follows Edelen et al. (2016), who define the long leg as the top 30% of stocks and the short leg as the bottom 30% of stocks ranked by an anomaly variable. We further use equal weights to combine the long legs and short legs of individual anomalies in a given category to form the corresponding log leg and short leg of the category-level anomaly portfolio.

We look at equal-weighted portfolios instead of value-weighted portfolios because the objective of our analysis is to see whether institutional investors trade on the anomalies, rather than to assess the economic magnitude or pervasiveness of mispricing in the financial market. Anomalies are typically stronger among smaller stocks. If institutional investors are to exploit an anomaly, they will likely weigh more on stocks believed to have a higher magnitude of mispricing rather than to follow value weights. Note that Edelen et al. (2016) also take equal weights across stocks when measuring institutional trading on stocks in an anomaly portfolio. When reporting portfolio returns, however, they take a mixed approach, by first splitting stocks in an anomaly portfolio into two size groups, taking value-weighted average returns within each size group and then taking equal-weighted average between the two groups.

II.C. Liquidity Measures

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

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

where r_t is the daily stock return, S_t is the daily number of shares traded, and P_t is the daily closing price. T is the total number of trading days during the measurement period. At the end of each quarter, we estimate ILLIQ using the daily data over the previous 12 months; thus T is approximately 252 (trading days).

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 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.

As we show subsequently, the long and short legs of anomaly portfolios have different characteristics in terms of liquidity change. For long-horizon anomalies, liquidity change is the difference of ILQ over a 6-quarter period, from quarter t-5 to quarter t (the portfolio formation quarter). For short-horizon anomalies, we measure liquidity change over a 2-quarter period, from quarter t-1 to quarter t. A high value of ΔILQ indicates deteriorating liquidity.

Liquidity is a multi-faceted concept and multiple liquidity measures are available in the existing literature. We choose the Amihud illiquidity ratio (ILLIQ) among various liquidity measures 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.

To ensure the robustness of inference, we also perform analysis using five alternative liquidity measures. Details of these liquidity measures are provided in Appendix C of the paper, with results reported in Table A4 of the appendix.

II.D. Institutional Holding and Trading

Following Edelen et al. (2016), we construct two measures of institutional trading using the Thomson-Reuters 13F data. The first measure of institutional trading is the change in the percentage of shares outstanding of the stock that is held by the 13F institutional investors at the end of the quarter. 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. The corresponding institutional trading measure, 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.

The second measure of institutional trading is the size-scaled change in number of institutions holding the stock. 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 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.

To alleviate the influence of outliers on statistical inference, we first winsorize institutional trading measures at the 0.5 and 99.5 percentiles across all stocks in each quarter, before using them in analysis.

III. Empirical Results

III.A. Return-Predictive Horizons of Anomalies

We first show that various types of anomalies have different return predictive horizons. This is 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 each of the 12 quarters after portfolio formation.[4]

[4] At the beginning of each holding quarter the portfolios are rebalanced to keep equal weights. But the portfolio constituents are determined at the time of initial portfolio ranking. 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

The table shows substantial heterogeneity in the return-predictive horizon across the 11 anomaly types. As reported in Panel A of the table, during the sample period from 1963 to 2018, the returns to the long-short hedge portfolios of 7 categories – Value, Investment, Financing, Quality, Efficiency, Intangible, and Long-term Profitability – are all significant at horizons beyond 4 quarters. Among them, Value, Quality, Efficiency, and Intangible have significant return spreads for at least 12 quarters. By contrast, the returns to the long-short portfolios of 4 categories – Momentum, Short-term profitability, Distress, and Uncertainty, are only significant for the less than four quarters after portfolio formation.[5] Based on these patterns, we classify the first 7 categories as long-horizon anomalies and the last 4 as short-horizon anomalies.

Panel B of the table shows that during the more recent sample period of 1980-2018 – the period relevant for our analysis on institutional trading, the return-predictive horizons of some of the long-horizon categories are reduced. In particular, returns to Value and Investment anomaly portfolios are only significant for the first 6 and 7 quarters respectively. Meanwhile, the significant return-predictive horizon of the Distress portfolio, one of the short-term anomalies, is extended to 4 quarters. Nonetheless, the general horizon pattern remains similar to that in Panel A. Averaged over the first 7 categories, the long-short return difference is significant for 12 quarters, same as in the longer sample period of 1963-2018. Averaged over the last 4 categories, the long-short return difference is significant for 3 quarters, one quarter longer than that in Panel A.

We further report the return-predictive horizons of the 24 individual anomalies in Table A1 of the appendix. The horizon pattern of individual anomalies is largely consistent with that at the category level. Noted that the return-predictive horizon patterns we report are consistent with those by Daniel, Hirshleifer and Sun (2019). In addition to the anomaly categories they examine, we additionally identify uncertainty (including the idiosyncratic volatility anomaly and the analyst forecast dispersion anomaly) as a short-horizon category.

Two caveats are noted here. First, the results in Table 1 are based on simple stock

removed from the portfolio and the remaining stocks in the portfolio are re-weighted to keep equal weights. When computing holding-period returns during a given quarter, we include the delisting returns from CRSP. Following Shumway (1997), when the CRSP delisting return is missing, we replace it with -30% if delisting is performance-related, and zero otherwise.

[5] We note the exception for the Short-term Profitability category, for which the long-short portfolio return becomes insignificant during quarter 4, but becomes significant again during quarters 5 and 6.

returns and serve as an intuitive indication of the return-predictive horizon of anomalies. We do not examine whether these anomalies survive state-of-art factor models with significant alphas. Second, for the reason discussed earlier, the anomaly portfolios are equal weighted. For value-weighted anomaly portfolios, we find in untabulated analysis that the return-predictive horizons are typically shorter, but the horizon differences remain significant between the categories identified as long-horizon and short-horizon here. Daniel et al. (2019) document return-predictive horizons of various anomalies using value-weighted portfolios (with portfolio weights based on firm size at the ranking month).

III.B. Institutional Trading on Anomalies

We now examine how institutions trade on anomalies. Institutional trading on individual stocks is based on the two measures introduced in Section II.D., Δ%**Inst** and Δ#**Inst**. In each quarter, we calculate the average institutional trading measures for the long leg and short leg of an anomaly separately, and then calculate the long-short difference. We then average over individual anomalies within a category to obtain category-level measures, and finally, estimate the time series averages and the corresponding t-statistics. Institutional trading is measured over 6 quarters for long-horizon anomalies and 2 quarters for short-horizon anomalies. Because of 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.[6]

The results based on Δ%Inst as the institutional trading measure are reported in Panel A of Table 2. Averaged over all 11 categories of anomalies, the net institutional trading, i.e., the long-short difference for Δ%Inst, is insignificantly negative, at -0.11% (with a t-statistic of -1.38). This suggests that although institutional investors on average trade in the opposite direction of what is suggested by the anomalies, they are not seriously wrong. Further, the pattern is not uniform across anomaly categories. Out of 11 categories, the net institutional trading is significantly negative for only 4 categories (Value, Investment, Financing, and Intangible). Further, the net institutional trading is insignificant for 3 categories (Quality, Efficiency, and Uncertainty) and significantly positive for 4 categories (Momentum, ST Prof-

[6]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, or liquidity change.

itability, Distress, and LT Profitability). More interestingly, whether institutions trade in the right or wrong directions of anomalies appears to be correlated with the return predictive horizons of the anomalies. Judged by the signs of the net institutional trading, institutions are in the wrong direction of 5 out of 7 long-horizon categories and are in the right direction of all 4 short-horizon categories. Averaged over the 7 long-horizon anomaly categories, the long-short difference for Δ%Inst is significantly negative (-0.63% with a t-stat of -6.75). Averaged over the 4 short-horizon categories, the long-short difference for Δ%Inst is significantly positive (0.75% with a t-stat of 5.97).

Panel B of Table 2 report the results based on Δ#Inst. The panel shows that averaged over all 11 categories, the long-short difference in Δ#Inst is insignificantly negative, at -0.54 (t = -1.02). This is consistent with the results reported in Panel A. Also consistent with that of Panel A, the long-short difference in Δ#Inst tends to be significantly negative for long-horizon anomalies, and significantly positive for short-horizon anomalies.

We further report institutional trading on the 24 individual anomalies in Table A2 of the appendix. The pattern on individual anomalies are generally consistent with that at the category level.

Our findings show that institutional investors are on the wrong side of the 11 categories of anomalies on average, but they are not significantly wrong. Further, they are not uniformly wrong on all anomalies. Rather, across anomalies, institutional trading exhibits a striking pattern related to the return-predictive horizons of anomalies. They tend to be more likely on the wrong side of the long-horizon anomalies while on the right side of short-horizon anomalies. It is worth noting that Edelen et al. (2016) include two short-horizon anomalies in their analysis – the O-score measure of financial distress, and price momentum. They do find that institutional investors trade in the right direction of these two anomalies. However, it appears that the short-horizon anomalies are not sufficiently represented in their analysis to reveal a significant pattern.

In the analysis that follows, we link the institutional trading patterns on anomalies 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 an individual anomaly and on an anomaly category, 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 long and short 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 the same category, and take the time series averages. As mentioned in Footnote (6), the time series t-statistics for the long-short difference in liquidity level and change are computed using the Newey-West (1987) standard errors with a lag of 8 quarters.

Table A and B of Table 3 report the liquidity level and change for the 11 anomaly categories over the period of 1963-2018. The distinction between long-horizon and short-horizon anomalies are clear. For long-horizon anomalies, their long legs tend to consist of stocks that are less liquid and with deteriorating liquidity relative to their short legs. Specifically, the long-short difference in ILQ is significantly positive for 6 out of 7 categories – Value, Investment, Financing, Efficiency, Intangible, and LT Profitability. The exception is the Quality category, which has a significantly negative long-short difference in ILQ. Further, the long-short difference in ΔILQ is significantly positive for 5 out of 7 categories (Value, Investment, Financing, Quality, Intangible), although it is insignificantly positive for Efficiency and significantly negative for LT Profitability. For the 4 short-horizon categories, the long legs of anomaly portfolios tend to have significantly lower ILQ and significantly lower ΔILQ than their short legs. The only exception that for the Uncertainty category, the long-short difference in ΔILQ is insignificantly negative.

The pattern for the more recent sample period of 1980-2018, reported in Panel C and D of Table 3, is largely consistent with that in Panel A and B. Further, as reported in Table A3 of the appendix, patterns of liquidity level and change for the 24 individual anomalies are consistent with the category-level findings. Finally, Table A4 of the appendix shows that the liquidity characteristics of anomalies also hold under 5 alternative liquidity measures.

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). By contrast, what we find is a more systematic pattern of liquidity and liquidity change 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 the effect of institutional liquidity preference on both their holdings and trades.

In Panel A of Table 4, we report the average liquidity and liquidity change for stock deciles sorted by institutional holding. Institutional holding is measured by either the percentage of shares outstanding held by institutional investors (%Inst), or the size-adjusted number of institutions holding the stock (#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 stock decile least held by institutions to 30.31 for the stock decile most held by institutions. The liquidity change measure ΔILQ, over both 2 quarters and 6 quarters, also declines with institutional holding ranks. Thus, institutional investors 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.

The same panel shows that #Inst also appears to be negatively correlated with the illiquidity level ILQ, consistent with institutional investors' liquidity preference. However the relation is not completely monotonic. ILQ for the top #Inst decile, at 51.31, is higher than all but the bottom two deciles. We note that this might be due to the particular way of adjusting for market cap, which results in a high proportion of small stocks in the top #Inst decile. Small stocks tend to have very 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 #Inst may 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 in the bottom and top #Inst deciles may cause the average ILQ for these two 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 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 first measure of institutional trading, Δ%Inst, has an inverse U-shaped relation with ILQ. That is, stocks experiencing large institutional buys and those experiencing large institutional sells are both liquid. This is consistent with the notion that a majority of the 13F institutions are long-only investors and the stocks they sell must be from what they already hold, which tend to be liquid. Perhaps what's more novel in this panel is that Δ%Inst is monotonically and negatively related to ΔILQ. The result 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 the liquidity of stocks changes over time, institutions trade to replace stocks that have become less liquid with those that have become more liquid.

The second measure of institutional trading, Δ#Inst, has a U-shaped relation with the illiquidity level ILQ. Stocks in both the bottom decile and the top decile of Δ#Inst appear to be more illiquid, relative to stocks in the middle ranks. This is opposite of the pattern for Δ%Inst. Again, this counter-intuitive pattern appears to be related to the size adjustment in constructing the measure. Small stocks tend to have a low denominator to Δ#Inst. Thus, with a reasonable dispersion in the numerator, change of number of institutions holding a stock, small stocks may easily have very high or very low Δ#Inst, causing them to show up disproportionally in both the top and bottom Δ#Inst deciles. Nonetheless, note that Δ#Inst has a relatively monotonic relation with liquidity change, consistent with the pattern for Δ%Inst.

Overall, the results in Table 4 suggest a positive relation between institutional holding and liquidity, and a positive relation between institutional trading and change in liquidity. 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 $\Delta\%\text{Inst}_{LIQ}$ or $\Delta\#\text{Inst}_{LIQ}$, is simply the average institutional trading (Δ%Inst or Δ#Inst) on all stocks in the same ΔILQ decile during the same period. And the non-liquidity component, denoted $\Delta\%\text{Inst}_{NLQ}$ or $\Delta\#\text{Inst}_{NLQ}$, is the institutional trading measure on a stock in excess of the liquidity-driven component. That is, $\Delta\%\text{Inst}_{NLQ} = \Delta\%Inst - \Delta\%\text{Inst}_{LIQ}$, and $\Delta\#\text{Inst}_{NLQ} = \Delta\#Inst - \Delta\#\text{Inst}_{LIQ}$. 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 across 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.

Panel C and D repeat the analysis in Panel A and B but use $\Delta\#\text{Inst}_{LIQ}$ and $\Delta\#\text{Inst}_{NLQ}$ as the liquidity-driven and non-liquidity components of institutional trading. The results are largely consistent with those in Panel A and B.

The key conclusion from this part of the analysis is that liquidity plays a very important role in driving institutions to trade in the wrong direction of market anomalies, especially long-horizon anomalies. After controlling for liquidity, institutional trading tends to be consistent with the direction suggested by anomalies. This finding is important because liquidity and liquidity change of a stock to a large extent are exogenous when institutions make the trading decisions, and thus liquidity-driven trades are more likely not driven by an intention to take advantage of mispricing. After removing the influence of liquidity, then, the non-liquidity component of trading is more likely related to institutional investors' response to their information about mispricing.

Given the relations among liquidity, institutional trading, and anomalies, we move on to explore two issues related to the magnitude of the anomalies. The first is the extent to which the magnitude of the anomalies can be explained by liquidity premium. The second is how institutional trading, when it is driven by liquidity or for non-liquidity reasons, affects the magnitude of anomalies.

III.F. 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. In Panel A of Table 6, we show that liquidity premium exists during the long sample period of 1963-2018 and is a long-horizon phenomenon. The return difference between the top and bottom decile portfolios (equal-weighted) sorted by ILQ is significant during most of the 12 quarters after initial portfolio formation, except for the 8th and 9th quarter. In the same panel we also find a liquidity change premium, as measured by the return difference between the top and bottom decile portfolios (equal-weighted) sorted by ΔILQ over either 2 quarters or 6 quarters. The liquidity change premium is also a long-horizon phenomenon, as the return difference remains significant for the 11th quarter after portfolio formation based on ΔILQ over 2 quarters and significant for the 12th quarter after formation based on ΔILQ over 6 quarters. Interestingly, liquidity change is not significantly related to returns during the initial one or two quarters after portfolio formation.

In Panel B of the table, we show that liquidity premium has changed somewhat during the recent period of 1980-2018. During this period, the level of illiquidity (ILQ) is no longer significantly related to stock returns. That is, the conventional notion of liquidity premium no longer exists. Liquidity change is still significantly related to returns, albeit at a shortened horizon of 6 or 7 quarters.

Given the above findings, we further examine whether the return premiums associated with liquidity level and liquidity change affect 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 level or liquidity change, where 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.

We have performed analysis for the sample period of 1963-2018 as well as for the period of 1980-2018. During the long sample period of 1963-2018, we find that after adjusting for liquidity premium or liquidity change premium, the magnitude of several anomalies is reduced, but all significant patterns for unadjusted returns, as reported in Table 1, retain their statistical significance. That is, adjusting for liquidity premium or liquidity change premium does not significantly alter any of the anomaly return patterns. To save space, we do not tabulate the results for this sample period in the paper. Instead, in Table 7, we report the results for the recent period of 1980-2018.

Panel A of Table 7 shows that after adjusting for the liquidity premium, the anomaly return patterns remain quite similar to the unadjusted results in Table 1 for the same period of 1980-2018. This is not surprising given that liquidity premium per se is no longer significant during this period.

Perhaps more interesting are the results reported in Panel B of the table, where anomaly portfolio returns are adjusted for the liquidity change premium. The panel shows that the long-short difference in adjusted returns to the value anomaly portfolio is no longer significant at any horizon. That is, the value anomaly appears to be mainly driven by the liquidity change premium during this period. The magnitude of other anomalies also appears to be 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 12 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 return premiums associated with the level and change of liquidity.

III.G. Magnitude of Market Anomalies Conditional on Institutional Trading Directions

A further issue we examine is the impact of institutional trading on the market 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 (either Δ%Inst or Δ#Inst), 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 "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. 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 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 8 reports the alphas to the anomaly subportfolios on which institutions trade in the wrong and right directions, where institutional trading is measured by Δ%Inst. 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 8 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 is largely unrelated to the magnitude of mispricing.

In Table 9, we use Δ#Inst to measure institutional trading and repeat the analysis of Table 8. Panel A of the table shows that when institutions are in the wrong direction of long-horizon anomalies, the magnitude of the anomalies tend to be larger but only (marginally) significant for two out of seven categories – Quality and Intangible. Meanwhile, for all 4 categories of short-horizon anomalies, when institutions trade in the wrong direction, the magnitude of the anomalies are significantly lower. In Panel B, we find that the liquidity-driven institutional trading, when in the wrong direction, significantly exacerbates the long-horizon anomalies and insignificantly exacerbates the short-horizon anomalies (except for the momentum category). Finally, the results in Panel C show that the magnitude of the long-horizon anomalies is not significantly affected by the direction of non-liquidity institutional trades. However, for the four short-horizon categories, the alpha differences between the "wrong" and "right" subportfolios of non-liquidity institutional trades are significantly negative. Or put it differently, non-liquidity institutional trades positively predict subsequent price moves for stocks in the short-horizon anomaly portfolios.

Despite somewhat different results between the two institutional trading measures, we can identify a common pattern in Tables 8 and 9 that wrong-directional institutional trades aggravate long-horizon anomalies, and that this happens mainly because of liquidity-driven trades. By contrast, for short-horizon anomalies, their magnitude tends to be either not affected or larger when institutional trading (and especially the non-liquidity component) is in the right direction. The latter finding is consistent with the notion that institutional investors have stock selection abilities when they trade on short-term anomalies.

IV. 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. At the same time, institutional investors somewhat exhibit stock selection skills when they trade on short-horizon anomalies.

Appendix

Appendix A: Market Anomalies

Below are details on the construction of the 24 individual anomaly variables. Compustat data items are indicated in parentheses. Unless otherwise noted, the variables are available from 1963 to 2018.

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): $3CE_{t\text{-}1}$ / ($CE_{t\text{-}2}$ + $CE_{t\text{-}3}$ + $CE_{t\text{-}4}$) -1, in which $CE_{t\text{-}1}$ 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 and available from 1972 to 2018.

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 and available from 1977 to 2018.

19. Return on Equity (ROE): Net income (item NIQ) divided by common equity (item CEQQ). The data are from Compustat quarterly files and available from 1973 to 2018.

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 $15). We winsorize all eight predictive variables at the 5$\hat{\text{t}}$h and 95$\hat{\text{t}}$h 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, and available from 1972 to 2017.

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 and available from 1977 to 2018.

Appendix B: Mapping 102 Anomalies of Green, Hand, and Zhang (2017) into Categories

The following table maps the 102 anomalies examined by Green, Hand, and Zhang (2017) into the 7 anomaly categories of this study. The anomalies are represented by the variables in Table 1 of Green et al. (2018). In addition to the 7 anomaly categories, we also include the variables in the liquidity category and a category for variables that cannot be classified into either the 7 categories or the liquidity category. The number of anomalies included in each category is in the parentheses.

- 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

Appendix C: Alternative Liquidity Measures

The following alternative liquidity measures are based on 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.

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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 each of the subsequent 12 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 12 quarters (Qtr). 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 Profitability are long-horizon categories. Momentum, ST Profitability, 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. In Panel A, the sample period is from 1963 to 2018. In Panel B, the sample period is from 1980 to 2018.

Panel A: 1963-2018

Qtr	Value	Investment	Financing	Quality	Efficiency	Intangible	LT Profitability
1	1.18^{a}	0.99^{a}	1.60^{a}	0.96^{a}	1.17^{a}	1.93^{a}	1.39^{a}
2	1.12^{a}	0.74^{a}	1.34^{a}	0.68^{a}	1.03^{a}	1.73^{a}	1.21^{a}
3	1.10^{a}	0.66^{a}	1.23^{a}	0.55^{a}	0.89^{a}	1.70^{a}	1.08^{a}
4	0.87^{a}	0.48^{a}	1.06^{a}	0.38^{a}	0.82^{a}	1.53^{a}	1.01^{a}
5	0.75^{b}	0.41^{a}	1.00^{a}	0.32^{b}	0.80^{a}	1.52^{a}	0.92^{a}
6	0.73^{b}	0.42^{a}	0.96^{a}	0.33^{b}	0.74^{a}	1.44^{a}	0.91^{a}
7	0.70^{b}	0.38^{b}	0.89^{a}	0.27^{c}	0.70^{a}	1.40^{a}	0.90^{a}
8	0.65^{b}	0.34^{b}	0.80^{a}	0.27^{c}	0.59^{a}	1.23^{a}	0.79^{a}
9	0.65^{b}	0.36^{b}	0.76^{a}	0.29^{c}	0.58^{a}	1.13^{a}	0.71^{b}
10	0.64^{b}	0.35^{b}	0.71^{b}	0.26^{c}	0.61^{a}	1.07^{a}	0.68^{b}
11	0.58^{c}	0.29^{c}	0.57^{b}	0.24^{c}	0.59^{a}	1.03^{a}	0.65^{b}
12	0.55^{c}	0.27	0.49	0.24^{c}	0.60^{a}	0.98^{a}	0.68^{b}
	Momentum	ST Profitability	Distress	Uncertainty	LT Avg	ST Avg	ALL Avg
1	1.93^{a}	1.61^{a}	0.82^{b}	0.70	1.32^{a}	1.23^{a}	1.29^{a}
2	0.95^{a}	1.06^{a}	0.68^{b}	0.47	1.12^{a}	0.77^{a}	1.00^{a}
3	0.29	0.41^{c}	0.55^{c}	0.23	1.03^{a}	0.36	0.80^{a}
4	−0.31	0.14	0.32	−0.08	0.88^{a}	0.00	0.57^{a}
5	−0.16	0.43^{b}	0.09	0.06	0.82^{a}	0.07	0.56^{a}
6	−0.09	0.41^{b}	−0.02	−0.02	0.79^{a}	0.03	0.53^{a}
7	−0.21	0.09	0.02	−0.17	0.75^{a}	−0.09	0.46^{a}
8	−0.21	0.16	−0.06	−0.18	0.67^{a}	−0.10	0.40^{a}
9	−0.10	0.16	−0.12	−0.24	0.64^{a}	−0.09	0.38^{a}
10	−0.03	0.14	−0.10	−0.17	0.62^{a}	−0.07	0.38^{a}
11	−0.09	0.00	0.01	−0.10	0.57^{a}	−0.07	0.35^{a}
12	−0.22	0.05	−0.07	−0.29	0.55^{a}	−0.14	0.30^{b}

Panel B: 1980-2018

Qtr	Value	Investment	Financing	Quality	Efficiency	Intangible	LT Profitability
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}
9	0.46	0.27	0.74^{b}	0.29^{b}	0.60^{a}	1.03^{a}	0.87^{a}
10	0.38	0.30	0.69^{c}	0.26^{c}	0.62^{a}	1.00^{a}	0.84^{a}
11	0.33	0.21	0.51	0.27^{b}	0.57^{a}	0.99^{a}	0.78^{a}
12	0.35	0.21	0.47	0.22^{c}	0.58^{a}	0.99^{a}	0.77^{a}

	Momentum	ST Profitability	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}
5	-0.08	0.51^{b}	0.38	0.52	0.87^{a}	0.33	0.68^{a}
6	0.00	0.42^{c}	0.26	0.47	0.80^{a}	0.29	0.61^{a}
7	-0.07	0.18	0.35	0.32	0.73^{a}	0.20	0.54^{a}
8	-0.15	0.29	0.32	0.19	0.65^{a}	0.16	0.47^{a}
9	-0.10	0.25	0.07	0.09	0.61^{a}	0.08	0.42^{a}
10	0.14	0.17	0.15	0.22	0.58^{a}	0.17	0.43^{a}
11	0.15	0.11	0.32	0.22	0.52^{a}	0.20	0.40^{b}
12	0.03	0.19	0.14	-0.09	0.51^{a}	0.06	0.35^{b}

Table 2. Institutional Trading on Market Anomalies

This table reports institutional trading measures on the 11 anomaly category portfolios. 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). They are 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 return differences 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. The sample period is from 1980 to 2018.

Panel A: Δ%Inst

	Value	Investment	Financing	Quality	Efficiency	Intangible	LT Profitability
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 Profitability	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)

Panel B: Δ#Inst

	Value	Investment	Financing	Quality	Efficiency	Intangible	LT Profitability
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 Profitability	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)

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 and B are for the sample period from 1963 to 2018. Panel C and D are for the sample period from 1980 to 2018.

Panel A: ILLIQ, 1963-2018

	Value	Investment	Financing	Quality	Efficiency	Intangible	LT Profitability
Short	42.35	45.26	46.07	51.04	45.42	39.26	46.87
Long	55.86	53.74	47.93	48.42	52.67	56.13	49.67
L-S	13.51^a	8.48^a	1.85^c	-2.63^a	7.25^a	16.87^a	2.81^a
t-stat	(21.09)	(17.30)	(1.92)	(−6.99)	(11.85)	(28.45)	(4.06)
	Momentum	ST Profitability	Distress	Uncertainty	LT Avg	ST Avg	ALL Avg
Short	48.43	54.89	59.04	56.17	45.18	54.69	48.46
Long	45.11	43.67	40.70	35.65	52.05	40.99	48.16
L-S	-3.32^a	-11.23^a	-18.34^a	-20.52^a	6.87^a	-13.70^a	−0.30
t-stat	(−5.42)	(−30.61)	(−44.38)	(−18.86)	(15.34)	(−28.79)	(−0.90)

Panel B: ΔILLIQ, 1963-2018

	Value	Investment	Financing	Quality	Efficiency	Intangible	LT Profitability
Short	−3.10	−2.12	−3.07	−1.26	−1.13	−2.14	−0.49
Long	0.81	0.30	0.19	−0.97	−1.10	0.94	−1.40
L-S	3.91^a	2.42^a	3.27^a	0.30^c	0.03	3.07^a	-0.91^a
t-stat	(12.77)	(13.53)	(10.20)	(1.82)	(0.18)	(9.07)	(−3.03)
	Momentum	ST Profitability	Distress	Uncertainty	LT Avg	ST Avg	ALL Avg
Short	1.46	0.17	−0.26	−0.26	−1.91	0.26	−1.15
Long	−2.48	−0.93	−0.58	−0.68	−0.18	−1.20	−0.56
L-S	-3.94^a	-1.09^a	-0.32^b	−0.42	1.72^a	-1.45^a	0.60^a
t-stat	(−28.41)	(−12.54)	(−2.37)	(−1.61)	(9.27)	(−10.15)	(4.72)

Panel C: ILLIQ, 1980-2018

	Value	Investment	Financing	Quality	Efficiency	Intangible	LT Profitability
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 Profitability	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 D: ΔILLIQ, 1980-2018

	Value	Investment	Financing	Quality	Efficiency	Intangible	LT Profitability
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 Profitability	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 the size-adjusted number of institutional owners (#Inst). Institutional trading is measured by the change in percentage of shares held by institutions (Δ%Inst) and the size-adjusted change in number of institutional owners (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 the two institutional holding measures, %Inst and #Inst. Panel B report the average level and change in illiquidity (ILQ, ΔILQ over 2 quarters, and *Delta*ILQ over 6 quarters) for stock deciles sorted by the two institutional trading measures, δ%Inst and 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. The sample period is from 1980 to 2018.

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

	by %Inst			by #Inst		
	ILQ	ΔILQ 2-Qtr	ΔILQ 6-Qtr	ILQ	ΔILQ 2-Qtr	ΔILQ 6-Qtr
Low	76.02	−0.58	0.19	70.06	−0.78	−0.46
2	70.83	−0.36	0.29	55.66	−1.02	−1.53
3	63.32	−0.37	0.23	49.39	−0.94	−1.66
4	54.60	−0.33	0.01	47.71	−0.75	−1.31
5	48.82	−0.35	−0.17	45.40	−0.69	−1.26
6	44.29	−0.34	−0.57	44.86	−0.48	−0.95
7	40.71	−0.34	−0.61	43.60	−0.35	−0.58
8	36.45	−0.36	−0.81	43.42	−0.22	−0.37
9	33.30	−0.45	−1.19	44.97	0.08	0.27
High	30.31	−0.73	−2.08	51.31	0.77	1.90
H-L	-45.71^{a}	−0.15	-2.26^{a}	-18.75^{a}	1.56^{a}	2.36^{a}
t-stat	(−26.61)	(−1.15)	(−6.95)	(−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 2-Qtr Δ#Inst		by 6-Qtr Δ%Inst		by 6-Qtr Δ#Inst	
	ILQ	ΔILQ 2-Qtr	ILQ	ΔILQ 2-Qtr	ILQ	ΔILQ 6-Qtr	ILQ	ΔILQ 6-Qtr
Low	44.03	0.04	56.46	1.42	46.39	2.58	58.42	7.19
2	46.48	0.30	48.91	0.98	48.81	1.91	50.54	4.67
3	49.60	0.25	43.33	0.61	52.22	1.13	48.48	2.80
4	55.51	0.17	46.52	0.34	53.93	0.84	43.92	1.75
5	55.99	0.06	42.23	0.09	51.12	0.50	43.86	0.76
6	51.61	−0.01	41.27	−0.17	48.96	0.23	44.01	−0.40
7	49.57	−0.23	44.24	−0.61	48.27	−0.34	46.63	−1.68
8	48.31	−0.63	47.87	−1.25	48.16	−1.26	48.21	−3.81
9	46.96	−1.41	53.09	−2.23	47.31	−3.65	50.77	−7.41
High	48.04	−3.22	60.13	−4.25	45.01	−9.72	52.65	−14.80
H-L	4.02^a	-3.26^a	3.67^a	-5.67^a	−1.38	-12.30^a	-5.77^a	-21.99^a
t-stat	(5.16)	(−18.21)	(3.16)	(−20.14)	(−1.44)	(−18.87)	(−3.15)	(−23.49)

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, reported in Panel A and B) and the size-adjusted change in number of institutional owners (Δ#Inst, reported in Panel C and D). 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. 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. The sample period is from 1980 to 2018.

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

	Value	Investment	Financing	Quality	Efficiency	Intangible	LT Profitability
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 Profitability	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 Profitability
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 Profitability	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)

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

	Value	Investment	Financing	Quality	Efficiency	Intangible	LT Profitability
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 Profitability	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 D: Non-liquidity Institutional Trading, $\Delta\#\text{Inst}_{NLQ}$

	Value	Investment	Financing	Quality	Efficiency	Intangible	LT Profitability
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 Profitability	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 6. 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 12 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. Panel A is for the sample period from 1963 to 2018. Panel B is for the sample period of 1980 to 2018.

	Panel A: 1963-2018			Panel B: 1980-2018		
Qtr	ILQ	ΔILQ over 2 qtrs	ΔILQ over 6 qtrs	ILQ	ΔILQ over 2 qtrs	ΔILQ over 6 qtrs
1	1.34^b	-0.50	0.54	0.66	-0.20	0.87
2	1.61^a	0.44	1.02^b	0.90	0.85	1.27^b
3	1.56^a	0.73^c	1.08^a	0.82	1.27^b	1.30^b
4	1.45^a	1.13^a	0.77^b	0.65	1.45^a	0.87^c
5	1.19^b	0.97^b	0.93^b	0.38	1.05^b	0.90^b
6	1.19^b	0.93^a	0.91^b	0.33	0.95^b	0.92^b
7	1.09^c	0.65^c	0.92^b	0.26	0.70	0.79^c
8	0.87	0.35	0.88^b	0.00	0.53	0.61
9	0.89	0.53^c	0.76^b	0.14	0.45	0.24
10	0.99^c	0.58^c	0.56	0.20	0.36	-0.11
11	1.02^c	0.61^c	0.62^c	0.23	0.22	-0.05
12	0.84^c	0.58^c	0.21	-0.04	0.08	-0.42

Table 7. Returns to Anomaly Portfolios: Adjusted for Liquidity Premium and 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 premium or liquidity change premium. The liquidity premium is the average return to the stocks in the same liquidity (ILQ) decile, and 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 12 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. Panel A reports the returns adjusted for liquidity premium. Panel B reports the returns adjusted for liquidity change premium. The sample period is from 1980 to 2018.

Panel A: Adjusted for Liquidity Premium

Qtr	Value	Investment	Financing	Quality	Efficiency	Intangible	LT Profitability
1	0.87^{b}	0.86^{a}	1.49^{a}	0.95^{a}	1.14^{a}	1.66^{a}	1.66^{a}
2	0.79^{b}	0.61^{a}	1.28^{a}	0.69^{a}	1.00^{a}	1.36^{a}	1.45^{a}
3	0.76^{b}	0.52^{a}	1.23^{a}	0.60^{a}	0.91^{a}	1.32^{a}	1.31^{a}
4	0.63^{b}	0.32^{c}	1.04^{a}	0.42^{a}	0.80^{a}	1.15^{a}	1.20^{a}
5	0.54^{c}	0.34^{b}	0.98^{a}	0.32^{b}	0.82^{a}	1.25^{a}	1.11^{a}
6	0.45	0.30^{c}	0.86^{a}	0.30^{b}	0.69^{a}	1.13^{a}	0.99^{a}
7	0.40	0.26	0.72^{b}	0.20	0.62^{a}	1.12^{a}	0.99^{a}
8	0.31	0.21	0.64^{b}	0.27^{b}	0.55^{a}	0.97^{a}	0.91^{a}
9	0.31	0.21	0.62^{c}	0.29^{b}	0.53^{a}	0.93^{a}	0.83^{a}
10	0.27	0.24	0.59^{c}	0.27^{b}	0.56^{a}	0.91^{a}	0.78^{a}
11	0.21	0.17	0.43	0.26^{b}	0.52^{a}	0.92^{a}	0.73^{a}
12	0.25	0.17	0.39	0.22^{c}	0.51^{a}	0.88^{a}	0.68^{b}
	Momentum	ST Profitability	Distress	Uncertainty	LT Avg	ST Avg	ALL Avg
1	1.71^{a}	1.78^{a}	1.36^{a}	1.25^{b}	1.23^{a}	1.53^{a}	1.34^{a}
2	0.87^{a}	1.25^{a}	1.17^{a}	1.00^{b}	1.03^{a}	1.07^{a}	1.04^{a}
3	0.16	0.65^{a}	1.03^{a}	0.71	0.95^{a}	0.64^{a}	0.83^{a}
4	−0.39^{c}	0.30	0.72^{a}	0.44	0.79^{a}	0.27	0.60^{a}
5	−0.10	0.56^{a}	0.44^{c}	0.54	0.76^{a}	0.36^{c}	0.62^{a}
6	−0.01	0.46^{b}	0.31	0.41	0.67^{a}	0.29	0.54^{a}
7	−0.05	0.24	0.40^{c}	0.33	0.62^{a}	0.23	0.48^{a}
8	−0.11	0.33^{c}	0.35	0.17	0.55^{a}	0.19	0.42^{a}
9	−0.06	0.28	0.12	0.10	0.53^{a}	0.11	0.38^{b}
10	0.15	0.18	0.17	0.22	0.52^{a}	0.18	0.40^{a}
11	0.20	0.13	0.32	0.22	0.46^{a}	0.22	0.37^{b}
12	0.06	0.22	0.10	−0.10	0.44^{a}	0.07	0.31^{b}

Panel B: Adjusted for Liquidity Change Premium

Qtr	Value	Investment	Financing	Quality	Efficiency	Intangible	LT Profitability
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
9	0.17	0.21	0.37	0.27^b	0.53^a	1.02^a	0.91^a
10	0.18	0.23	0.40	0.30^b	0.56^a	0.98^a	0.86^a
11	0.14	0.19	0.35	0.28^b	0.51^a	0.94^a	0.75^a
12	0.24	0.23	0.37	0.19	0.50^a	0.92^a	0.73^a
	Momentum	ST Profitability	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
9	−0.10	0.22	0.01	−0.08	0.50^a	0.01	0.32^b
10	0.15	0.19	0.05	0.12	0.50^a	0.13	0.37^a
11	0.22	0.15	0.25	0.09	0.45^a	0.18	0.35^a
12	0.09	0.26	0.11	−0.14	0.45^a	0.08	0.32^a

Table 8. Market Anomalies Conditional on Institutional Trading Δ%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. 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. The sample period is from 1980 to 2018.

Panel A: Conditional on Institutional Trading Δ%Inst

	Value	Investment	Financing	Quality	Efficiency	Intangible	LT Profitability
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 Profitability	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 Profitability
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 Profitability	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 Profitability
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 Profitability	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)

Table 9. Market Anomalies Conditional on Institutional Trading Δ#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 size-adjusted change in the number of institutions. 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-based 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. The sample period is from 1980 to 2018.

Panel A: Conditional on Institutional Trading Δ#Inst

	Value	Investment	Financing	Quality	Efficiency	Intangible	LT Profitability
Short+Low (SL)	−0.13	−0.23	−0.32	0.21	−0.19	−0.52	−0.39
Long+High (LH)	0.45	−0.03	0.71^c	0.15	0.09	0.24	0.25
LH-SL (Right)	0.58	0.19	1.03^c	−0.06	0.28	0.75	0.64
t-stat	(1.25)	(0.38)	(1.90)	(−0.12)	(0.55)	(1.56)	(1.12)
Short+High (SH)	-1.05^b	-0.90^b	-1.44^a	-0.88^b	-1.17^a	-1.43^a	-1.24^a
Long+Low (LL)	0.56	0.62	0.65	0.72	0.54	0.84	0.90
LL-SH (Wrong)	1.61^b	1.52^a	2.09^a	1.60^a	1.72^a	2.27^a	2.14^a
t-stat	(2.57)	(2.96)	(3.61)	(2.92)	(3.20)	(3.80)	(3.80)
Wrong-Right	1.03	1.33	1.06	1.66^c	1.44	1.51^c	1.50
t-stat	(1.27)	(1.40)	(1.14)	(1.73)	(1.52)	(1.68)	(1.57)

	Momentum	ST Profitability	Distress	Uncertainty	LT Avg	ST Avg	ALL Avg
Short+Low (SL)	-1.21^b	-1.47^a	-1.41^b	-1.81^a	−0.22	-1.47^a	−0.65
Long+High (LH)	0.85^c	0.95^b	0.93^b	1.01^a	0.26	0.94^b	0.56
LH-SL (Right)	2.05^a	2.42^a	2.34^a	2.82^a	0.49	2.41^a	1.22^a
t-stat	(4.05)	(5.15)	(4.86)	(6.10)	(1.08)	(5.39)	(3.02)
Short+High (SH)	−0.58	−0.53	−0.45	−0.29	-1.16^a	−0.46	-0.83^b
Long+Low (LL)	−0.07	−0.13	0.05	0.29	0.69	0.03	0.49
LL-SH (Wrong)	0.51	0.39	0.50	0.58	1.85^a	0.49	1.32^a
t-stat	(1.66)	(0.87)	(1.08)	(1.15)	(3.49)	(1.31)	(3.16)
Wrong-Right	-1.54^b	-2.03^b	-1.84^b	-2.24^a	1.36	-1.92^b	0.10
t-stat	(−2.42)	(−2.54)	(−2.45)	(−3.00)	(1.49)	(−2.64)	(0.13)

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

	Value	Investment	Financing	Quality	Efficiency	Intangible	LT Profitability
Short+Low (SL)	0.07	0.06	−0.19	0.25	−0.16	−0.39	−0.35
Long+High (LH)	0.24	−0.36	0.65	−0.28	−0.22	0.00	0.04
LH-SL (Right)	0.17	−0.43	0.83^c	−0.53	−0.06	0.40	0.39
t-stat	(0.34)	(−0.90)	(1.85)	(−1.16)	(−0.12)	(0.95)	(0.84)
Short+High (SH)	-1.32^a	-1.17^a	-1.74^a	-0.96^b	-1.44^a	-1.45^a	-1.64^a
Long+Low (LL)	0.52	0.39	0.61	0.66	0.55	0.76	0.95
LL-SH (Wrong)	1.84^a	1.56^a	2.35^a	1.62^a	1.99^a	2.21^a	2.59^a
t-stat	(3.24)	(3.28)	(4.14)	(3.26)	(4.02)	(3.94)	(4.37)
Wrong-Right	1.66^b	1.99^b	1.52^c	2.15^b	2.05^b	1.82^b	2.20^b
t-stat	(2.15)	(2.30)	(1.92)	(2.40)	(2.35)	(2.26)	(2.63)

	Momentum	ST Profitability	Distress	Uncertainty	LT Avg	ST Avg	ALL Avg
Short+Low (SL)	−0.90	-1.23^b	-1.24^b	-1.44^b	−0.10	-1.20^b	−0.47
Long+High (LH)	−0.23	−0.17	0.12	0.39	0.01	0.03	0.03
LH-SL (Right)	0.67	1.06^b	1.36^b	1.83^a	0.11	1.23^b	0.50
t-stat	(1.13)	(2.02)	(2.55)	(3.52)	(0.28)	(2.39)	(1.28)
Short+High (SH)	-1.98^a	-1.97^a	-1.96^a	-1.72^a	-1.39^a	-1.91^a	-1.55^a
Long+Low (LL)	0.61	0.44	0.57	0.68	0.63	0.57	0.64
LL-SH (Wrong)	2.58^a	2.41^a	2.53^a	2.40^a	2.02^a	2.48^a	2.19^a
t-stat	(5.33)	(4.10)	(4.11)	(4.31)	(4.07)	(4.77)	(5.05)
Wrong-Right	1.91^b	1.35	1.17	0.56	1.91^b	1.25	1.69^b
t-stat	(2.08)	(1.37)	(1.22)	(0.66)	(2.33)	(1.36)	(2.22)

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

	Value	Investment	Financing	Quality	Efficiency	Intangible	LT Profitability
Short+Low (SL)	-0.78^c	-0.61	-1.13^b	-0.26	-0.82^c	-0.94^b	-0.90^c
Long+High (LH)	0.64	0.19	0.81^c	0.41	0.30	0.46	0.42
LH-SL (Right)	1.43^a	0.80^b	1.94^a	0.66^c	1.12^a	1.39^a	1.32^a
t-stat	(3.77)	(2.40)	(5.13)	(1.95)	(3.43)	(3.34)	(3.04)
Short+High (SH)	-0.79^c	-0.57	-1.11^a	-0.55	-0.69^c	-1.13^a	-0.71^b
Long+Low (LL)	0.65	0.34	0.78	0.43	0.35	0.50	0.63
LL-SH (Wrong)	1.44^b	0.91^b	1.89^a	0.98^a	1.04^b	1.63^a	1.34^a
t-stat	(2.56)	(2.59)	(3.96)	(2.87)	(2.63)	(3.28)	(3.34)
Wrong-Right	0.01	0.11	-0.05	0.32	-0.08	0.24	0.01
t-stat	(0.02)	(0.19)	(-0.09)	(0.54)	(-0.16)	(0.38)	(0.02)

	Momentum	ST Profitability	Distress	Uncertainty	LT Avg	ST Avg	ALL Avg
Short+Low (SL)	-1.37^b	-1.69^a	-1.66^a	-2.04^a	-0.78^c	-1.69^a	-1.09^b
Long+High (LH)	0.98^b	1.03^b	0.99^b	1.04^a	0.46	1.01^b	0.71^c
LH-SL (Right)	2.35^a	2.71^a	2.65^a	3.09^a	1.24^a	2.70^a	1.79^a
t-stat	(5.48)	(7.39)	(6.29)	(7.58)	(4.15)	(7.39)	(6.53)
Short+High (SH)	-0.51	-0.45	-0.34	-0.28	-0.79^b	-0.40	-0.59
Long+Low (LL)	-0.37	-0.35	0.01	0.31	0.53	-0.10	0.31
LL-SH (Wrong)	0.15	0.10	0.35	0.59	1.32^a	0.30	0.90^a
t-stat	(0.45)	(0.32)	(0.99)	(1.36)	(3.49)	(1.04)	(3.04)
Wrong-Right	-2.20^a	-2.61^a	-2.30^a	-2.49^a	0.08	-2.40^a	-0.89^c
t-stat	(-4.66)	(-4.82)	(-4.24)	(-4.66)	(0.14)	(-4.69)	(-1.88)

Appendix D: Additional Tables

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 12 quarters (Qtr). 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. In Panel A, the sample period is from 1963 to 2018. In Panel B, the sample period is from 1980 to 2018.

Panel A: 1963-2018

A1: Long-Horizon Anomalies

	BP	EP	SG	CAPX	AI	AG	NS	XFIN	ACC	DACC	ATTO	NOA	GP	RD	SGA
1	1.55^a	1.31^a	0.68^b	0.90^a	0.71^a	1.35^a	1.53^a	1.74^a	0.89^a	1.09^a	0.95^b	1.40^a	1.39^a	1.79^a	1.99^a
2	1.48^a	1.32^a	0.55^b	0.67^a	0.51^a	1.06^a	1.27^a	1.48^a	0.66^a	0.78^a	0.88^b	1.20^a	1.21^a	1.54^a	1.79^a
3	1.50^a	1.24^a	0.55^b	0.58^a	0.43^b	0.97^a	1.26^a	1.24^a	0.54^a	0.67^a	0.75^b	1.05^a	1.08^a	1.48^a	1.77^a
4	1.26^a	0.99^a	0.34	0.47^b	0.26	0.71^a	1.04^a	1.18^a	0.40^b	0.45^a	0.75^b	0.90^a	1.01^a	1.28^a	1.60^a
5	1.13^a	0.91^a	0.22	0.43^b	0.16	0.64^b	1.01^a	1.06^a	0.35^c	0.33^b	0.69^b	0.91^a	0.92^a	1.37^a	1.57^a
6	1.08^a	0.84^b	0.27	0.39^c	0.25^c	0.61^b	1.00^a	0.94^a	0.37^b	0.33^a	0.66^c	0.82^a	0.91^a	1.35^a	1.47^a
7	1.13^a	0.82^b	0.17	0.34	0.25^c	0.56^b	0.92^a	0.79^b	0.23	0.32^b	0.62^c	0.77^a	0.90^a	1.35^a	1.43^a
8	1.02^a	0.71^b	0.22	0.33^c	0.24^c	0.44^c	0.86^a	0.65^b	0.23	0.32^b	0.51	0.64^a	0.79^a	1.18^a	1.29^a
9	0.96^b	0.72^b	0.26	0.27	0.31^b	0.50^c	0.79^a	0.64^b	0.25	0.31^a	0.50	0.66^a	0.71^b	1.13^a	1.17^a
10	0.89^b	0.73^b	0.28	0.28	0.30^a	0.46	0.78^a	0.58^c	0.23	0.23^c	0.52	0.68^a	0.68^b	1.07^a	1.13^a
11	0.81^b	0.72^b	0.19	0.29	0.25^b	0.33	0.61^b	0.47	0.20	0.20^c	0.53	0.63^a	0.65^b	1.11^a	1.09^a
12	0.77^b	0.72^b	0.17	0.26	0.23^c	0.32	0.55^c	0.37	0.18	0.27^b	0.56^c	0.63^a	0.68^b	1.06^a	1.02^a

A2: Short-Horizon Anomalies

	MOM	SUE	FRV	ROE	GM	OSCORE	CHS	IVOL	DISP
1	1.96^a	2.06^a	1.60^a	2.39^a	0.84^a	0.27	1.68^a	0.89	0.73^c
2	0.94^b	0.84^a	1.07^a	1.53^a	0.59^b	0.33	1.28^a	0.65	0.52
3	0.36	0.17	0.29	0.46	0.36	0.24	1.05^b	0.55	0.07
4	−0.41	-0.37^b	−0.16	0.10	0.17	0.28	0.44	0.23	−0.15
5	-0.58^c	0.17	0.09	0.56^c	0.31	0.15	0.04	0.30	0.06
6	-0.62^b	0.28	0.29	0.57^c	0.26	0.08	−0.15	0.12	0.11
7	-0.55^c	−0.07	0.22	−0.02	0.20	0.10	−0.08	0.02	−0.05
8	−0.45	0.06	−0.10	0.12	0.19	0.04	−0.17	0.01	−0.14
9	−0.23	−0.02	0.01	0.10	0.21	0.10	−0.43	−0.13	−0.10
10	−0.18	0.02	0.36	0.13	0.16	0.01	−0.25	−0.12	0.13
11	−0.26	−0.04	0.41^c	−0.23	0.23	0.01	0.04	0.00	0.08
12	−0.37	−0.05	0.09	−0.06	0.16	0.07	−0.26	−0.28	−0.10

Panel B: 1980-2018

B1: 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
9	0.76	0.49	0.12	0.22	0.18	0.42	0.65^c	0.83^b	0.20	0.38^a	0.59	0.62^b	0.87^a	0.89^c	1.17^a
10	0.61	0.43	0.11	0.22	0.27^c	0.40	0.65^c	0.74^c	0.18	0.34^b	0.60	0.64^b	0.84^a	0.92^b	1.07^b
11	0.55	0.46	−0.02	0.13	0.25^c	0.26	0.43	0.58	0.18	0.35^a	0.57	0.57^b	0.78^a	0.94^b	1.03^b
12	0.56	0.45	0.03	0.13	0.24	0.26	0.44	0.50	0.14	0.31^a	0.60	0.57^b	0.77^a	0.96^b	1.02^b

B2: 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
5	−0.64	0.32	0.09	0.71^b	0.31	0.41	0.36	0.94	0.09
6	-0.71^c	0.37	0.34	0.60	0.25	0.36	0.17	0.75	0.19
7	−0.55	0.10	0.25	0.10	0.27	0.37	0.33	0.66	−0.02
8	−0.46	0.11	−0.09	0.28	0.29	0.33	0.32	0.52	−0.15
9	−0.46	0.12	0.04	0.24	0.26	0.34	−0.19	0.30	−0.12
10	−0.11	0.14	0.39	0.16	0.17	0.27	0.03	0.31	0.13
11	−0.09	0.13	0.41^c	−0.11	0.33	0.24	0.39	0.38	0.06
12	−0.11	0.08	0.11	0.12	0.25	0.22	0.05	−0.03	−0.15

Table A2: Institutional Trading on Individual Anomalies

This table reports institutional trading measures on the 24 individual-anomaly portfolios. 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). They are 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. The sample period is from 1980 to 2018.

Panel A: Δ%Inst

A1: 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)

A2: 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)

Panel B: Δ#Inst

B1: Long-Horizon Anomalies

	BP	EP	SG	CAPX	AI	AG	NS	XFIN	ACC	DACC	ATTO	NOA	GP	RD	SGA
Short	30.36	25.26	33.88	22.18	21.38	32.66	32.89	27.93	25.62	22.02	17.72	25.87	18.26	23.91	25.55
Long	13.54	20.65	12.25	22.36	20.64	14.77	14.82	18.32	21.51	24.15	26.63	22.89	25.53	17.32	18.93
L-S	-16.82^a	-4.61^a	-21.63^a	0.17	−0.74	-17.89^a	-18.07^a	-9.61^a	-4.11^a	2.13^a	8.92^a	-2.98^b	7.27^a	-6.59^a	-6.62^a
t-stat	(−9.32)	(−2.81)	(−15.28)	(0.15)	(−1.11)	(−12.33)	(−12.15)	(−9.13)	(−4.01)	(2.85)	(4.14)	(−2.48)	(4.89)	(−7.20)	(−3.34)

B2: Short-Horizon Anomalies

	MOM	SUE	FRV	ROE	GM	OSCORE	CHS	IVOL	DISP
Short	−2.88	0.54	−0.41	3.17	5.71	8.67	2.18	8.09	2.62
Long	18.42	11.24	13.63	10.04	7.47	5.21	10.06	4.36	9.44
L-S	21.30^a	10.70^a	14.03^a	6.87^a	1.76^a	-3.46^a	7.89^a	-3.72^a	6.81^a
t-stat	(20.52)	(19.95)	(28.01)	(12.07)	(5.46)	(−8.23)	(13.12)	(−5.48)	(9.21)

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. Panel A and B are for the sample periods of 1963-2018 and 1980-2018, respectiely.

Panel A: 1963-2018

A1: ILQ for Long-Horizon Anomalies

	BP	EP	SG	CAPX	AI	AG	NS	XFIN	ACC	DACC	ATTO	NOA	GP	RD	SGA
Short	38.63	42.84	45.62	42.98	47.40	45.40	44.46	48.87	51.60	50.59	42.66	48.27	46.87	42.05	38.17
Long	59.68	54.17	53.79	55.43	51.35	54.44	47.96	48.51	49.18	48.01	55.29	50.09	49.67	51.57	60.98
L-S	21.05^a	11.34^a	8.17^a	12.46^a	3.95^a	9.04^a	3.50^a	-0.36	-2.42^a	-2.59^a	12.63^a	1.81^a	2.81^a	9.52^a	22.81^a
t-stat	(28.29)	(10.83)	(14.00)	(18.28)	(7.29)	(13.91)	(2.85)	(-0.42)	(-4.79)	(-6.41)	(18.81)	(2.68)	(4.06)	(14.40)	(36.71)

A2: ΔILQ for Long-Horizon Anomalies

	BP	EP	SG	CAPX	AI	AG	NS	XFIN	ACC	DACC	ATTO	NOA	GP	RD	SGA
Short	-3.46	-1.71	-4.09	-1.27	-1.41	-3.68	-3.69	-2.04	-1.53	-0.43	-0.56	-1.67	-0.49	-1.72	-2.36
Long	1.37	-0.82	1.92	-0.52	0.11	1.32	0.62	0.10	-0.74	-0.92	-1.54	-0.61	-1.40	1.24	1.07
L-S	4.83^a	0.89^b	6.01^a	0.75^a	1.52^a	4.99^a	4.31^a	2.14^a	0.78^a	-0.49^b	-0.98^a	1.06^a	-0.91^a	2.96^a	3.43^a
t-stat	(12.57)	(2.29)	(26.53)	(4.12)	(9.74)	(15.85)	(11.64)	(6.60)	(4.21)	(-2.60)	(-2.97)	(4.81)	(-3.03)	(8.82)	(8.15)

A3: ILQ for Short-Horizon Anomalies

	MOM	SUE	FRV	ROE	GM	OSCORE	CHS	IVOL	DISP
Short	49.89	48.49	46.74	55.94	53.84	58.93	59.80	61.36	45.80
Long	50.15	43.34	41.38	43.15	44.18	40.70	41.56	37.72	33.46
L-S	0.26	-5.15^a	-5.36^a	-12.79^a	-9.66^a	-18.23^a	-18.24^a	-23.64^a	-12.34^a
t-stat	(0.23)	(-13.00)	(-13.73)	(-18.68)	(-27.29)	(-40.52)	(-26.36)	(-19.76)	(-17.10)

A4: ΔILQ for Short-Horizon Anomalies

	MOM	SUE	FRV	ROE	GM	OSCORE	CHS	IVOL	DISP
Short	2.26	0.94	1.17	0.46	-0.12	-0.84	0.60	-0.66	0.44
Long	-3.71	-1.44	-1.83	-1.27	-0.58	-0.21	-0.98	-0.36	-1.12
L-S	-5.97^a	-2.38^a	-2.99^a	-1.73^a	-0.46^a	0.63^a	-1.58^a	0.29	-1.56^a
t-stat	(-31.55)	(-19.70)	(-19.02)	(-11.98)	(-5.24)	(5.97)	(-8.37)	(1.01)	(-7.56)

Panel B: 1980-2018

B1: 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)

B2: 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)

B3: 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)

B4: 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. The sample period is from 1963 to 2018.

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

	Value	Investment	Financing	Quality	Efficiency	Intangible	LT Profitability
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 Profitability	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 Between Long and Short Legs

	Value	Investment	Financing	Quality	Efficiency	Intangible	LT Profitability
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 Profitability	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