ERASMUS UNIVERSITY ROTTERDAM

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Master Thesis Financial Economics

Informed Trading by Short-term Institutional Investors: An Asset Pricing Perspective

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Abstract

Studying short-term institutional investors and the informational advantages of institutional trading, this paper shows how their ownership changes are predictive of future stock returns. Originally found by Yan and Zhang (2009), trading by this group of investors, distinguished by their high turnover, continues to show patterns of return predictability after the publication of their findings. By constructing multiple long-short portfolios with this characteristic, robustness from an asset pricing perspective is shown, with returns remaining significant multiple quarters after portfolio formation. Examining the influence of multiple limits-to-arbitrage, neither liquidity costs nor idiosyncratic risk offer a full explanation for excess returns, showing robustness from an investability perspective. After controlling for several asset pricing anomalies, returns following short-term institutional trading remain significant, indicating uniqueness of both the trading behavior and excess returns. Said uniqueness likely points to informational advantages of short-term institutional investors, as return predictability is stronger for stocks with high investor information asymmetry.

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1. Introduction

Information asymmetry in the stock market has been the subject of a longstanding debate; are there investors who consistently generate alpha? Institutional investors are often at the forefront of this debate. A multitude of papers document institutional investors as “smart money”, while plenty of evidence also exists pointing towards the contrary (Carhart, 1997; Badrinath & Wahal, 2002; Parrino, Sias & Starks, 2003; Fama & French, 2010). Thus, this is a question that may never get settled, and modern financial literature reflects this by taking a different approach, trying to unite these schools of thought. While Gompers and Metrick (2001) analyzed institutional ownership in its entirety, Baik, Kang and Kim (2010) accounted for the geographic location of investors. And whereas the former found no significant relationship between institutional trading and future stock returns, the latter came to different conclusions. Namely, they found that institutional investors located within the same state as a firm’s headquarters, possess significant informational advantages for those firms. Their trading behavior was predictive of future stock returns, whereas trading by nonlocal investors showed no significant effects. Similarly, specifically for investment advisers and large institutions, Bushee and Goodman (2007) find that informed trading is more likely, by analyzing institutional trades based on private information.

Apart from that, however, little research into the heterogeneity of institutional investors and asset pricing has been published, except for Yan and Zhang (2009). In their paper on institutional turnover and equity returns, they identify a certain subset of “skilled” investors based on investment horizon. A well-documented phenomenon is excessive trading by retail investors, where net returns are lower for those individuals who trade the most (Barber & Odean, 2000). A lack of informational advantages or investing skill for these individuals is evident. For the most part, performance of institutional investors, often styled as “rational” investors seems much the same. Edelen, Ince and Kadlec (2016) find no discernible (positive) predictive power of institutional trading on future stock returns, and institutional investors countertrade most asset pricing phenomena. Yan and Zhang (2009), however, find that overtrading does not necessarily apply to institutional investors. Analyzing so-called short-term institutional investors, so named after their relatively high turnover, they find that their ownership flows have a positive predictive power of future stock returns. On the other hand, trading behavior of long-term institutional investors seems to have no such predictive power. Thus, it seems there is significant variability in the skills of institutional investors. By differentiating between these investors with different investment horizons, this paper aims to establish common ground among the literature on smart money, from an asset pricing perspective.

Following calculations described by Yan and Zhang (2009), institutional investors are split into groups based on trading behavior. Those investors who trade the most (least) are classified as short-term (long-term) investors. Their change in holdings of specific stocks is then tracked from quarter to quarter, which is defined as short-term (long-term) institutional trading. Several factor portfolios – henceforth referred to as the "flow" factor – are constructed with this firm-specific measure, which reflect the predictive power of short-term institutional trading. In doing so, this paper attempts to answer the main research question, which is as follows: how are future stock returns related to short-term institutional trading? Whereas Yan and Zhang (2009) focused primarily on short-term institutional ownership, this paper focuses on short-term institutional trading, and examines it as an asset pricing characteristic. Short-term institutional trading from the dimension of limits-to-arbitrage also remains almost entirely unexplored, which this paper aims to test comprehensively. This allows for a more thorough analysis of stock returns associated with that which sets these institutional investors apart, their trading behavior.

Several hypotheses are also formulated to better answer the main research question. These will be listed in the following paragraphs. This paper starts off by reexamining the return predictability of short-term institutional trading found by Yan and Zhang (2009), and whether this phenomenon has continued after their paper was published. This need not necessarily be the case, as anomaly returns are often lower after being discovered by their initial publication (McLean & Pontiff, 2016). Given the ever-changing nature of institutional investors and their preferences (Bennett, Sias & Starks, 2003), the predictive ability of short-term institutional trading could have vanished. By examining short-term institutional trading from 1980 to 2022, nineteen years of additional data are analyzed, compared to the 2003 cutoff set by Yan and Zhang (2009). Thus, the first hypothesis of this paper is as follows: short-term institutional trading is predictive of future stock returns. Factor portfolios based on short-term institutional trading are constructed in a variety of ways to thoroughly test the robustness of associated excess returns. This paper finds evidence of significant excess returns for these portfolios.

Next, the relationship of the flow factor with other asset pricing anomalies is considered. Yan and Zhang (2009) show robustness to value, size, and momentum effects for short-term institutional trading by using DGTW benchmark-adjusted returns (Daniel, Grinblatt, Titman & Wermers, 1997). However, given the sorting techniques used by the DGTW method, anomaly returns may not be fully captured due to poor portfolio diversification (Fama & French, 2015). Furthermore, other asset pricing anomalies have since been formalized, such as the profitability- and investment factor (Aharoni, Grundy & Zeng, 2013; Novy-Marx, 2013). These may explain more of the return variation of the flow factor. Hence, the second hypothesis examined by this paper is as follows: stock returns following short-term institutional trading are not subsumed by other asset pricing anomalies. To thoroughly test this hypothesis, several portfolio double sorts are conducted, sorting first on short-term institutional trading, then on various firm characteristics. Several regression models with flow factor returns as the dependent variable are constructed as well, and residual return correlations are examined. In doing so, robustness of the flow factor is tested from a variety of dimensions, and this paper finds very little evidence of anomalies consistently subsuming its excess returns.

Next, potential limits-to-arbitrage for the flow factor are considered. This dimension of short-term institutional trading remains entirely unexplored from an asset pricing perspective. While short-term institutional trading may show significant predictive power of future stock returns, how exploitable are these returns practically? Once transaction costs, liquidity and other limits-to-arbitrage are considered, flow factor returns may be significantly lower. Therefore, the third hypothesis is as follows: stock returns following short-term institutional trading are not significantly associated with limits-to-arbitrage. To test this hypothesis, several limits-to-arbitrage are examined in portfolio double sorts, including idiosyncratic volatility, bid-ask spreads, illiquidity, and institutional ownership. By examining 12-month portfolio turnover ratios for the flow factor, transaction costs are considered as well, from the perspective of break-even costs. This paper finds no evidence of limits-to-arbitrage as a comprehensive explanation for flow returns, and those that do matter (e.g., idiosyncratic volatility) are avoidable for aspiring arbitrageurs.

Finally, potential sources of flow factor returns are considered. If returns aren't subsumed by known asset pricing anomalies, what else can explain the return predictability of short-term institutional trading? Yan and Zhang (2009) find that short-term institutional trading has stronger predictive power for small- and growth stocks returns, as opposed to large- and value stock returns. They use this finding to substantiate their claim of short-term institutional investors having informational advantages. As the theory behind this claim and the reasoning for it may seem somewhat unclear, interpretations from Section 3.4 will elaborate further on economic intuitions. While this paper finds similar evidence for growth stocks, the inverse seems to hold for small stocks, seemingly invalidating informational advantages as an explanation for flow factor returns (Baik, Kang & Kim, 2010). However, information asymmetry is reflected through other firm characteristics as well, such as return volatility (Baik, Kang & Kim, 2010). So, to reconcile findings with economic interpretations from Yan and Zhang (2009), several characteristics are considered. The fourth hypothesis is therefore as follows: stock returns following short-term institutional trading are driven by informational advantages. To test this hypothesis, idiosyncratic volatility is again considered, now as a proxy for information asymmetry, and used for portfolio triple sorts, sorting first on size. With size effects disentangled, this paper finds evidence for informational advantages as an explanation for the predictive power of short-term institutional trading.

Apart from attempting to explain flow factor returns with stock characteristics, the predictive power of short-term institutional trading is also examined from an investor perspective. As stated previously, Bushee and Goodman (2007) found that informed trading is more likely for large institutions. Various other investor characteristics exist that could explain predictive power of short-term institutional trading, such as fund age and trade size (O'Connell & Teo, 2009). If short-term institutional investors are more prone to exhibit these characteristics compared to other investors, flow factor returns may not be driven by investor turnover, raising endogeneity concerns. Therefore, the fifth hypothesis is as follows: the predictive power of short-term institutional trading is driven by investor turnover. To test this hypothesis, several robustness checks are conducted, where investor characteristics are examined by turnover group and controlled for through alternative investor sorts. While short-term institutional investors may exhibit certain characteristics that could explain their informational advantages, little evidence of either subsumption or endogeneity presents itself.

The approach to measure institutional trading taken by Yan and Zhang (2009) is often critiqued when used in the context of asset pricing. Changes in ownership reflect the quantity of shares traded, which have been found to contain little incremental informational for stock returns, compared to the number of trades (Sias, Starks & Titman 2006). Edelen, Ince and Kadlec (2016), for example, look at changes in the number of investors themselves, i.e., number of trades. They argue that this method is more reflective of alpha-motivated trades and puts less emphasis on large institutional investors. Edelen, Ince and Kadlec (2016) also mention, however, that results between the two methods are always qualitatively similar. Moreover, Bushee and Goodman (2007) argue that informational advantages are held primarily by large institutions, which have greater resources and potentially more access to management. They further find that large positions for these institutions are more reflective of informed trading, and Easley, Kiefer and O'Hara (1997) show how the information content of trades varies with trade size. This puts findings by Sias, Starks and Titman (2006) regarding the significance of quantity of shares traded into perspective. Finally, concerns of endogeneity with investor size are addressed by robustness checks; neither trade size nor equity portfolio size explain the performance gap between short- and long-term investors. Thus, ownership changes as per Yan and Zhang (2009) are unlikely to capture effects of potentially confounding variables and investor characteristics identified by Bushee and Goodman (2007).

Another critique of short-term institutional ownership as proposed by Yan and Zhang (2009) is its possible endogeneity. Baik, Kang and Kim (2010) argue that the superior performance of stocks held by short-term institutional investors may be a manifestation of the predictability of past trading volume for future returns. However, according to Lee and Swaminathan (2002), if past trading volume is indeed driving returns from short-term institutional ownership, these returns should decrease with said ownership. They document lower future returns for stocks with higher trading volume. Short-term institutional ownership, positively correlated with trading volume (Yan & Zhang, 2009), increases future returns. Furthermore, even if short-term institutional ownership is endogenous to trading volume, short-term institutional trading should be exogenous. Short-term institutional trading, being the change in short-term institutional ownership relative to the previous quarter, should only correlate with trading volume in its absolute value. Such a measure would be reflective of the total volume traded by short-term institutions, thus correlated with trading volume. For short-term institutional trading itself, there should be no difference in market volume between stocks with high- and low levels of said trading, as both extremes represent high levels of trading. Endogeneity concerns raised by Baik, Kang and Kim (2010) are thus dismissed.

Another method of approximating investment horizons of institutional investors is the measurement of ownership changes over differing periods of time. Whereas Yan and Zhang (2009) measure ownership changes from quarter to quarter, Edelen, Ince and Kadlec (2016) measure institutional trading over a five-quarter window. In doing so, they aim to capture all trading during anomaly portfolio formation, where investors build up positions over longer periods of time. The issue with this approach is twofold. First, it assumes all investors are equal in terms of investing skill; an unrealistic assumption – as posited previously – and acknowledged as a limitation by the authors themselves. Second, it assumes that, while investors cannot differ in term of investment horizon, their investments can. This once again overlooks the heterogeneity of investors; some investors may specialize in short-term trading, while others focus primarily on long-term investing. Thus, as this paper aims to examine informational advantages of investors themselves, not necessarily their investments, the approach of Yan and Zhang (2009) is chosen.

2. Data & Methodology

This paper obtains data through several sources. Most data and variables are gathered from CRSP. The exceptions are as follows: Institutional ownership data from Thomson Reuters/ CDA, book values from Compustat, MSCI U.S. index return data from Datastream, and factor returns from the Kenneth R. French data library. From CRSP, monthly data is used for most analyses conducted by this paper. For the calculation of illiquidity- and idiosyncratic volatility measures, daily data is used as well. The collected data is then transformed as detailed by the remainder of this section.

To determine investor turnover, Thomson Reuters/ CDA 13F data is subjected to multiple transformations and filters. With 13F data reported as the number of shares of individual stocks held by individual institutional investors, data is aggregated on a stock level to calculate institutional ownership. This paper includes in its stock universe those observations with either share code 10 or 11 in CRSP (common equity). This excludes ADRs, REITs and foreign shares. Compared to Yan and Zhang (2009), this may lead to slightly different results. Just as Thomson Reuters/CDA claims for its ownership data, Yan and Zhang (2009) report solely including common stocks. After referencing CRSP, however, observations without share code 10 or 11 (CRSP common equity) remain. There is even a separate share code variable available for Thomson Reuters/CDA data (less optimal than CRSP share codes, due to data availability). This would be rather redundant if only common equity was admitted. As stated on the SEC website, certain other types of securities, e.g., equity options and warrants, may also be reported on form 13F (U.S. Securities and Exchange Commission, n.d.). But Yan and Zhang (2009) never explicitly mention filtering data based on CRSP share codes. This may explain the difference in sample size. They report a quarterly average of 5,911 stocks, whereas this paper covers an average of 3,956 stocks per quarter from 1980 to 2003. This figure drops to 3,662 stocks over the entire sample period, from 1980 to 2022. Despite the inferior sample size, stocks with share code 10 or 11 are studied exclusively, as is often recommended by contemporary asset pricing literature (Fama & French, 2015; Asness, Moskowitz & Pedersen, 2013).

Next, quarterly observations of stocks with aggregated institutional ownership exceeding 100% of shares outstanding are dropped from the sample. This is done to eliminate data errors due to double counting of filings (Gompers & Metrick, 2001; Yan & Zhang, 2009). As mentioned before, 13F data is aggregated on a stock level to measure ownership. But in order to calculate portfolio turnover of institutional investors, 13F data is aggregated on an investor level as well. This is done as detailed below, where aggregated buys and sales for institution k during quarter t are calculated as follows:

$$Buy_{k,t} = \sum_{i=1}^{N_k} |S_{k,i,t}\, P_{i,t} - S_{k,i,t-1}P_{i,t-1} - S_{k,i,t-1}\Delta P_{i,t}|, \qquad \text{if } S_{k,i,t} > S_{k,i,t-1} \tag{1}$$

$$Sell_{k,t} = \sum_{i=1}^{N_k} |S_{k,i,t}\, P_{i,t} - S_{k,i,t-1}P_{i,t-1} - S_{k,i,t-1}\Delta P_{i,t}|, \qquad \text{if } S_{k,i,t} \leq S_{k,i,t-1}, \tag{2}$$

where $S_{k,i,t}$ and $S_{k,i,t-1}$ are the number of shares of stock i held by investor k at the end of quarter t and $t-1$, and $P_{i,t}$ and $P_{i,t-1}$ are the share prices for stock i at the end of quarter t and $t-1$, respectively. Stock splits and stock dividends are accounted for by using the CRSP price adjustment factor. Next, following Yan and Zhang (2009), institution k's churn rate during quarter t is calculated as follows:

$$CR_{k,t} = \frac{\min(Buy_{k,t}, Sell_{k,t})}{\sum_{i=1}^{N_k} \frac{S_{k,i,t}P_{i,t} + S_{k,i,t-1}P_{i,t-1}}{2}} \tag{3}$$

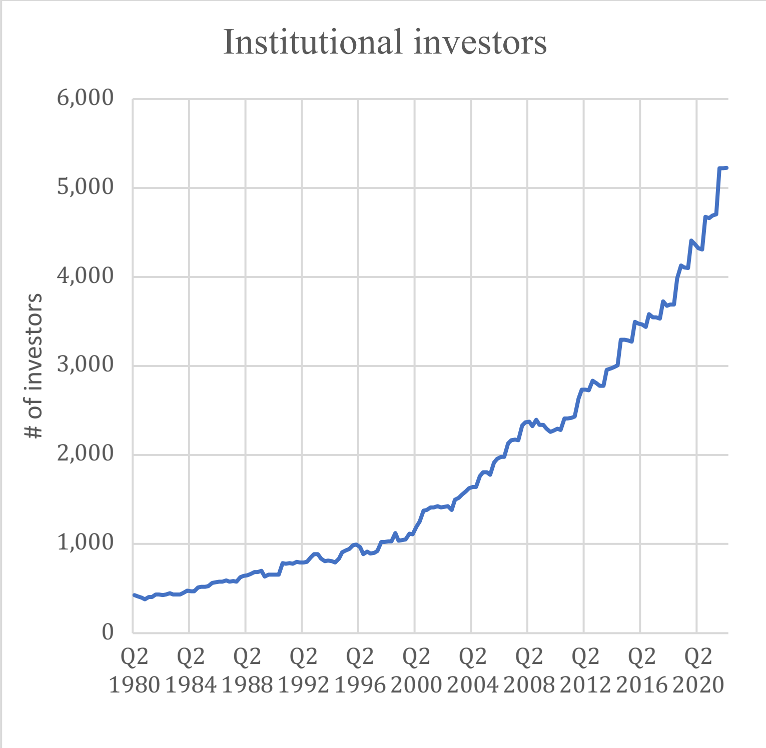
This is one of two widely adopted churn rate calculation methods. The sum of aggregate buys and sales, instead of the minimum, is also applied often. In this case, the minimum value reduces the impact of investor cash flows, which have been shown to contain little information (Alexander, Cici & Gibson, 2006). Lastly, investor turnover is computed by averaging the churn rates of the previous four quarters, as shown below:

$$Turnover_{k,t} = \frac{1}{4}\sum_{j=0}^{3} CR_{k,t-j} \tag{4}$$

This characteristic is used to divide institutional investors into tertiles every quarter. Those assigned to the bottom tertile are defined as long-term investors, while those ranked in the upper tertile are defined as short-term investors. Then, for each stock, short-term institutional ownership (SIO) is defined as the ratio between the number of shares held by short-term investors and the total number of shares outstanding. Long-term institutional ownership (LIO) is defined analogously, for shares held by long-term investors. Ownership of investors assigned to the middle turnover tertile is classified as medium-term institutional ownership, but these investors are irrelevant for the research of this paper. Total institutional ownership of all these investors combined is referred to as TIO, and IO is used to refer to any one of these ownership variables. Lastly, short-term institutional trading (ΔSIO) is defined as the difference between the current (t) and previous quarters' ($t-1$) short-term institutional ownership for stock i, $SIO_{i,t} - SIO_{i,t-1}$. Long-term institutional trading (ΔLIO) is defined analogously for ownership changes of long-term institutional investors. Total institutional trading of all institutional investors combined is referred to as ΔTIO, and ΔIO is used to refer to any one of these trading variables. ΔSIO is the main variable of interest for this paper. It represents the total ownership change of short-term institutional investors from quarter to quarter, thus serves as a crude measure of their aggregated trading. It is crude in the sense that intra-quarter trading is not encompassed within this measure. This also means that the actual predictive power of short-term institutional trading on future stock returns is greater than what ΔSIO measures, as intra-quarter institutional trades contain significant alpha (Puckett & Yan, 2011). With this, excess returns of institutional trading measured by quarterly changes of institutional trading (ΔSIO) are likely biased downwards compared to more comprehensive measures of their trading. This may be the case for short-term institutional investors especially. Their frequent inter-quarter trading, implied by their high turnover as measured per Equation (4), likely extrapolates to frequent intra-quarter trading, implying that more intra-quarter alpha is lost. Therefore, the predictive power of ΔSIO is likely lower than the predictive power of actual institutional trading; similar implications hold for their trading skills and informational advantages.

Figure 1 shows the number of total institutional investors over time (as investors are divided into tertiles, the number of short-term investors would be one third of the total investors for each quarter). Offered here is another reason for the importance of this paper and why short-term institutional trading need not necessarily be predictive of future stock returns anymore. The number of investors has grown more than threefold over the last 20 years, thereby potentially diluting the definition of short-term institutional investors and their aggregated investment skills. Competition between investors is a potentially influencing factor as well. Several papers have documented decreased information asymmetry for stocks with higher non-concentrated institutional ownership, i.e., ownership dispersed over a greater number of investors (Schnatterly, Shaw & Jennings, 2007; Akins, Ng & Verdi, 2012). Informational advantages of short-term institutional investors could therefore have eroded over time as more investors have entered the market.

Figure 1 Number of institutional investors included in the sample, plotted by quarter



Note. The number of institutional investors included after calculations as detailed in Section 2, from Q2 1980 to Q2 2022

If the predictive power of short-term institutional trading on future stock returns is indeed shown as robust, informational advantages need not necessarily be driving these returns. Short-term institutional investors could potentially trade based on known asset pricing anomalies, and these anomalies could explain ΔSIO excess returns. To control for value, size and momentum effects, this paper uses – among other methodologies – the DGTW method, originally introduced by Daniel, Grinblatt, Titman and Wermers (1997). Up until 2012, the DGTW benchmarks are available via Russ Wermers' DGTW page (2013). As this page is no longer updated, these benchmarks are recreated manually. To do this accurately, steps outlined by these sources are followed closely, as well as methods described by supporting papers (Daniel & Titman, 1997; Wermers, 2004). As such, common stocks from CRSP with Compustat book values are triple-sorted into value-weighted portfolios. These portfolios, 125 in total, are reconstituted every year at the end of June. Quintiles are based on firm size, industry-adjusted book-to-market ratios and momentum returns, triple-sorted in that order. Given the obfuscated nature of DGTW book-to-market calculations, methods used to calculate the characteristic are presented below. Following Daniel and Titman (1997), book value of equity for individual firms is defined as follows:

$$Book\ value = SEQ + TXDB + ITCB - PREF, \tag{5}$$

where SEQ, $TXDB$, $ITCB$, and $PREF$ equal fiscal year-end stockholders' equity, deferred taxes, investment tax credit, and the value of preferred stock, respectively, all from Compustat. The value of preferred stock is defined as either redemption-, liquidating- or carrying value, in that order of preference. Next, instructions by Russ Wermers' DGTW page (2013) are followed. Book values used for portfolio sorts in June use current fiscal year-end book values if a fiscal year ends during January through May. If not, previous fiscal year-end book values are used. Following Daniel et al. (1997), book-to-market ratios are then computed using market values at the end of December. Lastly, in accordance with Wermers (2004), these book-to-market ratios are industry adjusted as follows:

$$Adjusted\_BTM_{i,t}^{j} = \frac{\ln(BTM_{i,t}^{j}) - \ln(BTM_{t}^{j})}{\sigma_j\left[\ln(BTM_{i,t}^{j}) - \ln(BTM_{t}^{j})\right]}, \tag{6}$$

where $\ln(BTM_{i,t}^{j})$, $\ln(BTM_{t}^{j})$, and $\sigma_j\left[\ln(BTM_{i,t}^{j} - \ln(BTM_{t}^{j})\right]$ equal the log book-to-market ratio of firm i belonging to industry j at June 30th of year t, the log book-to-market ratio of industry j (defined as the total book value divided by the total market value of industry j), and the cross-sectional standard deviation across industry j of a measure subtracting these two values, respectively. Industries are identified by CRSP SIC codes, following Fama and French (1997). This yields the book-to-market characteristic used for the triple-sorted DGTW benchmark portfolios. Returns for the 125 portfolios are shown in Appendix A, where their efficacy is visible; across size quintiles, value and momentum effects are visible, and returns generally decrease with size. For portfolio double-sorts using adjusted book-to-market ratios in Section 3.3, calculations are similar to those detailed above, but updated every quarter instead of every June.

Limits-to-arbitrage are a focal point for this paper, as excess returns of ΔSIO could potentially be explained, thus invalidated, by sources of arbitrage risk or transaction costs. Liquidity is one of these relevant limits-to-arbitrage. This stock characteristic will be examined from multiple viewpoints, one of which is the illiquidity measure introduced by Amihud (2002). Following his calculations, an illiquidity variable from daily stock data is created every day for each stock individually, defined as follows:

$$ILLIQ_{idq} = \left|R_{idq}\right| / VOLD_{idq}, \tag{7}$$

where R_{idq} is the return on stock i of day d of quarter q and $VOLD_{idq}$ is the respective daily trading volume in dollars. This measure can be interpreted as the daily price response associated with one dollar of trading volume and is shown to be positively and strongly related to microstructure estimates of illiquidity (Amihud, 2002). Then, daily $ILLIQ_{idq}$ measures of stock i are averaged over the days of quarter q. Similarly, Amihud (2002) uses monthly and yearly averages, but quarterly averages are more suited for research on institutional ownership, which is updated quarterly. Thus, when this paper mentions $ILLIQ$, it refers to the quarterly average of $ILLIQ_{idq}$.

According to Shleifer and Vishny (1997), another important limit-to-arbitrage is idiosyncratic risk. In multiple sections of this paper, portfolio double- and triple-sorts will be conducted using a measure of return volatility, commonly denoted as idiosyncratic volatility ($IVOL$), or idiosyncratic risk. To calculate said measure, methods of Ang, Hodrick, Xing and Zhang (2006) are followed. Using daily stock returns data, value-weighted DGTW portfolio returns are calculated on a day-to-day basis. These portfolios are then used to construct several risk factors, applied in the following regression model:

$$r_t^i = a^i + \beta_{MKT}^i MKT_t + \beta_{SMB}^i SMB_t + \beta_{HML}^i HML_t + \beta_{UMD}^i UMD_t + \varepsilon_t^i, \tag{8}$$

where MKT, SMB, HML, and UMD are returns on day t for a value-weighted market portfolio (from CRSP), a size factor, a value factor, and a momentum factor, respectively. Value and momentum (and size) are defined as the average returns of all 25 respective P5 (P1) DGTW portfolios, minus the average returns of all 25 respective P1 (P5) DGTW portfolios. For example, the value factor is constructed as follows:

$$SMB_t = \frac{1}{25}\sum_{v=101}^{125} r_t^v - \frac{1}{25}\sum_{v=1}^{25} r_t^v, \tag{9}$$

where r_t^v equals the average return on day t for book-to-market portfolio v. Here, a v of 1 through 25 signifies one of the 25 bottom book-to-market quintile portfolios. Conversely, a v of 101 through 125 signifies one of the 25 upper book-to-market quintile portfolios. The same calculations are applied to construct size- and momentum factors. This methodology is similar in spirit to the one used by Fama and French (1993) to create market, size, and value factors. Ang et al. (2006) calculated idiosyncratic volatility relative to this three-factor model, without including any momentum effects. Over the years, the momentum factor has become increasingly well-established in the financial literature (Asness, Moskowitz & Pedersen, 2013; Asness, Frazzini, Israel & Moskowitz, 2014). By also controlling for momentum, the model from Equation (8) should be an even more comprehensive measure of idiosyncratic risk, compared to the model used by Ang et al. (2006). The daily residuals from this regression equation are then used to compute idiosyncratic volatility as follows:

$$IVOL_j^i = \sigma_j^i\left[\varepsilon_t^i\right], \tag{10}$$

where $\sigma_j^i\left[\varepsilon_t^i\right]$ equals the standard deviation of residuals ε_t^i for stock i over all days t during quarter j. This is comparable to methods applied by Ang et al. (2006). In this case, though, lookback- and holding periods for the portfolios are set to three months, instead of one month. This is done to better fit the windows of calculation for ΔSIO, which is only updated quarterly.

Table 1 shows time-series summary statistics for cross-sectional averages of stock characteristics. On average, short-term institutional investors account for approximately half of total institutional ownership, while long-term institutional ownership is only a quarter of total ownership. This is somewhat in accordance with Yan and Zhang (2009), who also find that short-term institutional investors account for a higher percentage of ownership. The relative gap between investors has narrowed, as short-term (long-term) ownership accounted for 9.1% (4.4%) of shares outstanding in Q3 of 1980, while this was 26.9% (22.7%) in Q2 of 2022. Average total institutional ownership has also increased, reflecting the ever-growing importance of their status as market participants. Table 2 shows time-series averages of cross-sectional correlation coefficients for all variables. Short-term institutional ownership is strongly related to total institutional ownership, though their changes from previous quarter not as much. Short-term institutional ownership is negatively correlated with $ILLIQ$, slightly more so than long-term institutional ownership, reflective of preferences for liquidity. Short-term institutional ownership changes are correlated with momentum returns, but no more than total institutional ownership changes. Strong negative correlations with $IVOL$ are observed for all institutional ownership variables. Interpreting these correlations, investors seemingly avoid stocks with high limits-to-arbitrage.

3. Results

3.1 Comparative performance

In spite of the reduced cross-sectional sample size discussed in the previous section, results for quarterly stock returns of ΔSIO-sorted portfolios from 1980 to 2003 are similar to Yan and Zhang (2009). For reference, their original results are shown in Appendix B. Table 3 shows returns and t-statistics for portfolios sorted by quarterly institutional ownership changes, henceforth denoted as ΔIO. Quarterly excess returns are all significant for the P5-P1 ΔSIO portfolio, except for DGTW benchmark-adjusted returns from Q1 to Q2 after portfolio formation. Portfolios sorted on ΔLIO also show no significant return spread, consistent with the findings of Yan and Zhang (2009). One major difference is the fact that t-statistics are significantly lower across the board. The smaller sample size employed by this paper could be an explanation for this.

Table 4 shows results for quarterly returns over the entire sample period, from Q3 1980 to Q2 2022. A P5-P1 portfolio sorting on total institutional ownership changes, ΔTIO, is also shown. Excess returns are much less significant compared to the ΔSIO-sorted long-short portfolio; only first quarter returns are

Table 1 Time-series summary statistics of cross-sectional averages

	Mean	**Median**	**Maximum**	**Minimum**	**Std. Dev.**
TIO, %	40.00	36.06	63.52	17.74	16.34
ΔTIO, %	0.38	0.35	4.89	-3.00	1.02
SIO, %	18.82	18.27	28.60	8.48	7.11
ΔSIO, %	0.12	0.02	2.65	-2.78	0.85
LIO, %	9.98	6.98	25.13	3.16	6.71
ΔLIO, %	0.17	0.17	6.60	-6.35	1.55
Market value, $million	3531.70	2437.47	14851.32	365.86	3522.94
$ILLIQ$	3.13	2.58	15.91	0.19	2.40
$IVOL$, %	2.73	2.57	5.10	1.72	0.69
$\mathrm{RET}_{t-3,\, t}$, %	4.47	4.34	37.50	-29.76	11.48
$\mathrm{RET}_{t-12,\, t-1}$, %	17.36	15.15	143.92	-42.07	25.22
B/M	0.79	0.80	1.66	0.52	0.19
Adj. B/M	0.25	0.23	0.83	-0.18	0.21
Profitability, %	0.00	0.00	0.71	-0.38	0.06
Investment	0.18	0.16	0.90	0.00	0.09
Number of stocks	3,662	3,619	5,321	2,333	742

Note. Summary statistics, showing the time-series mean, median, maximum, minimum, and standard deviation of quarterly cross-sectional averages. TIO is total institutional ownership as a percentage of total shares outstanding, and ΔTIO is its change from previous quarter. SIO (LIO) is short-term (long-term) institutional ownership as a percentage of total shares outstanding, and ΔSIO (ΔLIO) is its change from previous quarter. Market value is the total market capitalization. $ILLIQ$ is the quarterly average of daily $ILLIQ_{idq}$ values. $IVOL$ is the quarterly standard deviation of daily return residuals, regressing stock returns on market, size, value, and momentum factors. RET_{t-3} is the lagged 3-month return. $\mathrm{RET}_{t-12,\, t-1}$ is the lagged 12-month return, excluding the most recent month. B/M is the book-to-market ratio, computed using as per Asness, Moskowitz and Pedersen (2013). Adj. B/M is the book-to-market ratio as per the Section 2 but recalculated every quarter. Profitability and investment are computed as per Fama and French (2015) but recalculated every quarter. Number of stocks is the cross-sectional sample size of stocks with available institutional ownership data.

Table 2 Correlation matrix, showing time-series averages of cross-sectional correlation coefficients

	1.	**2.**	**3.**	**4.**	**5.**	**6.**	**7.**	**8.**	**9.**	**10.**	**11.**	**12.**	**13.**	**14.**	**15.**
1. TIO	1.00														
2. ΔTIO	0.11	1.00													
3. SIO	0.84	0.12	1.00												
4. ΔSIO	0.06	0.57	0.17	1.00											
5. LIO	0.62	0.05	0.27	-0.01	1.00										
6. ΔLIO	0.04	0.27	0.01	-0.02	0.22	1.00									
7. Market value	0.14	-0.01	0.08	0.00	0.16	0.00	1.00								
8. $ILLIQ$	-0.20	-0.01	-0.17	-0.01	-0.12	-0.01	-0.04	1.00							
9. $IVOL$	-0.39	-0.05	-0.27	-0.03	-0.29	-0.01	-0.17	0.30	1.00						
10. $\mathrm{RET}_{t-3,\,t}$	0.00	0.12	0.02	0.12	-0.02	0.00	0.01	-0.02	0.11	1.00					
11. $\mathrm{RET}_{t-12,\,t-1}$	0.04	0.14	0.09	0.12	-0.02	0.02	0.03	-0.07	-0.06	0.32	1.00				
12. B/M	-0.16	-0.06	-0.18	-0.04	-0.07	-0.02	-0.07	0.17	0.11	-0.12	-0.19	1.00			
13. Adj. B/M	-0.15	-0.08	-0.20	-0.06	-0.07	-0.02	-0.11	0.14	0.11	-0.18	-0.30	0.57	1.00		
14. Profitability	0.05	0.01	0.04	0.00	0.03	0.00	0.02	-0.01	-0.07	0.00	0.03	-0.02	-0.05	1.00	
15. Investment	0.01	0.01	0.06	-0.01	-0.04	0.01	0.00	-0.04	0.01	-0.03	0.03	-0.07	-0.10	0.01	1.00

Note. Cross-sectional correlation matrix for the variables discussed in Table 1. Correlations are time-series averages of cross-sectional correlations.

Table 3 Returns on portfolios sorted on changes in institutional ownership, from Q3 1980 to Q4 2003

		Quarters			
	Quarterly average	**t + 1**	**t + 1 through t + 2**	**t + 1 through t + 3**	**t + 1 through t + 4**
ΔSIO, 1980Q3 - 2003Q4					
P5	3.53	3.84	7.36	10.93	14.38
P1	2.97	2.88	5.91	8.59	12.00
P5-P1	**0.56**	**0.97**	**1.44**	**2.34**	**2.38**
	(2.65)	**(2.62)**	**(2.70)**	**(3.07)**	**(2.56)**
P5-P1 (DGTW	**0.38**	**0.59**	0.54	**1.29**	**1.51**
adjusted)	**(2.72)**	**(2.33)**	(1.41)	**(2.67)**	**(2.71)**
ΔLIO, 1980Q3 - 2003Q4					
P5	3.33	3.58	7.24	10.39	13.67
P1	3.33	3.39	6.79	10.54	13.68
P5-P1	0.01	0.20	0.45	-0.14	-0.01
	(0.03)	(0.50)	(0.74)	(-0.20)	(-0.01)
P5-P1 (DGTW	-0.00	0.15	0.19	-0.32	-0.01
adjusted)	(-0.02)	(0.55)	(0.52)	(-0.87)	(-0.02)

Note. Value-weighted cumulative quarterly returns for portfolios sorted on the change in previous quarter's institutional ownership, ΔIO. Both raw returns and DGTW benchmark adjusted returns are shown. P5-P1 return spreads significant at the 5% significance level are in boldface. t-statistics are in parentheses.

Table 4 Returns on portfolios sorted on changes in institutional ownership, from Q3 1980 to Q2 2022

		Quarters			
	Quarterly average	**t + 1**	**t + 1 through t + 2**	**t + 1 through t + 3**	**t + 1 through t + 4**
ΔSIO, 1980Q3 - 2022Q2					
P5	3.17	3.35	6.66	9.86	12.95
P1	2.85	2.70	5.73	8.45	11.57
P5-P1	**0.31**	**0.64**	**0.94**	**1.41**	**1.38**
	(2.09)	**(2.41)**	**(2.39)**	**(2.59)**	**(2.10)**
P5-P1 (DGTW	**0.21**	**0.42**	0.42	**0.84**	**0.84**
adjusted)	**(2.06)**	**(2.14)**	(1.51)	**(2.38)**	**(2.06)**
ΔLIO, 1980Q3 - 2022Q2					
P5	3.07	3.21	6.57	9.50	12.66
P1	3.15	3.05	6.16	9.76	12.93
P5-P1	-0.08	0.15	0.40	-0.26	-0.27
	(-0.52)	(0.57)	(0.86)	(-0.48)	(-0.40)
P5-P1 (DGTW	-0.11	-0.02	-0.06	-0.50	-0.45
adjusted)	(-1.12)	(-0.09)	(-0.22)	(-1.65)	(-1.11)
ΔTIO, 1980Q3 - 2022Q2					
P5	3.01	3.25	6.22	9.33	12.35
P1	2.92	2.74	6.00	9.12	12.11
P5-P1	0.09	0.51	0.22	0.21	0.24
	(0.63)	(1.94)	(0.50)	(0.39)	(0.41)
P5-P1 (DGTW	0.02	0.29	-0.14	-0.07	0.06
adjusted)	(0.18)	(1.43)	(-0.47)	(-0.21)	(0.15)

Note. Value-weighted cumulative quarterly returns for portfolios sorted on changes in previous quarter's institutional ownership, ΔIO. Both raw returns and DGTW benchmark adjusted returns are shown. P5-P1 return spreads significant at the 5% significance level are in boldface. t-statistics are in parentheses.

significant, as detailed by a multitude of studies (Gompers & Metrick, 2001; Edelen, Ince & Kadlec, 2016). This highlights the importance of a model that distinguishes between different institutional investor types. Further shown is a substantially lower P5-P1 ΔSIO return spread, compared to excess returns observed during the original timeframe. While quarterly returns of 0.64% in the first quarter following the formation date are still high and significant, quarterly average returns are almost halved, (from 0.56% to 0.31%) compared to Table 3. Returns also seem to diminish more quickly as the holding period increases. Nevertheless, significant excess returns are still visible across the board, even after adjusting for benchmark returns. Thus, it seems that findings of Yan and Zhang (2009) have survived their publication. The following sections will attempt to find potential explanations for these returns.

3.2 Investability and limits-to-arbitrage

While the predictive power of short-term institutional trading on future stock returns seemingly remains robust when including recent returns data, the finer details of these returns are not yet explored. Table 5 shows a variety of performance metrics for value-weighted ΔSIO-sorted portfolios. All metrics are annualized from quarterly data. For a 3-month holding period, the P5-P1 portfolio delivers a significant annual excess return of 2.4%, with an alpha of 0.5%, significant at the 10% level. A relatively low annualized volatility of 7.5% shows significant risk-adjusted performance, with a Sharpe ratio of 0.31. A signal-weighted factor, as proposed by Asness, Moskowitz and Pedersen (2013), has much lower returns and significance compared to the P5-P1 portfolio. This is indicative of a non-linear relationship between stock returns and ΔSIO, potentially brought about by those observations where no short-term institutional trading happened during a quarter. Looking at average 12-month rolling turnovers, a turnover ratio 673.3% for the P5-P1 portfolio is extremely high, indicating that the practical implementation of this portfolio is unfeasible. This is a reasonably expected finding, as high-turnover institutional trading, by its very nature, is extremely volatile. Tracking it from quarter to quarter should therefore be costly from the perspective of transactional volume. Increasing the holding period to 12 months lowers turnover, but excess returns (though still significant) are halved, and portfolio alpha is no longer significant. Volatility and drawdowns are much less stringent, however, and returns are more robust to transaction costs.

Implementing this portfolio, even after lowering turnover, may yet be impractical; micro-cap stocks are still included in the sample. The lowest observed market capitalization for either P5 or P1 of ΔSIO is \$207K. Following Asness, Moskowitz and Pedersen (2013), the smallest stocks, those cumulatively accounting for 10% of the total market capitalization, are dropped from the sample. This is repeated every quarter, greatly reducing cross-sectional stock sample sizes. The number of firms with available benchmark returns and institutional ownership data drops to an average of 496 firms per quarter. This

Table 5 Performance metrics for ΔSIO-sorted portfolios, including small stocks

		Panel A: 3-month holding period				Panel B: 12-month holding period			
		P1	**P5**	**L-S, value**	**L-S, signal**	**P1**	**P5**	**L-S, value**	**L-S, signal**
ΔSIO,	Mean	10.8%	13.4%	2.6%	0.3%	11.4%	12.7%	1.3%	0.1%
1980Q3 - 2022Q2	(t-stat)	(3.55)	(4.26)	(2.41)	(0.47)	(3.94)	(4.30)	(2.32)	(0.29)
	Stdev	19.7%	20.4%	6.9%	4.9%	18.8%	19.2%	3.6%	3.0%
	Sharpe	0.55	0.66	0.37	0.07	0.61	0.66	0.36	0.04
	Alpha	-2.8%	-0.7%	2.2%	0.6%	0.0%	0.7%	0.7%	0.2%
	(t-stat)	(-2.64)	(-0.59)	(1.91)	(0.74)	(0.01)	(0.22)	(1.02)	(0.50)
	Beta	1.13	1.16	0.03	-0.02	0.24	0.25	0.01	-0.01
	(t-stat)	(36.80)	(35.94)	(1.01)	(-0.86)	(6.50)	(6.69)	(1.34)	(-0.66)
	Drawdown	-51.3%	-52.6%	-30.2%	-40.4%	-43.8%	-47.5%	-16.9%	-30.5%
	Turnover	333.0%	338.1%	671.1%	522.3%	83.2%	84.5%	167.8%	130.6%
	BE-costs	3.2%	4.0%	0.4%	0.1%	13.8%	15.1%	0.8%	0.1%

Note. Annualized performance metrics for ΔSIO-sorted portfolios. All stocks allowed to the cross-section after following DGTW inclusion requirements are included in portfolio sorts. Alphas and betas are calculated from regressions of portfolio returns on U.S. MSCI index returns, obtained through Datastream. P1 and P5 columns show performance metrics of the upper- and lower quintile of ΔSIO-sorted portfolios, respectively. L-S, value shows returns for a value weighted long-short portfolio of these quintiles. L-S, signal shows returns for a signal-weighted long-short portfolio, where weightings are as per Asness, Moskowitz and Pedersen (2013). In Panel A (Panel B), portfolios are sorted every three months and held for three months (twelve months). Turnover statistics are average 12-month rolling turnovers. Break-even costs are calculated by dividing annualized mean returns by turnover ratios. t-statistics are in parentheses.

figure is roughly 20% of the 2,438 firms originally included (the 3,956 figure mentioned previously includes stocks with only institutional ownership data, not necessarily benchmark returns data). Though portfolio returns are already value-weighted, Asness, Moskowitz and Pedersen (2013) advocate the application of both practices. An extremely liquid and tradable set of stocks is hereby created, ensuring most theoretical investment portfolios can be actualized.

Table 6 shows performance metrics for value-weighted ΔSIO-sorted portfolios, excluding the smallest stocks cumulatively accounting for 10% of the total market capitalization. Surprisingly, the P5-P1 return spread widens; annual excess returns for a long-short portfolio increase up to 4.4%, with a t-statistic in excess of 3. Thus, excluding small firms therefore not only makes sense from a liquidity perspective (the minimum market capitalization rises to \$178M), but also in terms of profitability. Panel A for Table 6 further shows a higher Sharpe ratio and alpha, and a reduced maximum drawdown for the P5-P1 portfolio compared to Table 5. High portfolio turnover is still an obstacle for this long-short portfolio, though. Panel B once again shows performance metrics for a 12-month holding period, excluding the smallest stocks cumulatively accounting for 10% of the total market capitalization. An average 12-month rolling turnover of 170.7% allows for a P5-P1 return spread much more robust to transaction costs. Break-even transaction costs are more than doubled compared to a P5-P1 ΔSIO portfolio with a 3-month holding period. Figure 2 shows plots of value-weighted cumulative returns for P5-P1 ΔSIO long-short portfolios from Table 6. The cumulative returns series are relatively stable due to low portfolio volatility and the absence of large drawdowns. Drawdowns may also be low due to Figure 2 showing quarterly returns. Figures from Section 3.3 will show monthly cumulative returns plots, although portfolios are constructed slightly differently.

Yan and Zhang (2009) report a positive correlation between stock liquidity and short-term institutional ownership. This is also somewhat reflected by correlation coefficients from Table 2, as SIO has a stronger negative correlation with $ILLIQ$ (illiquidity) compared to LIO. But their preference of liquid stocks is not particularly telling of ΔSIO returns themselves; returns could be concentrated in those stocks they trade the least. To examine liquidity effects on ΔSIO-sorted portfolios, a spread analysis in the style of Amihud and Mendelson (1986) is conducted. Using bid-ask spread data from CRSP, several double-sorted portfolios are created. Amihud and Mendelson (1986) reportedly only use data on NYSE stocks. This analysis includes stocks on other exchanges as well, as NYSE bid-ask spread data availability is extremely sparse. Another difference is the sorting interval employed by Amihud and Mendelson (1986). ΔSIO and its double-sorted portfolios are updated quarterly, as opposed to yearly intervals of market β estimations.

Table 6 Performance metrics for ΔSIO-sorted portfolios, excluding small stocks

		Panel A: 3-month holding period				**Panel B: 12-month holding period**			
		P1	**P5**	**L-S, value**	**L-S, signal**	**P1**	**P5**	**L-S, value**	**L-S, signal**
ΔSIO, 1980Q3 - 2022Q2, excluding small caps	Mean	9.7%	14.0%	4.4%	1.7%	11.0%	13.3%	2.3%	0.9%
	(t-stat)	(3.19)	(4.43)	(3.48)	(2.51)	(3.81)	(4.54)	(3.80)	(2.53)
	Stdev	19.6%	20.5%	8.2%	4.5%	18.7%	18.9%	3.9%	2.4%
	Sharpe	0.49	0.68	0.54	0.39	0.59	0.70	0.59	0.39
	Alpha	-3.9%	-0.1%	3.9%	1.6%	-0.5%	1.2%	1.7%	0.7%
	(t-stat)	(-3.68)	(0.30)	(2.70)	(2.11)	(-0.17)	(0.37)	(2.26)	(1.78)
	Beta	1.13	1.17	0.04	0.01	0.24	0.25	0.01	0.02
	(t-stat)	(36.86)	(32.83)	(1.12)	(0.68)	(6.62)	(6.81)	(1.18)	(1.76)
	Drawdown	-57.2%	-52.4%	-20.2%	-13.9%	-47.1%	-47.1%	-8.7%	-9.5%
	Turnover	338.3%	344.6%	682.9%	556.5%	84.6%	86.1%	170.7%	139.1%
	BE-costs	2.9%	4.1%	0.6%	0.3%	13.0%	15.4%	1.4%	0.7%

Note. Annualized performance metrics for ΔSIO-sorted portfolios. Following Asness, Moskowitz and Pedersen (2013), the smallest stocks cumulatively accounting for the bottom 10% of the total market value are excluded. Alphas and betas are calculated from regressions of portfolio returns on U.S. MSCI index returns, obtained through Datastream. P1 and P5 columns show performance metrics of the upper- and lower quintile of ΔSIO-sorted portfolios, respectively. “L-S, value” shows returns for a value weighted long-short portfolio of these quintiles. “L-S, signal” shows returns for a signal-weighted long-short portfolio, where weightings are as per Asness, Moskowitz and Pedersen (2013). In Panel A (Panel B), portfolios are sorted every three months and held for three months (twelve months). Turnover statistics are average 12-month rolling turnovers. Break-even costs are calculated by dividing annualized mean returns by turnover ratios. t-statistics are in parentheses.

Figure 2 Cumulative returns plot for value-weighted ΔSIO P5-P1 long-short portfolios

Note. Quarterly cumulative log returns for the P5-P1 portfolios from Table 6, computed from cumulative monthly returns. Both return series are scaled to 10% annual volatility for ease of comparison.

Table 7 shows results for double-sorted portfolios, sorting first on spread and then on ΔSIO, dividing stocks into septiles every quarter accordingly. Reported are the time-series averages for the portfolios over a period of 40 quarters. As spread data availability drops after the early 1990s, the analysis was conducted on a 10-year period from Q3 of 1980 to Q2 of 1990. This double-sorting method should yield 1,960 portfolios, with 49 time series averages $(7 * 7 * 40)$. In this case, though, only 1,439 portfolios and 46 time-series averages were created. For the lower spread septile, zero-values of ΔSIO made (evenly) sorting observations into ΔSIO septiles impossible. This, in and of itself, is a significant finding. It shows how short-term institutional trading (ΔSIO) is primarily focused on liquid stocks, through either ownership increases (P5) or decreases (P1). A positive P7-P1 ΔSIO excess return spread for stocks in the two lowest bid-ask spread septiles is observed, showing positive excess returns for liquid stocks. Conversely, the return spread inverts for higher bid-ask spread septiles (3 through 5). This finding was already alluded to by the results from Table 6, implicit in the strong correlation between firm size and bid-ask spreads (Amihud & Mendelson, 1986). This indicates that liquidity risk premia can't explain the ΔSIO return spread, thereby making ΔSIO robust to these measures. However, stronger ΔSIO predictability for large firm stock returns, as implied by Table 6, suggests evidence contrary to conclusions drawn by Yan and Zhang (2009). In Section 3.4, the negative (positive) correlation of ΔSIO returns with bid-ask spreads (firm size) will be further interpreted and discussed.

Table 7 Time-series averages of portfolios double-sorted on spread and change in short-term institutional ownership, from Q3 1980 to Q2 1990

Spread septile		**ΔSIO septile**							
		P1	**P2**	**P3**	**P4**	**P5**	**P6**	**P7**	**Mean**
1	Spread	0.0225	0.0229	0.0220	0.0188	0.0194	0.0224	0.0222	0.0217
	Excess returns	0.0006	-0.0077	-0.0026	0.0060	-0.0006	0.0054	0.0041	0.0002
	ΔSIO	-0.0434	-0.0065	-0.0014	0.0014	0.0051	0.0126	0.0573	0.0027
	Size	1.11E+08	1.16E+08	1.14E+08	1.29E+08	1.36E+08	1.19E+08	1.14E+08	1.19E+08
	Observations	625	761	729	452	505	593	593	4258
2	Spread	0.0400	0.0399	0.0348	0.0253	0.0305	0.0394	0.0401	0.0369
	Excess returns	-0.0097	0.0013	0.0049	0.0051	0.0049	-0.0054	-0.0047	-0.0007
	ΔSIO	-0.0324	-0.0048	-0.0006	0.0010	0.0041	0.0099	0.0448	0.0021
	Size	5.27E+07	6.11E+07	5.72E+07	7.38E+07	8.29E+07	6.57E+07	5.90E+07	6.25E+07
	Observations	622	920	823	310	423	548	589	4235
3	Spread	0.0568	0.0569	0.0520	0.0306	0.0416	0.0568	0.0566	0.0532
	Excess returns	-0.0010	-0.0056	-0.0079	0.0013	0.0179	-0.0024	-0.0018	-0.0023
	ΔSIO	-0.0352	-0.0037	-0.0003	0.0005	0.0022	0.0067	0.0439	0.0010
	Size	4.21E+07	4.15E+07	3.97E+07	6.81E+07	5.91E+07	3.92E+07	3.68E+07	4.28E+07
	Observations	622	946	1025	180	353	524	587	4237
4	Spread	0.0778	0.0769	0.0573	0.0458	0.0504	0.0694	0.0775	0.0698
	Excess returns	-0.0018	-0.0096	0.0020	-0.0044	0.0122	0.0070	-0.0061	-0.0020
	ΔSIO	-0.0318	-0.0032	-0.0003	0.0003	0.0014	0.0057	0.0364	-0.0005
	Size	2.60E+07	3.19E+07	3.10E+07	4.58E+07	4.96E+07	3.44E+07	2.86E+07	3.22E+07
	Observations	705	1238	825	110	292	489	583	4242
5	Spread	0.1066	0.1055	0.0713	0.0468	0.0593	0.1013	0.1074	0.0956
	Excess returns	0.0009	-0.0026	0.0070	0.0177	0.0052	-0.0107	-0.0102	-0.0014
	ΔSIO	-0.0275	-0.0018	0.0000	0.0002	0.0010	0.0040	0.0292	-0.0006
	Size	2.20E+07	2.21E+07	2.15E+07	3.36E+07	3.43E+07	2.72E+07	2.05E+07	2.29E+07
	Observations	706	1318	947	17	178	487	581	4234
6	Spread	0.1596	0.1568	0.0971		0.0783	0.1469	0.1588	0.1452
	Excess returns	-0.0164	-0.0057	0.0066		-0.0214	0.0026	-0.0096	-0.0054
	ΔSIO	-0.0235	-0.0008	0.0000		0.0006	0.0018	0.0255	-0.0006
	Size	1.25E+07	1.30E+07	1.62E+07		2.37E+07	1.70E+07	1.52E+07	1.43E+07
	Observations	709	1792	733	0	66	356	579	4235
7	Spread	0.3346	0.3590	0.3986			0.3212	0.3350	0.3500
	Excess returns	-0.0083	-0.0049	0.0190			-0.0023	0.0075	-0.0031
	ΔSIO	-0.0196	-0.0001	0.0000			0.0004	0.0191	-0.0021
	Size	6.52E+06	5.36E+06	5.10E+06			8.84E+06	6.84E+06	5.96E+06
	Observations	985	2360	146	0	0	168	556	4215
Mean	Spread	0.1301	0.1575	0.0654	0.0259	0.0373	0.0803	0.1120	0.1101
	Excess returns	-0.0054	-0.0050	0.0019	0.0041	0.0061	-0.0007	-0.0030	-0.0021
	ΔSIO	-0.0295	-0.0022	-0.0004	0.0010	0.0032	0.0069	0.0368	0.0003
	Size	3.57E+07	3.09E+07	4.39E+07	9.27E+07	8.08E+07	5.20E+07	4.06E+07	4.29E+07
	Observations	4974	9335	5228	1069	1817	3165	4068	29656

Note. Time-series averages of double-sorted portfolios on spread and change in short-term institutional ownership, with stocks being assigned to spread septiles and ΔSIO septiles every quarter. Septile excess returns are time-series averages of average monthly returns in excess of the monthly T-Bill rate for all securities in the portfolio. Size is the average market value of portfolio stocks.

Short-term institutional investors thus seem to prefer liquid stocks. Intuitively, institutional investors that trade the most, avoid the transaction costs and liquidity risks associated with owning and trading illiquid stocks. While results from Table 7 also imply decreased performance of ΔSIO as illiquidity increases, it doesn't yet offer a comprehensive liquidity analysis; only 10 years of bid-ask spread data is used. Thus, to thoroughly test the influence of illiquidity as a limit-to-arbitrage, another dimension of liquidity, price impact of trading volume, is explored. Amihud (2002) construct this measure, called

$ILLIQ$, to measure illiquidity more easily, showing its strong correlation with microstructure estimates of liquidity. Using daily CRSP data on volume and returns, $ILLIQ$ is calculated, as detailed in Section 2. Constructing 5x5 double-sorted portfolios, sorted first on $ILLIQ$, then on ΔSIO, the properties of illiquidity as a limit-to-arbitrage are examined. Returns of these double-sorted portfolios are shown in Table 8. Return spreads from Panel A indicate a strong negative relationship between ΔSIO and $ILLIQ$, as ΔSIO return spreads strictly decrease with $ILLIQ$. The ΔSIO monthly return spread of 0.33% for $ILLIQ$ P1 is significant at the 1% level, while no other $ILLIQ$ quintile shows significant return spreads. DGTW returns from Panel B are much the same, as the ΔSIO return spread is only significant for $ILLIQ$ P1, showing how these returns are also robust to size, value, and momentum effects. These results imply that ΔSIO returns are concentrated in the most liquid stocks, showing how liquidity is not a particularly relevant limit-to-arbitrage.

Idiosyncratic volatility presents another fundamental challenge to the execution of arbitrage strategies. Shleifer and Vishny (1997) explain in their paper on limits to arbitrage how idiosyncratic risk can severely restrict the actions of arbitrageurs. While regular investors may simply diversify their portfolio to minimize this risk, arbitrage opportunities are usually more specialized and less diversifiable. Thus, to account for this specific type of risk in the analysis of ΔSIO, a portfolio double-sort is conducted, sorting first on $IVOL$, then on ΔSIO. Table 9 shows results for these double-sorted portfolios, from 1980 to 2022. Panel A shows that, while the ΔSIO return spread may be highest for $IVOL$ P5, t-statistics of these returns are decreasing in significance as the $IVOL$ quintile increases. In other words, the predictive power of changes in short-term institutional ownership is statistically strongest for those stocks with the lowest exposure to idiosyncratic risk. DGTW benchmark-adjusted returns are shown in Panel B. Here, this effect appears to be even more pronounced; P5 $IVOL$ returns are entirely insignificant. Thus, it seems that even after accounting for value, size, and momentum returns, limits to arbitrage induced by idiosyncratic risk can't fully explain excess returns for a ΔSIO long-short portfolio.

Institutional ownership itself also presents a limit to arbitrage. Nagel (2005) argues that, for stocks with low institutional ownership, short sale constraints are more likely to be present. Institutional investors are shown to be the main supplier of stock loans, and if loan supply is sparse, short sellers may have to pay a significant fee (D'Avolio, 2002). To examine excess returns of short-term institutional trading across different levels of institutional ownership, double-sorted portfolios are constructed, sorted first on TIO, then on ΔSIO. Table 10 shows returns for these portfolios, and Table 11 shows statistics. Some indicators of limits to arbitrage are visible from Table 10; the highest excess returns, significant at the 1% level, are concentrated in the first two ownership quintiles. This implies that when short-sale constraints are more likely, the ΔSIO return spread is highest. However, the upper ownership quintile,

Table 8 Double-sorted portfolio returns on $ILLIQ$ and ΔSIO, from 1980 to 2022

Panel A: Raw returns						
$ILLIQ$	ΔSIO quintile					
quintile	**P1**	**P2**	**P3**	**P4**	**P5**	**P5-P1**
P1	0.76	0.92	1.02	1.05	1.08	**0.33**
	(2.88)	(4.47)	(5.15)	(4.74)	(4.13)	**(2.98)**
P2	1.02	1.00	0.97	1.03	1.16	0.14
	(3.51)	(3.94)	(4.10)	(4.12)	(3.95)	(1.51)
P3	1.09	1.11	0.98	1.12	1.18	0.09
	(3.46)	(3.96)	(3.87)	(4.23)	(3.80)	(0.92)
P4	1.12	1.07	0.83	1,10	1.15	0.04
	(3.42)	(3.84)	(3.22)	(4.05)	(3.95)	(0.34)
P5	1.12	0.89	1.01	1.13	1.11	-0.01
	(3.62)	(3.20)	(3.45)	(4.21)	(3.93)	(-0.11)
Average	1.02	1.00	0.99	1.09	1.14	0.12
	(3.56)	(4.16)	(4.60)	(4.61)	(4.16)	(1.77)
Panel B: DGTW returns						
P1	-0.15	-0.02	0.05	0.06	0.07	**0.22**
	(-2.14)	(-0.48)	(1.20)	(1.12)	(0.94)	**(2.43)**
P2	0.09	0.03	-0.02	0.09	0.18	0.08
	(1.67)	(0.43)	(-0.28)	(1.56)	(2.56)	(0.97)
P3	0.16	0.19	0.03	0.15	0.23	0.07
	(2.31)	(2.99)	(0.36)	(2.17)	(3.36)	(0.81)
P4	0.18	0.10	-0.06	0.11	0.21	0.03
	(2.10)	(1.19)	(-0.55)	(1.33)	(2.83)	(0.26)
P5	0.19	-0.03	0.23	0.19	0.12	-0.08
	(1.92)	(-0.29)	(1.12)	(1.32)	(1.11)	(-0.65)
Average	0.10	0.05	0.03	0.12	0.16	(0.07
	(2.24)	(1.20)	(0.50)	(2.36)	(4.18)	(1.17)

Note. Average monthly returns for portfolios, sorted first on $ILLIQ$, then on changes in short-term institutional ownership. Panel A (Panel B) shows raw (DGTW) portfolio returns. Portfolios are sorted every three months and held for three months. The last row of each panel shows returns averaged over B/M quintiles. P5-P1 return spreads significant at the 5% significance level are in boldface. t-statistics are in parentheses.

Table 9 Double-sorted portfolio returns on $IVOL$ and ΔSIO, from 1980 to 2022

Panel A: Raw returns						
$IVOL$	ΔSIO quintile					
quintile	**P1**	**P2**	**P3**	**P4**	**P5**	**P5-P1**
P1	0.99	1.10	1.10	1.02	1.21	**0.22**
	(4.59)	(5.60)	(5.67)	(5.27)	(5.65)	**(2.06)**
P2	0.87	1.10	0.91	1.11	1.16	**0.29**
	(3.41)	(4.64)	(3.62)	(4.46)	(4.14)	**(1.96)**
P3	0.98	0.89	1.07	1.04	1.19	0.21
	(3.02)	(2.79)	(3.49)	(3.08)	(3.45)	(1.14)
P4	0.63	0.79	0.84	0.80	0.72	0.09
	(1.68)	(1.99)	(2.41)	(2.07)	(1.73)	(0.41)
P5	0.21	0.78	0.07	0.23	0.77	0.56
	(0.45)	(1.61)	(0.16)	(0.50)	(1.73)	(1.82)
Average	0.74	0.93	0.85	0.84	1.01	**0.27**
	(2.46)	(3.26)	(3.23)	(2.91)	(3.21)	**(2.40)**

Continued

Table 9 (Continued)

$\boldsymbol{IVOL}$ quintile	**Panel B: DGTW returns**					
	$\boldsymbol{\Delta SIO}$ **quintile**					
	P1	**P2**	**P3**	**P4**	**P5**	**P5-P1**
P1	-0.01	0.03	0.09	0.03	0.18	**0.19**
	(-0.17)	(0.48)	(1.17)	(0.47)	(2.26)	**(2.18)**
P2	-0.16	0.03	-0.05	0.10	0.13	**0.30**
	(-1.82)	(0.36)	(-0.63)	(1.33)	(1.55)	**(2.66)**
P3	0.09	0.08	0.11	0.01	0.23	0.14
	(0.65)	(0.62)	(0.83)	(0.11)	(1.70)	(0.89)
P4	-0.11	0.07	-0.02	-0.06	-0.19	-0.08
	(-0.72)	(0.39)	(-0.14)	(-0.39)	(-0.99)	(-0.37)
P5	-0.40	-0.01	-0.70	-0.57	-0.02	0.38
	(-1.57)	(-0.05)	(-2.71)	(-2.06)	(-0.08)	(1.32)
Average	-0.12	0.04	-0.09	-0.10	0.07	0.19
	(-1.47)	(0.56)	(-1.26)	(-1.23)	(0.74)	(1.87)

Note. Average monthly returns for portfolios, sorted first on idiosyncratic volatility, then on changes in short-term institutional ownership. Idiosyncratic volatility is constructed from the volatility of daily stock return residuals, following Ang et al. (2006). Residuals are calculated relative to a factor model based on DGTW characteristics, as described in Section 2. Panel A reports raw returns, and Panel B shows returns adjusted to DGTW benchmarks. The last row of both panels reports returns averaged over $IVOL$ quintiles. P5-P1 return spreads significant at the 5% significance level are in boldface. t-statistics are in parentheses.

Table 10 Double-sorted portfolio returns on TIO and ΔSIO, from 1980 to 2022

$\boldsymbol{TIO}$ quintile	$\boldsymbol{\Delta SIO}$ **quintile**					
	P1	**P2**	**P3**	**P4**	**P5**	**P5-P1**
P1	0.49	0.74	0.86	0.84	1.13	**0.64**
	(1.65)	(3.20)	(3.46)	(3.76)	(4.18)	**(2.76)**
P2	0.83	1.11	0.97	1.13	1.53	**0.70**
	(2.74)	(4.86)	(4.47)	(4.98)	(5.01)	**(2.71)**
P3	0.78	1.15	1.06	1.04	0.87	0.09
	(2.94)	(5.16)	(4.91)	(4.73)	(3.42)	(0.54)
P4	1.02	1.00	1.05	1.02	1.12	0.10
	(4.15)	(4.77)	(5.20)	(4.85)	(4.36)	(0.63)
P5	0.91	0.96	1.09	1.06	1.20	**0.30**
	(3.62)	(4.28)	(4.98)	(4.58)	(4.57)	**(2.65)**
Average	0.81	0.99	1.05	1.01	1.17	**0.37**
	(3.32)	(5.04)	(5.81)	(5.15)	(4.85)	**(3.41)**

Note. Average monthly returns for portfolios, sorted first on total institutional ownership, then on changes in short-term institutional ownership. Portfolios are sorted every three months and held for three months. The last row shows returns averaged over TIO quintiles. P5-P1 returns spread significant at the 5% significance level are in boldface. t-statistics are in parentheses.

Table 11 Double-sorted portfolio statistics on TIO and ΔSIO, from 1980 to 2022

TIO quintile		**ΔSIO quintile**				
		P1	**P2**	**P3**	**P4**	**P5**
P1	ΔSIO	-0.0248	-0.0018	0.0000	0.0019	0.0173
	Size	3.14E+08	5.39E+08	6.23E+08	6.22E+08	3.20E+08
P2	ΔSIO	-0.0457	-0.0077	0.0003	0.0088	0.0442
	Size	9.63E+08	3.28E+09	3.81E+09	2.56E+09	7.63E+08
P3	ΔSIO	-0.0581	-0.0125	0.0007	0.0144	0.0599
	Size	2.94E+09	9.14E+09	1.23E+10	7.73E+09	2.48E+09
P4	ΔSIO	-0.0635	-0.0162	0.0007	0.0181	0.0677
	Size	3.15E+09	5.95E+09	7.26E+09	5.77E+09	2.88E+09
P5	ΔSIO	-0.0644	-0.0164	0.0034	0.0245	0.0822
	Size	2.56E+09	3.76E+09	4.16E+09	3.40E+09	2.23E+09

Note. Time series averages for portfolios, sorted first on total institutional ownership, then on changes in short-term institutional ownership. Portfolios are sorted every three months and held for three months.

where short-sale constraints are least likely, also shows excess returns significant at the 1% level. Therefore, even though excess returns may be concentrated in stocks with relatively high short-sale constraints, for stocks where these constraints are (mostly) lifted, excess returns persist. Furthermore, if short-sale constraints are indeed driving excess returns, higher return spreads for lower TIO quintiles should be caused by lower short-leg returns, not higher long-leg returns (Nagel, 2005; Chu, Hirshleifer & Ma, 2020). While this is the case for the lowest TIO quintile (0.49 is much lower compared to other ΔSIO P1 returns), TIO P2 excess returns seem to be concentrated mainly in the long-leg. Lastly, stocks with lower TIO are less likely to be included in independently-sorted ΔSIO P5 and P1 quintiles, as these stocks are also inherently traded less by (short-term) institutions. This is shown by statistics from Table 11; average values of P1- and P5 ΔSIO are much less extreme in the lowest TIO quintile (-2.48% to 1.73%), compared to the highest (-6.44% to 8.22%). Even if these stocks were included, they would be allocated smaller portfolio weights, as stocks in the lowest TIO also have lower market values on average. Therefore, most ΔSIO long-short portfolios discussed in this paper are unlikely to encounter significant short-sale constraints due to low institutional ownership.

3.3 Robustness to anomalies

Returns to ΔSIO may still be correlated with underlying asset pricing factors, even after adjusting for benchmark returns. Yan and Zhang (2009) find that the predictive power of short-term institutional trading (ΔSIO) is stronger for small stocks. This might mean that the P5-P1 ΔSIO return spread is correlated with firm size. Table 12 shows the average DGTW quintile for stocks held and traded by institutional investors. Characteristics seem to indicate a negligible size quintile difference between ΔSIO P5 and P1 (2.04 – 2.09), indicating that the P5-P1 portfolio has little to no exposure to the size factor. For equal-weighted holdings the average size quintile is relatively low; for SIO, but even more

Table 12 Average DGTW quintile for institutional holdings

	Panel A: equal-weighted holdings			**Panel B: value-weighted holdings**		
	Average size quintile	**Average book-to-market quintile**	**Average momentum quintile**	**Average size quintile**	**Average book-to-market quintile**	**Average momentum quintile**
IO characteristics						
TIO	2.50	2.78	3.12	4.57	2.79	3.07
SIO	2.53	2.72	3.18	4.53	2.76	3.14
LIO	2.59	2.84	3.05	4.65	2.80	2.99
ΔIO characteristics						
ΔTIO P5 (P1)	1.99 (1.98)	2.63 (2.80)	3.57 (2.77)	3.93 (4.24)	2.82 (2.84)	3.30 (3.17)
ΔSIO P5 (P1)	2.03 (2.09)	2.72 (2.74)	3.45 (2.91)	3.91 (4.21)	2.84 (2.78)	3.37 (2.98)
ΔLIO P5 (P1)	2.14 (2.02)	2.78 (2.95)	3.22 (2.94)	4.16 (3.93)	2.82 (2.94)	3.08 (3.21)

Note. Time-series averages from 1981 to 2022, showing the average DGTW quintile to which a stock with institutional ownership is assigned. In calculating the average quintile, Panel A weights holdings (IO) and changes in holdings (ΔIO) based on percentage ownership, while Panel B further weights holdings by their market value. The bottom section shows average DGTW quintiles for stocks assigned to their respective P5 (P1) ΔIO quintile.

so for ΔSIO. This indicates that the upper- and lower quintiles of ΔSIO are comprised primarily of small stocks, which is likely due to NYSE breakpoints used in DGTW sorting; more stocks are assigned to size P1. Value-weighted holdings are of course much less exposed to small stocks. Both value-weighted and equal-weighted holdings imply a potential loading on the momentum factor, though. This is shown by ΔSIO P5 and P1 average momentum quintiles. The difference seems relatively high, both for equally-weighted- and value-weighted holdings (3.35 – 2.77 and 3.30 – 2.86, respectively).

While Table 12 may indicate no evidence of size factor investing by short-term institutional investors, the former could still subsume the latter. From Table 7, an interesting relationship with bid-ask spreads, a variable highly correlated with firm size, can be deduced; as the bid-ask spread quintile increases, the ΔSIO return spread inverts. Table 6 shows stronger performance of a flow factor when it is constructed solely based on large stocks. These findings are not in accordance with Yan and Zhang (2009), however; they found evidence of stronger predictive power of ΔSIO for small stocks. If this were the case, with size being negatively correlated with numerous limits-to-arbitrage, this could also pose a problem for the investability of the flow factor. To further examine these contradictory findings, a portfolio double-sort is conducted, sorting first on firm size using NYSE breakpoints, then on ΔSIO. Table 13 shows monthly returns for these portfolios. These results seem to confirm the findings from Table 6 and Table 7; returns for ΔSIO are concentrated in the upper size quintile. While this may show robustness from an investability perspective, the economic interpretation for this finding is less clear if informational advantages are assumed. This will be discussed in detail in the next section.

Momentum effects could also explain ΔSIO returns. As found by Yan and Zhang (2009), short-term institutional investors, specifically, show characteristics of momentum traders. A large body of literature also shows this to be the case for institutional investors in general (Badrinath & Wahal, 2002; Bennett, Sias & Starks, 2003; Edelen, Ince & Kadlec, 2016). Yan and Zhang (2009) further posit that the momentum effect cannot fully explain ΔSIO excess returns. Results from Table 4 are in accordance with this finding, as DGTW returns are consistently significant. However, the nonuniformity of momentum should be considered; 12-month cumulative returns may be the most popular definition, but not the only relevant one. As shown by Jegadeesh and Titman (1993), various profitable momentum investing strategies exist, differing in terms of both lookback- and holding periods. These measures may be more correlated with short-term institutional trading and negate its excess returns. Most importantly, the relationship between momentum and ΔSIO remains unexplored in terms of double-sorts, which are effective at controlling for potentially subsuming factors (Ang, Hodrick, Xing & Zhang, 2006).

Double-sorted portfolio returns, sorted first on various momentum lookback periods, then on ΔSIO, are shown in Table 14. Panel A, Panel B and Panel C, using 12-month, 9-month and 6-month momentum

Table 13 Double-sorted portfolio returns on size and ΔSIO, from 1980 to 2022

Size quintile	ΔSIO quintile					
	P1	**P2**	**P3**	**P4**	**P5**	**P5-P1**
P1	1.13	1.05	0.80	1.26	1.29	0.16
	(3.76)	(4.02)	(3.44)	(5.11)	(4.62)	(1.80)
P2	1.01	1.09	1.21	1.26	1.37	**0.26**
	(3.74)	(4.31)	(5.19)	(4.89)	(4.62)	**(2.41)**
P3	1.05	1.10	1.12	1.12	1.25	0.20
	(3.97)	(4.64)	(5.02)	(4.64)	(4.49)	(1.67)
P4	1.05	1.11	1.08	1.18	1.13	0.08
	(4.18)	(5.01)	(5.04)	(5.22)	(4.51)	(0.79)
P5	0.82	0.97	0.98	1.09	1.13	**0.31**
	(3.60)	(4.79)	(5.19)	(5.43)	(5.04)	**(2.57)**
Average	1.03	1.06	1.05	1.18	1.23	**0.20**
	(4.05)	(4.82)	(5.17)	(5.36)	(4.88)	**(2.89)**

Note. Average monthly returns for portfolios, sorted first on size using NYSE breakpoints, then on changes in short-term institutional ownership. Portfolios are sorted every three months and held for three months. The last row shows returns averaged over size quintiles. P5-P1 returns spread significant at the 5% significance level are in boldface. t-statistics are in parentheses.

Table 14 Double-sorted portfolio returns on momentum and ΔSIO, from 1980 to 2022

Panel A: 12-month momentum returns						
Momentum quintile	ΔSIO **quintile**					
	P1	**P2**	**P3**	**P4**	**P5**	**P5-P1**
P1	0.59	0.77	0.50	1.05	0.75	0.16
	(1.53)	(2.09)	(1.33)	(2.80)	(2.05)	(0.80)
P2	0.95	0.96	1.29	1.06	1.21	0.25
	(3.35)	(3.84)	(5.17)	(4.12)	(4.40)	(1.72)
P3	0.92	1.11	1.18	0.97	1.01	0.09
	(3.97)	(5.31)	(5.51)	(4.74)	(4.51)	(0.72)
P4	0.98	1.04	0.95	0.97	1.12	0.15
	(4.37)	(5.12)	(4.61)	(4.59)	(5.05)	(1.20)
P5	1.04	1.21	1.05	1.24	1.35	0.31
	(3.96)	(4.77)	(4.21)	(4.85)	(4.53)	(1.91)
Average	0.90	1.02	1.00	1.06	1.09	**0.19**
	(3.64)	(4.68)	(4.74)	(4.73)	(4.40)	**(2.45)**
Panel B: 9-month momentum returns						
P1	0.65	0.76	0.70	1.14	0.67	0.02
	(1.69)	(2.15)	(1.90)	(3.00)	(1.75)	(0.11)
P2	0.79	0.93	0.86	1.06	1.08	**0.28**
	(2.93)	(3.68)	(3.35)	(4.20)	(4.09)	**(1.98)**
P3	1.02	1.07	1.07	1.08	1.02	0.01
	(4.46)	(5.11)	(4.89)	(5.24)	(4.32)	(0.04)
P4	1.00	1.11	0.88	0.83	1.03	0.03
	(4.58)	(5.38)	(3.85)	(4.00)	(4.62)	(0.30)
P5	1.05	1.12	1.27	1.27	1.55	**0.50**
	(4.03)	(4.37)	(4.88)	(4.93)	(5.21)	**(3.13)**
Average	0.90	1.00	0.96	1.08	1.07	**0.17**
	(3.73)	(4.56)	(4.46)	(4.82)	(4.28)	**(2.26)**

Continued

Table 14 (Continued)

Momentum quintile	ΔSIO quintile					
	P1	P2	P3	P4	P5	P5-P1
Panel C: 6-month momentum returns						
P1	0.73	0.77	0.85	1.11	0.86	0.12
	(2.00)	(2.21)	(2.39)	(3.09)	(2.36)	(0.64)
P2	1.06	1.05	1.22	1.12	1.09	0.03
	(3.89)	(4.25)	(4.60)	(4.46)	(4.12)	(0.21)
P3	0.97	1.08	1.22	0.90	1.20	0.23
	(4.27)	(5.17)	(6.07)	(4.19)	(5.11)	(1.83)
P4	0.93	1.03	0.89	0.96	1.04	0.11
	(4.22)	(4.87)	(4.10)	(4.55)	(4.52)	(0.92)
P5	0.85	1.00	1.07	1.24	1.35	**0.50**
	(3.27)	(3.89)	(4.35)	(4.71)	(4.74)	**(3.10)**
Average	0.91	0.98	1.05	1.07	1.11	**0.20**
	(3.80)	(4.53)	(4.98)	(4.81)	(4.48)	**(2.65)**
Panel D: 3-month momentum returns						
P1	0.84	0.78	0.81	0.99	0.69	-0.15
	(2.37)	(2.29)	(2.43)	(2.98)	(1.96)	(-0.72)
P2	0.98	1.23	1.24	1.05	1.17	0.19
	(3.84)	(5.36)	(5.04)	(4.21)	(4.55)	(1.38)
P3	1.00	0.95	1.21	1.04	1.09	0.09
	(4.56)	(4.36)	(5.56)	(4.94)	(4.65)	(0.72)
P4	0.96	1.02	0.80	1.15	0.96	0.00
	(4.20)	(4.70)	(3.74)	(5.57)	(4.00)	(-0.01)
P5	0.98	1.18	1.03	1.17	1.34	**0.36**
	(3.75)	(4.71)	(3.91)	(4.64)	(4.74)	**(2.16)**
Average	0.95	1.03	1.02	1.08	1.05	0.10
	(4.05)	(4.79)	(4.81)	(5.06)	(4.26)	(1.30)

Note. Average monthly returns for portfolios, sorted first on momentum, then on changes in short-term institutional ownership. Panel A, Panel B, Panel C, and Panel D show sorts on 12-month, 9-month, 6-month, and 3-month momentum returns, respectively. Portfolios are sorted every three months and held for three months. The last row of each panel shows returns averaged over momentum quintiles. P5-P1 return spreads significant at the 5% significance level are in boldface. t-statistics are in parentheses.

returns, respectively, all point towards similar conclusions. ΔSIO excess returns are not fully explained by momentum effects, with all averaged return spreads significant at the 5% significance level. Averaged return spread results from Panel D, showing returns for a double sort on 3-month momentum returns, are insignificant. Interestingly, though, the return spread in the upper momentum quintile from Panel D is significant. This result is also observed from the other panels, with return spreads in the P1 momentum quintile being insignificant, or inverted for 3-month momentum returns. In other words, short-term institutional trading is more profitable for stocks in the long-leg of momentum returns, as opposed to the short-leg. This is somewhat in accordance with Edelen, Ince and Kadlec (2016). They find that institutional trading in the short-leg of anomalies is significantly unprofitable, while trading in the long-leg is insignificantly profitable. The main difference between these conclusions is overall profitability. The average institutional investor, analyzed by Edelen, Ince and Kadlec (2016), suffers losses from trading loser stocks, and doesn't profit from trading winner stocks. Whereas the short-term institutional investor, analyzed by this paper, not only profits from trading winner stocks, but also isn't unprofitable by trading loser stocks. This further supports the hypothesis of short-term institutional investors being more skilled than institutional investors in general.

As shown in Table 12, short-term institutional investors are unlikely to be value investors. Intuitively, as the value factor also requires less portfolio rebalancing compared to anomalies such as momentum, turnover for value-investing institutions should be relatively low. This is also demonstrated by correlations from Table 2, as long-term (low-turnover) institutional ownership shows a smaller negative correlation with B/M ratios compared to short-term ownership. Nevertheless, to make sure ΔSIO excess returns are robust to the value factor, portfolio double-sorts are constructed, sorted first on book-to-market ratios, then on ΔSIO. Table 15 shows results for these portfolios. Results from Panel A show a strong variability of excess returns across book-to-market quintiles. While averaged excess returns are insignificant, the middle B/M quintile shows a positive return spread significant at the 1% level. Furthermore, the ΔSIO return spread for the P1 (P5) B/M quintile is positive (negative) and significant at the 10% level. This is in accordance with Yan and Zhang (2009). They find that short-term institutional trading has strong predictive power for returns to growth stocks, and less so for value stocks. One major difference this paper finds, however, is the negative ΔSIO return spread for the upper value quintile. This suggests that there is not only reduced predictive power for value stocks, but also that this predictive power appears to be inverted. Averaged excess returns are likely insignificant due to this return spread inversion.

Panel B of Table 15 offers a different conclusion, one which seems more plausible given previous results. Using industry-adjusted B/M ratios (calculated as detailed in the methodology, using quarterly data), ΔSIO excess returns are mostly concentrated in the lower two B/M quintiles (growth stocks). The ΔSIO return spread for the upper two B/M quintiles (value stocks), though insignificant, is still positive, and averaged excess returns are now significant. This leaves the question whether, between these two book-to-market measures, ΔSIO is robust to the value effect. First, in this case, the industry-adjusted B/M ratio is arguably a "better" value measure. The value return spread averaged across ΔSIO is 0.34% and 0.41% for the regular- and industry-adjusted B/M ratio sorts, respectively. Thus, adjusted B/M sorts likely hold more weight. Secondly, as mentioned before, short-term institutions are unlikely to be classified as value investors, both from a theoretical- and an empirical perspective. Finally, as will be shown in the following paragraphs, ΔSIO long-short returns are almost entirely uncorrelated to returns for a long-short portfolio of portfolios sorted on regular book-to-market ratios. Thus, the insignificance of the averaged ΔSIO return spread from Table 15, along with the slightly significant negative ΔSIO return spread for growth stocks, is most likely not a robust finding.

Table 15 Double-sorted portfolio returns on value and ΔSIO, from 1980 to 2022

Panel A: B/M sorts						
B/M quintile	**ΔSIO quintile**					
	P1	**P2**	**P3**	**P4**	**P5**	**P5-P1**
P1	0.86	1.02	0.82	1.24	1.14	0.29
	(3.25)	(4.47)	(3.43)	(5.53)	(3.88)	(1.77)
P2	1.04	0.92	0.89	0.91	1.05	0.01
	(4.27)	(4.40)	(4.32)	(4.26)	(4.44)	(0.11)
P3	0.94	1.02	0.96	1.18	1.30	**0.36**
	(3.81)	(4.78)	(4.38)	(5.56)	(5.39)	**(2.81)**
P4	1.05	0.86	1.02	0.90	1.23	0.19
	(4.20)	(3.75)	(4.32)	(3.98	(5.08)	(1.42)
P5	1.40	1.29	1.44	1.60	1.05	-0.34
	(4.49)	(4.39)	(5.61)	(5.79)	(3.42)	(-1.84)
Average	1.06	1.02	1.02	1.17	1.16	0.10
	(4.44)	(4.96)	(5.30)	(5.82)	(4.80)	(1.19)
Panel B: industry-adjusted B/M sorts						
P1	0.78	1.09	0.87	1.17	1.08	**0.31**
	(3.06)	(4.83)	(3.70)	(5.06)	(3.95)	**(2.18)**
P2	0.89	0.85	0.91	0.97	1.13	0.24
	(3.86)	(4.06)	(4.95)	(4.79)	(4.90)	(1.77)
P3	1.15	1.01	1.12	0.96	1.15	0.00
	(4.78)	(4.60)	(5.10)	(4.41)	(4.78)	(-0.00)
P4	1.04	1.03	1.33	1.28	1.22	0.18
	(3.85)	(4.35)	(5.59)	(5.71)	(4.64)	(1.30)
P5	1.24	1.49	1.48	1.38	1.44	0.20
	(3.73)	(5.13)	(5.20)	(5.21)	(4.79)	(1.05)
Average	1.02	1.09	1.15	1.15	1.20	**0.19**
	(4.16)	(5.19)	(5.83)	(5.63)	(4.95)	**(2.16)**

Note. Average monthly returns for portfolios, sorted first on B/M ratios, then on changes in short-term institutional ownership. Panel A shows results for regular B/M ratios and Panel B shows results for industry-adjusted B/M ratios. Portfolios are sorted every three months and held for three months. The last row of each panel shows returns averaged over B/M quintiles. P5-P1 return spreads significant at the 5% significance level are in boldface. t-statistics are in parentheses.

Finally, ΔSIO robustness to two other popular asset pricing anomalies is examined: the investment- and profitability factors. Originally formalized into a single asset pricing model with the size- and value factors by Fama and French (2015), these characteristics are well documented within the literature (Aharoni, Grundy & Zeng, 2013; Novy-Marx, 2013). Edelen, Ince and Kadlec (2016) find that, aside from the momentum factor, profitability is one of the only characteristics related to institutional trading. Therefore, to test whether ΔSIO excess returns are subsumed by either profitability or investment, two sets of double-sorted portfolios are constructed. Table 16 shows results for these portfolios. Returns for double-sorted portfolios, sorted first on profitability and then on ΔSIO, shown in Panel A, indicate the robustness of ΔSIO excess returns. Return spreads in the upper two profitability quintiles are significant at the 5% level, and the averaged return spread is significant at the 1% level. Results from Panel B,

Table 16 Double-sorted portfolio returns on profitability and investment, and ΔSIO, from 1980 to 2022

Pro/Inv quintile	**ΔSIO quintile**					
	P1	**P2**	**P3**	**P4**	**P5**	**P5-P1**
Panel A: Profitability double-sort						
P1	0.86	0.69	0.34	0.72	1.27	**0.41**
	(2.61)	(2.29)	(1.06)	(2.33)	(3.86)	**(2.11)**
P2	0.83	0.98	0.64	0.89	1.15	**0.32**
	(2.87)	(3.86)	(2.63)	(3.68)	(4.01)	**(1.99)**
P3	0.84	0.80	1.03	0.95	1.10	0.26
	(3.47)	(3.50)	(4.51)	(4.08)	(4.61)	(1.86)
P4	0.98	1.03	1.09	1.14	1.22	0.24
	(4.00)	(4.74)	(5.12)	(5.41)	(4.99)	(1.63)
P5	1.02	1.21	1.21	1.15	1.16	0.14
	(3.93)	(5.54)	(5.86)	(5.27)	(4.51)	(0.95)
Average	0.91	0.94	0.88	0.97	1.18	**0.27**
	(3.64)	(4.36)	(4.43)	(4.54)	(4.74)	**(3.14)**
Panel B: Investment double-sort						
P1	1.11	1.26	1.09	1.32	1.34	0.23
	(4.37)	(5.33)	(4.10)	(5.46)	(5.14)	(1.42)
P2	1.31	1.11	1.26	1.12	1.30	-0.02
	(5.90)	(5.32)	(5.52)	(5.59)	(5.74)	(-0.14)
P3	0.92	1.05	1.19	0.97	1.14	0.21
	(4.10)	(5.11)	(6.17)	(5.05)	(5.23)	(1.78)
P4	0.89	1.13	1.01	1.03	1.11	0.22
	(3.62)	(4.94)	(4.62)	(4.63)	(4.45)	(1.45)
P5	0.78	0.68	0.93	0.98	0.85	0.07
	(2.42)	(2.53)	(3.34)	(3.51)	(2.74)	(0.41)
Average	1.00	1.05	1.09	1.09	1.15	0.14
	(4.35)	(5.17)	(5.55)	(5.38)	(4.92)	(1.88)

Note. Average monthly returns for portfolios, sorted first on either profitability or investment, then on changes in short-term institutional ownership. Panel A shows results for profitability and Panel B shows results for investment. Portfolios are sorted every three months and held for three months. The last row of each panel shows returns averaged over either profitability or investment quintiles. P5-P1 return spreads significant at the 5% significance level are in boldface. t-statistics are in parentheses.

where profitability is replaced by investment in the double-sort, are less significant. Only the averaged- and middle quintile return spreads are significant at the 10% level, and the latter is almost halved compared to Panel A (from 0.27% to 0.14% monthly). Nevertheless, averaged excess returns are still significant. Also, as will be shown in later paragraphs, returns for both the profitability- and investment factors as defined by the Fama and French 5-factor model are mostly unrelated to flow factor returns.

While tests conducted in this section so far have been focused on identifying explanations for ΔSIO returns in the form of anomaly returns, how these returns relate to one another remains unexplored. To better illustrate how ΔSIO returns interact with other asset pricing factors, multiple asset pricing anomalies are combined into long-short portfolios, where return correlations can be examined. Table 17

Table 17 Performance metrics for value-weighted factor portfolios

		Panel A: 1-month holding period				Panel B: 12-month holding period			
		Flow	**+Val&Mom**	**+Pro&Inv**	**+All**	**Flow**	**+Val&Mom**	**+Pro&Inv**	**+All**
Factor portfolios, October 1980 - September 2022, excluding small caps	Mean	4.6%	2.8%	3.5%	2.9%	2.0%	1.0%	2.3%	1.6%
	(t-stat)	(3.63)	(3.14)	(4.31)	(3.94)	(3.03)	(1.66)	(3.38)	(2.84)
	Stdev	8.3%	5.8%	5.3%	4.8%	4.2%	4.0%	4.3%	3.6%
	Sharpe	0.56	0.48	0.66	0.61	0.47	0.26	0.52	0.44
	Alpha	4.7%	3.4%	4.8%	4.0%	1.9%	1.2%	3.5%	2.5%
	(t-stat)	(3.60)	(3.78)	(5.88)	(5.52)	(2.84)	(1.96)	(5.46)	(4.53)
	Beta	-0.07	-0.05	-0.10	-0.09	0.01	-0.02	-0.10	-0.07
	(t-stat)	(-0.31)	(-3.16)	(-6.85)	(-6.90)	(0.55)	(-1.53)	(-8.81)	(-7.41)
	Drawdown	-20.4%	-22.3%	-11.1%	-12.9%	-12.0%	-24.9%	-10.5%	-14.6%
	Turnover	764.0%	457.8%	371.2%	320.0%	171.4%	89.6%	87.7%	63.4%
	BE-costs	0.6%	0.6%	1.0%	0.9%	1.1%	1.2%	2.6%	2.5%
			Correlation(Flow,Val)		-0.06		Correlation(Flow,Val)		-0.06
			Correlation(Flow,Mom)		0.25		Correlation(Flow,Mom)		0.31
			Correlation(Flow,Pro)		-0.07		Correlation(Flow,Pro)		-0.12
			Correlation(Flow,Inv)		0.03		Correlation(Flow,Inv)		0.06

Note. Performance metrics annualized from monthly returns, for value-weighted flow factors and combinations with other factors. +Val&Mom shows performance metrics for a 33/33/33 combination of the value, momentum, and flow factors. +Pro&Inv shows performance metrics for a 33/33/33 combination of the profitability, investment, and flow factors. +All shows performance metrics for a 20/20/20/20/20 combination of the value, momentum, profitability, investment, and flow factors. For the portfolios of Panel A (Panel B), portfolios are sorted every month and held for one month (twelve months). Alphas and betas are calculated from regressions of portfolio returns on U.S. MSCI index returns, obtained through Datastream. Turnover statistics are average 12-month rolling turnovers. Break-even costs are calculated by dividing annual mean returns by turnover ratios. Correlations are calculated as the correlations of residual returns, i.e., factor returns unexplained by market (U.S. MSCI) returns (Asness, Moskowitz and Pedersen, 2013). t-statistics are in parentheses.

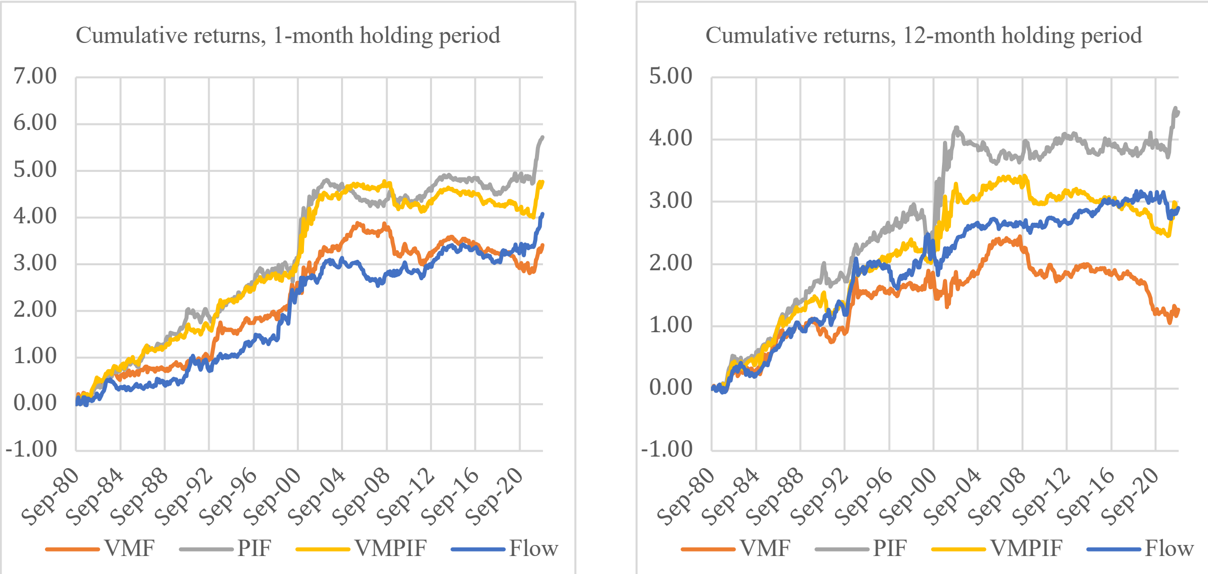
shows performance metrics for these portfolios. Compared to Table 5 and Table 6, inclusion requirements of Asness, Moskowitz and Pedersen (2013) are followed – as opposed to those set by DGTW – and portfolios are sorted monthly. This is done to examine robustness to other inclusion requirements, and because monthly portfolio sorts are more suited here; DGTW sorts are primarily focused on quarterly intervals. Contrary to institutional ownership, underlying variables of most other factors are updated more frequently than once every quarter. Thus, in order to fairly assess comparative performances, and to ensure investability of factors as per Asness, Moskowitz and Pedersen (2013), their inclusion requirements are followed.

Panel A of Table 17 shows results for 1-month holding periods. Examining the flow factor individually, performance is very similar to Table 6, showing robustness from a sorting interval perspective. Combining the flow factor with momentum and value yields poor results; returns, risk-adjusted performance and alpha decreases, while maximum drawdown increases. This may be due to the positive correlation of 0.25 between flow- and momentum returns, or due to the poor performance of value and momentum factors as per Asness, Moskowitz and Pedersen (2013). Combining the flow factor with investment and profitability factors yields better results; Sharpe ratios and alpha increase, while maximum drawdown decreases. Robustness of the flow factor to other factors is also once again shown; returns seem almost entirely uncorrelated to value, investment and profitability factors. Turnover ratios shown here also have interesting implications, referring to the limits-to-arbitrage discussed in Section 3.2. Table 5 and Table 6 showed how transaction costs could be reduced by longer holding periods, while Table 17 shows how this can also be achieved by combinations with other factors. Results from Panel B, where 12-month holding periods are used, are comparatively similar to Panel A, as combinations with the investment- and profitability factors again increase performance. With turnover reduced to less than 100% percent, transaction costs are also much less significant; break-even costs are upwards of 2.6%. Thus, insofar as transaction costs as a limit-to-arbitrage explain flow factor returns, any aspiring arbitrageur has multiple options to decrease their impact. Figure 3 and Figure 4 show cumulative return plots for the long-short portfolios of Panel A and Panel B, respectively. From this perspective as well, it seems the flow factor is best combined with other factors, particularly investment- and profitability factors, to increase risk-adjusted performance.

Finally, to examine robustness of the flow factor to a multitude of asset pricing anomalies all together, a regression analysis in the style of Fama and French (2015) is conducted. The regression equation is as follows:

$$IMO_t = a + \beta_1 UMD_t + \beta_2 MKT_t + \beta_3 SMB_t + \beta_4 HML_t + \beta_5 RMW_t + \beta_6 CMA_t + \varepsilon_t, \quad (11)$$

Figure 3 & 4 Cumulative returns plot for value-weighted factor portfolios



Note. Figure 3 (Figure 4) shows the monthly cumulative log returns for the 1-month (12-month) holding period value-weighted long-short portfolios from Table 17, Panel A (Panel B). VMF refers to a 33/33/33 combination of value, momentum, and flow factor returns. PIF refers to a 33/33/33 combination of profitability, investment, and flow factor returns, VMPIF refers to a 20/20/20/20/20 combination of value, momentum, profitability, investment, and flow factor returns. All return series are scaled to 10% annual volatility for ease of comparison.

where IMO_t, UMD_t, MKT_t, SMB_t, HML_t, RMW_t, and CMA_t are flow, momentum, market, size, value, profitability, and investment factor returns, respectively. a is the regression constant and ε_t are the residuals. All factor returns – except for the flow- and market factor – are retrieved from the Kenneth R. French data library. The market factor is defined as U.S. MSCI index monthly returns in excess of the U.S. 1-month T-bill rate. For regression models including (excluding) the profitability- and investment factors, Fama and French 5 factor model (Fama and French 3 factor model) returns are used. Results from a regression with Equation (11) are shown in Table 18. In Panel A, IMO is constructed from all stocks (following DGTW inclusion requirements). As shown, the IMO factor is not robust to momentum returns; the regression constant is insignificant, even if momentum is the only included factor. The IMO factor is robust to both the Fama and French 3- and 5 factor models. Once again adding a momentum factor to either model reduces the significance of the regression constant below the 10% significance level. These results show how the IMO factor is robust to most anomalies, except momentum. Panel B, showing results for IMO_{90}, a factor that excludes the smallest stocks cumulatively accounting for 10% of the total market value, shows robustness to momentum as well. All regression constants are significant at the 5% level. Furthermore, only the regression coefficients for the size, value and momentum factor are consistently positive and significant. This adds to the robustness of the findings using DGTW benchmarks, as these are the three characteristics incorporated in its sorting technique. Further adding the profitability- and investment factors to explain ΔSIO returns would likely be of no added benefit.

Table 18 Time-series regression results for IMO factor returns, from October 1980 to September 2022

Model	a	UMD	MKT	SMB	HML	RMW	CMA	R^2
Panel A: regressions on IMO, constructed using all stocks								
IMO								
UMD	0.14	0.14						0.09
	(1.58)	(7.24)						
$FF3$	**0.20**		-0.03	0.15	0.08			0.05
	(2.20)		(-1.34)	(4.72)	(2.75)			
$FF3$ & UMD	0.06	0.17	0.01	0.15	0.15			0.17
	(0.73)	(8.49)	(0.75)	(5.12)	(5.28)			
$FF5$	**0.20**		-0.03	0.15	0.04	0.00	0.05	0.06
	(2.06)		(-1.15)	(4.47)	(1.00)	(-0.09)	(0.78)	
$FF5$ & UMD	0.09	0.17	0.01	0.14	0.14	-0.04	-0.02	0.18
	(1.00)	(8.55)	(0.32)	(4.53)	(3.74)	(-1.09)	(-0.35)	
Panel B: regressions on IMO_{90}, constructed using large stocks								
IMO_{90}								
UMD	**0.33**	0.11						0.04
	(3.13)	(4.49)						
$FF3$	**0.36**		-0.02	0.16	0.11			0.05
	(3.37)		(-0.73)	(4.26)	(3.22)			
$FF3$ & UMD	**0.25**	0.14	0.02	0.16	0.17			0.10
	(2.36)	(5.64)	(0.69)	(4.44)	(4.81)			
$FF5$	**0.38**		-0.03	0.17	0.11	0.00	-0.05	0.05
	(3.43)		(-1.06)	(4.20)	(2.33)	(-0.06)	(-0.68)	
$FF5$ & UMD	**0.29**	0.15	0.00	0.16	0.20	-0.04	-0.11	0.11
	(2.69)	(5.86)	(-0.03)	(4.16)	(4.16)	(-0.75)	(-1.51)	

Note. Regression results for regressions with monthly-sorted *IMO* factor returns as the dependent variable. In Panel A, IMO is constructed from all stocks conforming to DGTW inclusion criteria. Panel B shows results for IMO_{90}, a factor that further excludes the smallest stocks cumulatively accounting for the bottom 10% of total market value every month, following Asness, Moskowitz and Pedersen (2013). UMD, SMB, HML, RMW, and CMA are factor returns for the momentum, size, value, profitability, and investment factors, respectively. These factor returns are retrieved from the Kenneth R. French data library. MKT is derived by subtracting the U.S. 1-month T-bill rate from MSCI U.S. index returns. Intercepts (a) significant at the 5% level are shown in boldface. t-statistics are in parentheses.

3.4 Informational advantages

So far, no definitive source of the predictive power of short-term institutional trading on future stock returns has been established. Neither value- nor momentum effects seem to consistently subsume ΔSIO excess returns, and limits-to-arbitrage don't offer a comprehensive explanation either. But momentum could be important still. While Table 14 shows the inability of momentum to completely subsume ΔSIO, this need not necessarily be the case for all stocks. Short-term institutions could be momentum traders solely for large stocks, thereby explaining high excess returns without the assumption of informational advantages. This makes sense from a theoretical perspective; momentum is a high-turnover investing strategy, which makes it particularly costly to implement on small- and illiquid stocks (Amihud & Mendelson, 1986). Though institutional investors may trade strategically to reduce liquidity costs, they still trade larger volumes than average investors (Chan & Lakonishok, 1993). Thus, being more adversely affected by illiquidity (Glosten & Harris, 1988), it is reasonably assumed they might be relatively less inclined to trade small stocks based on momentum. Therefore, if short-term investors indeed trade large (small) stocks based on momentum (informational advantages), momentum effects should (not) subsume ΔSIO excess returns. To test this hypothesis, a 2x5x5 triple-sort is conducted. First, portfolios are sorted on size using NYSE median breakpoints. Then, portfolios are further sorted on 12-month momentum returns. Finally, portfolios are sorted on ΔSIO, yielding 50 portfolios that control for size- and momentum effects. Monthly portfolio returns, shown in Table 19, do not support the selective momentum trading explanation. In fact, they suggest the opposite; excess returns for small stocks, shown in Panel A, are insignificant, while Panel B indicates significant return spreads for large stocks. This implies that ΔSIO returns for small firms are explained by known anomalies and not driven by informational advantages. On the other hand, momentum effects do not subsume ΔSIO returns for large stocks, which does not rule out informational advantages as an explanation.

Testing whether short-term institutional investors actually trade based on informational advantages is not straightforward, though. Simply showing robustness of ΔSIO returns to a variety of firm characteristics may show what does not explain returns, but it fails to offer evidence in the way of what does. Informational advantages are, by their very nature, unique per stock and investor, but the dichotomy between informed- and uninformed investors – information asymmetry – is always implied. In the theoretical model of Easley and O'Hara (2004), investors are classified as "informed traders" if they efficiently structure their portfolio of stocks with high information asymmetry. Applying this reasoning, short-term institutional investors are likely to be "informed", i.e., trading based on informational advantages, if they also exhibit said efficiency. Potential informational advantages can therefore be examined by analyzing ΔSIO returns across stocks with varying degrees of investor information asymmetry. If short-term investors are informed, their trading – reflecting their ability to

Table 19 Triple-sorted portfolio returns on size, momentum and ΔSIO, from 1980 to 2022

Momentum quintile	P1	P2	P3	P4	P5	P5-P1
			Panel A: Small stocks			
P1	0.61	0.46	-0.05	0.39	0.63	0.02
	(1.42)	(1.19)	(-0.14)	(1.03)	(1.65)	(0.10)
P2	0.97	0.92	0.79	1.15	1.10	0.13
	(3.33)	(3.37)	(2.95)	(4.16)	(3.71)	(1.12)
P3	1.10	1.07	1.13	1.09	1.12	0.03
	(4.40)	(4.75)	(5.14)	(4.82)	(4.37)	(0.28)
P4	1.31	1.32	1.16	1.30	1.29	-0.02
	(5.39)	(6.12)	(5.54)	(5.84)	(5.16)	(-0.22)
P5	1.43	1.33	1.59	1.72	1.57	0.14
	(4.99)	(4.80)	(5.73)	(5.96)	(4.72)	(0.97)
Average	1.08	1.02	0.94	1.13	1.14	0.06
	(3.88)	(4.03)	(3.90)	(4.45)	(4.06)	(0.90)
			Panel B: Large stocks			
P1	0.72	0.67	1.05	0.79	0.89	0.17
	(2.22)	(2.29)	(3.77)	(2.77)	(2.82)	(0.93)
P2	0.97	0.98	1.01	0.98	1.14	0.16
	(3.90)	(4.57)	(4.61)	(4.58)	(4.69)	(1.06)
P3	0.85	1.05	0.92	0.80	1.04	0.19
	(3.67)	(5.06)	(4.61)	(3.88)	(4.64)	(1.27)
P4	1.14	1.16	1.05	1.04	1.06	-0.07
	(4.99)	(5.64)	(4.86)	(4.89)	(4.39)	(-0.46)
P5	1.04	1.20	1.03	1.45	1.55	**0.51**
	(3.70)	(4.55)	(3.97)	(5.31)	(5.29)	**(2.86)**
Average	0.94	1.01	1.01	1.02	1.13	**0.19**
	(4.13)	(5.06)	(5.16)	(5.03)	(4.95)	**(2.30)**

Columns P1–P5: **ΔSIO quintile**

Note. Average monthly returns for portfolios, sorted first on size using NYSE breakpoints, then on momentum, then on changes in short-term institutional ownership. Panel A (Panel B) shows returns for triple-sorted portfolios of stocks with a market value below (above) the NYSE median size breakpoint. Portfolios are sorted every three months and held for three months. The last row of each panel shows returns averaged over momentum quintiles. P5-P1 return spreads significant at the 5% significance level are in boldface. t-statistics are in parentheses.

structure a portfolio – should show no decrease in predictive power of stock returns as information asymmetry increases. In this regard, results from previous sections have been relatively inconclusive. Institutional ownership has been shown to reduce investor information asymmetry through greater management disclosure, analyst following, and liquidity (Boone & White, 2015). Results from Table 10 thus imply informational advantages as a source of ΔSIO returns; returns are highest and most significant for stocks with low TIO, i.e., high investor information asymmetry. On the other hand, insofar as small firms represent environments of high information asymmetry, ΔSIO returns should manifest primarily in these firms if informational advantages are at play (Baik, Kang & Kim, 2010). However, size double-sorts of Table 13, among other results, show higher excess returns for large stocks, thus opposing the narrative of informational advantages.

Another proxy for information asymmetry is return volatility (Baik, Kang & Kim, 2010). Roll (1988) reasons that firm-specific return variation, i.e., idiosyncratic volatility, reflects pricing of unique information about firms, and is associated with trading based on private information. Durnev, Morck and Yeung (2004), expanding upon theory of Grossman and Stiglitz (1980), also find evidence for high firm-specific return variation stemming from more intensive informed trading. Finally, in their research on the pricing of information risk, Yang, Zhang and Zhang, (2020) use idiosyncratic volatility as a measure to capture information asymmetry faced by uninformed investors. The literature has thus long recognized idiosyncratic volatility as reflective of investor information asymmetry (Morck, Yeung & Yu, 2000; Ferreira & Laux, 2007). As was shown by results from Table 9, idiosyncratic volatility itself can neither explain ΔSIO, nor completely inhibit the arbitrage of its returns. While returns may be highest for the upper $IVOL$ quintile, returns from lower $IVOL$ quintiles are far more significant, especially when considering results from Panel B.

Volatility and size are negatively correlated, but effects of the former are not subsumed by the latter, particularly in the case of idiosyncratic volatility. (Ang, Hodrick, Xing & Zhang, 2006). Given their correlation, idiosyncratic volatility could potentially be misrepresented by the double-sort used for the results from Table 9. As ΔSIO returns are highest for large stocks, lower quintiles of idiosyncratic volatility could be capturing these returns, which would not necessarily reflect the effects of $IVOL$ itself. As posited above, idiosyncratic volatility can also be used to proxy for information asymmetry between informed- and uninformed investors, potentially in conjunction with firm size. Thus, to account for the possibility of effects of $IVOL$ – proxying for information asymmetry – varying across firm size, a 2x5x5 triple-sort is conducted. First, portfolios are sorted on size using NYSE median breakpoints. Then, portfolios are further sorted on idiosyncratic volatility, calculated as detailed in the Section 2. Finally, portfolios are sorted on ΔSIO, yielding 50 portfolios that control for size- and idiosyncratic volatility effects. Results from Table 20 show strong evidence for the fourth hypothesis. Panel A, showing raw returns for the portfolios of small stocks, indicate small stock ΔSIO returns are mostly subsumed by $IVOL$, as the averaged return spread is only significant at the 10% level. Excess returns in the upper $IVOL$ quintile are also significant at the 10% level, while other quintiles show no significant excess returns. This implies that ΔSIO returns, even for small stocks, are positively related to information asymmetry.

Similar conclusions can be drawn from Panel B of Table 20, which shows raw returns for the portfolios of large stocks. With the exception of $IVOL$ P4, ΔSIO excess returns increase with idiosyncratic volatility. The ΔSIO return spread is largest for stocks in the upper $IVOL$ quintile, and significant at the 5% level, while excess returns for the lowest $IVOL$ quintile are insignificant. Compared to the portfolio

Table 20 Triple-sorted portfolio returns on size, idiosyncratic volatility and ΔSIO, from 1980 to 2022

$IVOL$ quintile	ΔSIO quintile P1	P2	P3	P4	P5	P5-P1
Panel A: Raw returns, small stocks						
P1	1.23	1.16	1.08	1.16	1.30	0.08
	(5.23)	(5.75)	(5.14)	(5.38)	(5.46)	(1.30)
P2	1.23	1.05	1.25	1.30	1.16	-0.07
	(4.16)	(4.00)	(4.93)	(4.79)	(4.00)	(-0.70)
P3	1.09	1.12	1.19	1.31	1.29	0.21
	(3.09)	(3.45)	(3.73)	(4.21)	(3.72)	(1.58)
P4	0.81	0.84	0.69	0.90	0.97	0.16
	(1.96)	(2.11)	(1.81)	(2.29)	(2.40)	(0.94)
P5	0.23	0.59	0.32	0.68	0.75	0.49
	(0.52)	(1.18)	(0.64)	(1.42)	(1.67)	(1.72)
Average	0.92	0.95	0.98	1.06	1.10	0.17
	(2.70)	(3.05)	(3.45)	(3.54)	(3.38)	(1.85)
Panel B: Raw returns, large stocks						
P1	1.00	1.08	1.10	0.94	1.14	0.13
	(4.88)	(5.44)	(5.75)	(4.67)	(5.71)	(0.99)
P2	0.90	1.05	1.13	1.00	1.21	**0.31**
	(3.88)	(4.95)	(5.39)	(4.69)	(5.29)	**(2.24)**
P3	0.78	1.01	0.79	1.22	1.21	**0.44**
	(3.05)	(4.07)	(3.30)	(4.96)	(4.31)	**(2.35)**
P4	1.07	0.70	1.12	1.07	0.91	-0.15
	(3.55)	(2.39)	(3.65)	(3.71)	(2.98)	(-0.81)
P5	0.58	0.86	0.96	0.94	1.18	**0.59**
	(1.50)	(2.48)	(2.97)	(2.55)	(2.71)	**(2.19)**
Average	0.87	0.94	1.02	1.03	1.13	**0.26**
	(3.53)	(4.09)	(4.56)	(4.38)	(4.34)	**(2.78)**
Panel C: DGTW returns, small stocks						
P1	0.20	0.09	0.17	0.11	0.28	0.08
	(2.71)	(0.96)	(1.52)	(1.14)	(3.43)	(1.25)
P2	0.23	0.07	0.24	0.26	0.16	-0.07
	(2.97)	(0.85)	(2.57)	(2.98)	(2.06)	(-0.72)
P3	0.18	0.21	0.27	0.36	0.31	0.13
	(1.75)	(2.45)	(2.53)	(4.16)	(3.10)	(1.11)
P4	0.02	-0.02	-0.15	0.04	0.09	0.06
	(0.14)	(-0.13)	(-0.97)	(0.26)	(0.57)	(0.38)
P5	-0.44	-0.23	-0.50	-0.23	-0.09	0.35
	(-1.78)	(-0.93)	(-1.82)	(-0.79)	(-0.43)	(1.26)
Average	0.04	0.03	0.05	0.10	0.15	0.11
	(0.53)	(0.43)	(0.64)	(1.57)	(2.37)	(1.26)
Panel D: DGTW returns, large stocks						
P1	0.01	0.05	0.10	0.03	0.12	0.11
	(0.09)	(0.57)	(1.36)	(0.29)	(1.19)	(1.04)
P2	-0.08	0.05	0.11	-0.08	0.12	0.20
	(-0.83)	(0.59)	(1.19)	(-1.02)	(1.43)	(1.73)
P3	-0.23	-0.01	-0.11	0.18	0.11	**0.34**
	(-2.11)	(-0.05)	(-1.23)	(1.78)	(1.18)	**(2.26)**
P4	0.08	-0.18	0.10	0.06	0.01	-0.07
	(0.66)	(-1.58)	(0.74)	(0.52)	(0.05)	(-0.41)
P5	-0.21	0.07	0.05	-0.04	0.18	0.39
	(-1.12)	(0.48)	(0.38)	(-0.26)	(0.77)	(1.60)

Continued

Table 20 (Continued)

$IVOL$ quintile	ΔSIO quintile					
	P1	**P2**	**P3**	**P4**	**P5**	**P5-P1**
Average	-0.09	0.00	0.05	0.03	0.11	**0.19**
	(-1.50)	(-0.04)	(1.20)	(0.56)	(1.73)	**(2.44)**

Note. Average monthly returns for portfolios, sorted first on size using NYSE breakpoints, then on idiosyncratic volatility, then on changes in short-term institutional ownership. Panel A (Panel B) shows raw returns for triple-sorted portfolios of stocks with a market value below (above) the NYSE median size breakpoint. Panel C (Panel D) shows DGTW returns for triple-sorted portfolios of stocks with a market value below (above) the NYSE median size breakpoint. Portfolios are sorted every three months and held for three months. The last row of each panel shows returns averaged over $IVOL$ quintiles. P5-P1 return spreads significant at the 5% significance level are in boldface. t-statistics are in parentheses.

double-sort from Table 9, ΔSIO excess returns are seemingly most significant for stocks with high $IVOL$. As hypothesized, this shows how the predictive power of short-term institutional trading is stronger for large stocks with high degrees of information asymmetry. Informational advantages are thus implied. However, this once again raises the issue of limits-to-arbitrage; if ΔSIO returns are concentrated in large stocks with high idiosyncratic volatility, does it truly offer a practical arbitrage opportunity? Results from Panel B offer perspective on this concern as well. While ΔSIO returns may be highest for the upper $IVOL$ quintile, both P2 and P3 also show excess returns significant at the 5% level. This implies that ΔSIO long-short portfolios don't rely exclusively on stocks with high idiosyncratic volatility for returns, but also offer relatively safe arbitrage opportunities on less "risky" stocks. In fact, DGTW returns from Panel D paint an even clearer picture. Though excess returns still exhibit the same pattern of increasing with idiosyncratic volatility, the P3 $IVOL$ quintile is also the only quintile where these returns are significant. Thus, results show that short-term investors are efficient at trading stocks with high information asymmetry, while also showing how $IVOL$, as a limit-to-arbitrage, does not eliminate excess returns.

Insofar as long-term institutional investors may be the uninformed counterparts of short-term investors, Table 21 replicates the triple-sort for ΔLIO, showing ΔSIO (ΔLIO) return spreads in Panel A (Panel B). Congruent with the theory of Easley and O'Hara (2004) on the inability of uninformed investors to structure their portfolio in the face of information asymmetry, ΔLIO return spreads decrease with $IVOL$. For both small- and large stocks, as well as both categories combined, the P5-P1 ΔLIO return spread in $IVOL$ P5 is consistently less than or equal to that of $IVOL$ P1. For large stocks in $IVOL$ P4, the ΔLIO monthly return spread of -0.42% is significant at the 5% level, and small stocks in $IVOL$ P5 show a return spread of -0.49% significant at the 10% level. On the other hand, when looking at all stocks, $IVOL$ P2, representing stocks with relatively low information asymmetry, a positive monthly return spread of

Table 21 Triple-sorted portfolio return spreads on size, idiosyncratic volatility and ΔIO, from 1980 to 2022

Stock sample	*IVOL* quintile P1	P2	P3	P4	P5	Average
Panel A: ΔSIO						
Small firms	0.08	-0.07	0.21	0.16	0.49	0.17
	(1.30)	(-0.70)	(1.58)	(0.94)	(1.72)	(1.85)
Large firms	0.13	**0.31**	**0.44**	-0.15	**0.59**	**0.26**
	(0.99)	**(2.24)**	**(2.35)**	(-0.81)	**(2.19)**	**(2.78)**
All firms	**0.22**	**0.29**	0.21	0.09	0.56	**0.27**
	(2.06)	**(1.96)**	(1.14)	(0.41)	(1.82)	**(2.40)**
Panel B: ΔLIO						
Small firms	-0.07	0.00	-0.26	-0.21	-0.49	**-0.21**
	(-0.98)	(-0.05)	(-1.92)	(-0.98)	(-1.95)	**(-2.28)**
Large firms	-0.12	-0.08	-0.10	**-0.42**	-0.12	**-0.17**
	(-0.93)	(-0.63)	(-0.65)	**(-2.16)**	(-0.53)	**(-1.98)**
All firms	0.01	0.21	-0.01	-0.14	-0.10	-0.01
	(0.08)	(1.77)	(-0.09)	(-0.83)	(-0.49)	(-0.07)

Note. Average monthly return spreads for triple-sorted portfolios. Panel A (Panel B) shows P5-P1 ΔSIO (ΔLIO) returns spreads for portfolios sorted first on size, then on idiosyncratic volatility, then on ΔSIO (ΔLIO). Each row indicates the size quintile, where small (large) firms are stocks below (above) the NYSE median size breakpoint. The "all firms" rows report results for both small- and large stocks, disregarding the size sort; the last row of Panel A is identical to the last column of Table 9, Panel A. Portfolios are sorted every three months and held for three months. The last row of each panel shows returns averaged over $IVOL$ quintiles. Return spreads significant at the 5% significance level are in boldface. t-statistics are in parentheses.

0.29% is shown, significant at the 10% level. While results from Panel B are not consistently significant, when compared with Panel A, they do indicate informational advantages of short-term investors, certainly relative to long-term investors. ΔSIO (ΔLIO) return spreads across firm size generally increase (decrease) with $IVOL$, and are higher (lower) for $IVOL$ P5 compared to $IVOL$ P1. Thus, relating their ability to structure their portfolio in the face of information asymmetry to that of either informed- or uninformed investors, short-term investors are much more likely to be informed.

4. Robustness Checks

In previous sections, the predictive power of ΔSIO on future stock returns of has been shown as a robust finding, and informational advantages offer a more likely explanation than firm characteristics. The question remains, however, whether institutional turnover itself is related to these informational advantages and the associated excess returns. As discussed in Section 1, certain papers have raised endogeneity concerns regarding the classification of investors based on turnover (Baik, Kang & Kim, 2010). Institutional turnover could simply be proxying for other investor-specific variables. Trading by investors that exhibit these characteristics themselves may be associated with high stock returns. After accounting for these characteristics in investor distinction, return differentials between short- and long-term institutional trading could converge to zero. This would prove redundancy or endogeneity of investor turnover. Thus, to test for this possibility, a number of investor characteristics are considered. As stated before, Bushee and Goodman (2007) concluded a higher likelihood of informed trading for large institutions. On average, large institutions comprise 30% of short-term institutional investors every quarter, as shown by Table 22. In contrast, only 11% of long-term institutional investors belong to the top quintile of equity portfolio size every quarter. Investor turnover could thus be endogenous to investor size. Another defining investor characteristic is fund age. As found by O'Connell and Teo (2009), younger and less experienced funds are more likely to succumb to overconfidence and increase their risk more after gains (Gervais & Odean, 2001). Table 22 also shows the average fund age for institutional investors, which is higher for short-term investors compared to long-term investors. Therefore, the effects of institutional turnover could be endogenous to both the size and age of an investor. To account for this possibility, institutional investors are double-sorted into groups every quarter, sorting first on investor size, then on investor age. The turnover measure from Equation (4) is then normalized within these quintiles as follows:

$$Adjusted\_turnover_{k,t}^{s,a} = \frac{Turnover_{k,t}^{s,a} - Turnover_{t}^{s,a}}{\sigma_{s,a}\left[Turnover_{k,t}^{s,a} - Turnover_{t}^{s,a}\right]}, \tag{12}$$

where $Turnover_{k,t}^{s,a}$, $Turnover_{t}^{s,a}$, and $\sigma_{s,a}\left[Turnover_{k,t}^{s,a} - Turnover_{t}^{s,a}\right]$ equal the turnover measure from Equation (4) for institutional investor k belonging to investor size quintile s and investor age quintile a during quarter t, the turnover measures from Equation (4) averaged within quintiles, and the cross-sectional standard deviation across investor size quintile s and investor age quintile a of a measure subtracting these two values, respectively. This adjusted turnover ratio is then used to divide institutional investors into tertiles every quarter, essentially replacing the turnover measure from Equation (4) for investor turnover tertile construction. Results for long-short portfolios based on institutional trading, constructed similarly to portfolios from Table 4, are shown in Table 23. Results from Panel A show no evidence of any consistently significant predictive power of short-term institutional trading on future stock returns. Endogeneity to other investor characteristics would hereby be implied. Panel B offers a different conclusion; the difference in return spreads between short-term- and long-term institutional trading portfolios is consistently greater compared to portfolios from Table 4. This implies that the distinction of institutional investors based on turnover ratios still explains significant differences in performance across investors. Comparing results from Panel A and Panel B, the latter likely holds more weight. Endogeneity to other investor characteristics should decrease the performance difference between investors, as the turnover measure would be less effective at proxying for these characteristics. Instead, the performance difference is widened, thereby invalidating endogeneity concerns.

Table 22 Time-series means for size- and age characteristics of institutional investors

Investor characteristic	**Time-series mean**	
	Short-term investors	**Long-term investors**
Equity portfolio size	3.88E+09	2.51E+09
Investor age	7.0	6.3
% of large investors	30.3	11.2
% of old investors	20.9	16.4

Note. Reported are time-series means for various investor characteristics, averaged over investors turnover tertiles. Equity portfolio size is the average portfolio total dollar value of an institutional investor its stock holdings. Investor age is the average number of years for which an institutional investor has data. % of large investors is the average percentage of investors belonging to the top quintile of equity portfolio size for all institutional investors, following Bushee and Goodman (2007). % of old investors is the average percentage of investors belonging to the top quintile of investor age for all institutional investors.

Table 23 Returns on portfolios sorted on ΔIO, adjusted for equity portfolio size and investor age, from Q3 1980 to Q2 2022

Panel A: ΔSIO & ΔLIO returns					
		Quarters			
	Quarterly average	**t + 1**	**t + 1 through t + 2**	**t + 1 through t + 3**	**t + 1 through t + 4**
Adjusted ΔSIO, 1980Q3 - 2022Q2					
P5	3.22	3.32	6.50	10.06	13.28
P1	2.93	2.98	6.06	8.74	12.03
P5-P1	0.28	0.34	0.43	**1.32**	1.25
	(1.90)	(1.27)	(1.07)	**(2.60)**	(1.96)
P5-P1 (DGTW adjusted)	0.16	0.23	0.20	**0.72**	0.68
	(1.52)	(1.06)	(0.66)	**(1.98)**	(1.56)
Adjusted ΔLIO, 1980Q3 - 2022Q2					
P5	3.06	2.88	6.02	9.30	12.52
P1	3.22	3.27	6.65	10.18	13.18
P5-P1	-0.16	-0.39	-0.63	-0.88	-0.67
	(-1.19)	(-1.51)	(-1.49)	(-1.81)	(-1.16)
P5-P1 (DGTW adjusted)	-0.14	-0.31	-0.54	-0.64	-0.55
	(-1.53)	(-1.55)	(-1.89)	(-1.90)	(-1.55)
Panel B: ΔSIO - ΔLIO return spread difference					
ΔSIO - ΔLIO, 1980Q3 - 2022Q2					
Non-adjusted	0.39	0.49	0.54	1.67	1.65
Adjusted	0.44	0.73	1.06	2.20	1.92

Note. Panel A shows value-weighted cumulative quarterly returns for portfolios sorted on the change in previous quarter's institutional ownership. Both raw returns and DGTW benchmark adjusted returns are shown. P5-P1 return spreads significant at the 5% significance level are in boldface. Panel B shows the difference in P5-P1 return spreads between ΔSIO- and ΔLIO-sorted portfolios for every quarter, defined as the ΔSIO return spread minus the ΔLIO return spread. Non-adjusted refers to the results from Table 4. t-statistics are in parentheses.

Other defining characteristics of institutional investors could also impact their predictive power of future stock returns. Apart from the two institution-specific characteristics mentioned previously, two additional characteristics of ownership may explain the predictive power of short-term institutional trading. Bushee and Goodman (2007) find that trading by institutions with large holdings (relative to both other investors and own portfolio size) in individual stocks, is more likely to reflect informed trading. This could imply endogeneity if short-term institutional investors are more likely to have large holdings. These endogeneity concerns are alleviated by results from Table 24, which shows ownership characteristics for short- and long-term institutional investors as per Equation (12). While short-term institutional investors have more investments of blockholder- and overweighted size compared to long-term investors, this is not the case relative to their other investments. On average, a short-term institutional investor is a blockholder for 20% of the stocks in its portfolio, while a long-term investor is a blockholder for 24%. Similarly, short-term institutional investors on average have less overweighted investments relative to other investments compared to long-term institutional investors. With the average short-term institutional investor not more likely to be a significant holder of any single one of its investments, endogeneity concerns are rejected here as well. Therefore, it seems investor turnover is its own defining characteristic in the realms of institutional trading and asset pricing.

5. Conclusions

All in all, results found by this paper provide evidence for short-term institutional trading as its own asset-pricing anomaly, with several distinctive characteristics. Starting off, flow factor returns remain statistically significant after the publication of research by Yan and Zhang (2009), indicative of the robustness of these results. Furthermore, after examining a wide variety of limits-to-arbitrage, flow factor returns show considerable robustness to most measures. Idiosyncratic volalitility and transaction costs through portfolio turnover are most indicative of arbitrage difficulties for flow returns. Even these, however, cannot entirely explain returns. Controlling for other asset pricing effects, only momentum explains variation of return predictability of short-term institutional trading. Examining trading on large stocks exclusively leads to different conclusions, however; momentum cannot fully explain returns in this case. This also connects to the important finding of flow factor returns varying across firm size, in opposite patterns to those identified by Yan and Zhang (2009). Short-term institutional trading is seemingly significantly more predictive of future stock returns for large stocks. Such a pattern in returns is unintuitive, as most anomaly returns, such as the value, momentum, profitability, and investment anomalies, are higher for small stocks (Novy-Marx, 2012; Fama & French, 2015). Yan and Zhang (2009) find greater return predictability for small stocks, and use said finding to interpret short-term institutional trading as reflective of informed trading. In order to reconcile these opposing results with one another, investor information asymmetry is taken into account by examining its proxy variables. In doing so, informational advantages of short-term institutional investors remain a plausible source for excess returns associated with their trading. Relating these results to traditional asset pricing theories, the persistence of excess returns from short-term institutional trading contrasts with the idea of

Table 24 Time-series means for block- and bet characteristics of institutional investors

Investor characteristic	**Time-series mean**	
	Short-term investors	**Long-term investors**
# of blockholdings	41.1	31.9
# of overweightings	42.7	25.1
% of blockholdings	20.3	24.4
% of overweightings	49.2	51.7

Note. Reported are time-series means for investor characteristics, averaged within investor turnover tertiles. Blockholdings and overweightings are defined as per Bushee and Goodman (2007). # of blockholdings is the average number of an institutional investor its individual stock holdings which belong to the top quintile of holdings for a stock. # of overweightings is the average number of investments for which the portfolio allocation percentage of an institutional investor belongs to the top quintile of portfolio allocations for a stock. Percentage metrics are defined similarly, relative to the institutional investors their total number of different stock investments.

efficient markets. With limits-to-arbitrage failing to provide a comprehensive explanation for return predictability, short-term institutional trading should be copied by rational investors and its returns arbitraged away. Intuitively, flow returns are already innately arbitraged to at least a certain degree; short-term institutional trading itself precedes this characteristic and its associated returns. Following theory of institutional herding by Nofsinger and Sias (1999), uninformed traders may emulate investing patterns of short-term institutional investors; a feedback loop in returns would be implied (Nofsinger & Sias, 1999). Overall, as robustness tests also imply endogeneity of investor distinction using portfolio turnover, significant evidence for short-term investors as a skilled subset of "smart money" is found. This paper thus underlines the importance of investor differences within asset pricing and investor skill fields, and unifies the literature thereon by following theories on both sides of market efficiency debates.

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Appendix

Appendix A Triple-sorted DGTW benchmark returns, from July 1973 to December 2022

Size quintile	Adj. B/M quintile	Momentum quintile P1	P2	P3	P4	P5
Panel A: Size P1						
P1	P1	0.74	0.72	0.79	0.97	0.81
		(2.16)	(2.44)	(3.16)	(3.90)	(2.69)
	P2	1.05	1.20	1.08	1.21	1.06
		(3.06)	(4.31)	(4.52)	(5.10)	(3.91)
	P3	1.29	1.40	1.29	1.38	1.24
		(3.78)	(5.10)	(5.02)	(5.79)	(4.55)
	P4	1.26	1.35	1.33	1.47	1.79
		(3.52)	(4.67)	(5.23)	(5.65)	(5.39)
	P5	1.26	1.39	1.70	1.59	1.57
		(3.13)	(4.67)	(5.56)	(6.39)	(5.36)
Panel B: Size P2						
P2	P1	0.71	0.92	1.06	1.03	0.91
		(2.23)	(3.73)	(4.45)	(4.22)	(3.00)
	P2	0.90	1.11	1.16	1.17	1.27
		(2.90)	(4.44)	(5.07)	(5.08)	(4.37)
	P3	1.17	1.23	1.28	1.34	1.11
		(3.90)	(4.85)	(5.24)	(5.61)	(4.03)
	P4	1.17	1.20	1.38	1.40	1.31
		(2.98)	(4.78)	(5.57)	(5.78)	(4.51)
	P5	0.97	1.26	1.24	1.22	1.21
		(2.61)	(4.25)	(5.06)	(4.99)	(3.86)
Panel C: Size P3						
P3	P1	0.81	0.95	1.01	1.15	1.18
		(2.75)	(4.04)	(4.46)	(4.46)	(3.75)
	P2	0.83	0.98	0.97	1.01	1.20
		(3.16)	(4.40)	(4.65)	(4.32)	(4.26)
	P3	1.10	1.21	1.20	1.14	1.29
		(4.12)	(5.40)	(5.52)	(5.15)	(4.64)
	P4	1.08	1.25	1.04	1.23	1.24
		(3.70)	(5.54)	(4.57)	(5.36)	(4.35)
	P5	1.35	1.18	1.38	1.54	1.21
		(3.96)	(4.46)	(5.71)	(6.21)	(4.24)
Panel D: Size P4						
P4	P1	0.83	1.08	0.95	1.09	1.23
		(3.13)	(5.06)	(4.18)	(4.74)	(4.12)
	P2	0.96	1.09	1.12	1.03	1.23
		(3.84)	(5.31)	(5.32)	(4.60)	(4.38)
	P3	0.98	1.03	1.24	1.09	1.04
		(3.59)	(4.71)	(6.09)	(4.93)	(3.83)
	P4	1.16	1.09	1.15	1.14	1.15
		(4.21)	(4.52)	(5.15)	(4.88)	(4.14)
	P5	1.36	1.28	1.38	1.12	1.09
		(4.28)	(5.15)	(6.18)	(4.63)	(4.07)

Continued

Appendix A (Continued)

		Panel E: Size P5				
Size quintile	**Adj. B/M quintile**	**Momentum quintile**				
		P1	**P2**	**P3**	**P4**	**P5**
	P1	0.67	0.85	0.81	0.87	1.12
		(2.66)	(4.03)	(3.53)	(3.81)	(3.92)
	P2	0.86	0.75	0.83	0.77	0.98
		(3.58)	(3.86)	(4.10)	(3.79)	(3.84)
P5	P3	1.10	0.93	0.99	1.19	1.08
		(4.41)	(4.66)	(5.14)	(5.86)	(4.51)
	P4	0.86	1.05	0.96	0.97	1.07
		(3.23)	(5.08)	(4.74)	(4.87)	(4.45)
	P5	1.00	1.03	1.14	1.02	0.99
		(3.76)	(4.94)	(5.57)	(5.00)	(3.88)

Note. Average monthly returns for triple-sorted portfolios are in percentages. Portfolios are sorted first on size using NYSE breakpoints, then on adjusted book-to-market ratios using NYSE breakpoints, then on 12-month momentum returns excluding the most recent month using NYSE breakpoints. Portfolios are sorted every year and held for one year, as detailed in Section 2. t-statistics are in parentheses.

Appendix B Original results from Yan and Zhang (2009)

Returns on portfolios sorted by changes in short- and long-term institutional ownership

		Quarters			
	Quarterly Average	$t+1$	$t+1$ through $t+2$	$t+1$ through $t+3$	$t+1$ through $t+4$
Short-term institutional trading portfolios					
Q5	3.62	3.61	6.91	10.61	14.88
Q1	3.09	2.97	5.86	8.74	12.72
Q5 – Q1	**0.53**	**0.64**	**1.05**	**1.87**	**2.16**
	(3.16)	(2.02)	(2.42)	(3.16)	(2.77)
Q5 – Q1 (DGTW	**0.41**	**0.42**	**0.62**	**1.24**	**1.62**
adjusted)	(3.34)	(1.73)	(1.86)	(2.74)	(2.82)
Long-term institutional trading portfolios					
Q5	3.21	2.91	5.90	9.08	13.27
Q1	3.40	3.08	6.55	10.18	14.02
Q5 – Q1	−0.19	−0.17	−0.64	**−1.09**	−0.75
	(−1.20)	(−0.49)	(−1.52)	(−2.25)	(−1.41)
Q5 – Q1 (DGTW	−0.03	−0.04	−0.35	−0.55	−0.16
adjusted)	(−0.29)	(−0.16)	(−1.12)	(−1.52)	(−0.41)

This table reports the returns on portfolios sorted by the quarterly change in short- and long-term institutional ownership. The sample period is from 1980:Q3 to 2003:Q4. Institutional holdings are obtained from CDA/Spectrum. Stock returns are from the CRSP. An institutional investor is classified as a short-term investor if its past 4-quarter portfolio turnover rate ranks in the top tertile. An institutional investor is classified as a long-term investor if its past 4-quarter turnover rate ranks in the bottom tertile. Each quarter, we group all stocks available in CDA/Spectrum into 5 portfolios based on their rankings on change in short- and long-term institutional ownership, respectively. Portfolio Q5 contains stocks that experience the largest increase in institutional ownership. Portfolio Q1 contains stocks that experience the largest decrease in institutional ownership. For each of portfolios Q5 and Q1, we report their value-weighted cumulative quarterly returns up to 4 quarters after the portfolio formation. We also report the average quarterly returns on an investment strategy that is long in Q5 and short in Q1. We report the time-series means of both raw returns as well as the Daniel et al. (1997) (DGTW) benchmark adjusted returns. The returns are in percent. Numbers in parentheses are t-statistics. Return differences that are statistically significant at 10% are in bold. All returns are in percent.