Liquidity Shocks and Institutional Trading[1]

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Abstract

This paper analyzes the role of institutional trading in stock level liquidity shocks. We find institutions, especially the transient ones, buy stocks that experience positive liquidity shocks and sell those that experience negative ones. High-low liquidity shock deciles are associated with future increase in institutions' ownership 53% higher than the amount of average monthly institutional trading. Trading induced by such shocks positively predict 5.03% annualized return in the subsequent month. This trading activity also amplifies the future liquidity risk of underlying stocks. The results suggest that institutional investors improve market efficiency by exploiting the mispricing associated with liquidity shocks, while their trading exacerbates stock level liquidity risk at the same time.

Liquidity is one of the major economic forces that affect market efficiency (see, e.g., Chordia, Roll, and Subrahmanyam, 2008, 2011). Institutional investors are majority owners and traders of stocks in the US that can have significant impact on the market efficiency and liquidity. The recent financial crisis further highlights the importance of understanding institutional trading in response to liquidity shocks. In light of these, numerous studies have examined how institutions react to systematic market liquidity shocks (mostly liquidity crises), which in turn affects the efficiency of asset prices (see, e.g., Scholes, 2000; Chordia, Roll and Subrahmanyam, 2000; Manconi, Massa and Yasuda, 2012; Ben-David Franzoni, and Moussawi, 2012; Anand, Irvine, Puckett and Venkataraman, 2013; Dong, Feng, Sadka, 2014 among many others). However, little is known on how institutions respond to idiosyncratic, individual stock level liquidity shocks, and the implication of such response on the efficiency of asset prices. This paper fills this gap.

Institutional trading on stock level liquidity shocks provides different insight on the relation between liquidity and market efficiency. First, while the asset pricing effects of systematic liquidity shocks center around liquidity beta, idiosyncratic liquidity shocks affect asset prices in different ways. On the one hand, (idiosyncratic) liquidity is priced (e.g., Amihud and Mendelson, 1986; Brennan and Subrahmanyam, 1996). Therefore, a persistent negative liquidity shock should be associated with lower current price, just to reflect the increase in expected trading costs (e.g., Amihud, 2002; Jones, 2002; Acharya and Pedersen, 2005). On the other hand, unlike market-wide liquidity shocks, individual stock liquidity shocks are not as easy to observe. Bali, Peng, Shen and Tang (BPST, 2014) show that market significantly underreacts to the pricing effect of stock-level liquidity shocks due to investor limited attention. Much of the effect is delayed up to 6 months after the shocks. What role institutions play in the price-liquidity dynamics is unclear. Do they trade to correct the price inefficiency associated with liquidity shocks or they themselves cause such inefficiency?

Second, systematic market liquidity shocks are often coupled with market-wide funding liquidity shocks (Brunnermeier and Pedersen, 2009). They could also trigger fund-level performance-based limits to arbitrage (e.g., the LTCM crisis; Shleifer and Vishny, 1997). As such, institutions are often forced to trade in a way exacerbating market inefficiency to meet margin calls and redemption demands, as is the focus of many prior studies. However, forced fire sales by the entire institution industry are much less likely to be driven by individual stock liquidity shocks, which can be diversified at the fund level and at the industry level. Therefore, idiosyncratic liquidity shocks provide an ideal testing ground to study the role of institutional trading in market efficiency in the event of market liquidity shocks with little confounding effects from funding and performance concerns.

We start by examining how institutional investors respond after observing a liquidity shock. Our main liquidity shock measure (LIQUS) is the standardized difference between the monthly Amihud (2002) illiquidity measure and its preceding 12-month average. To measure institutional trading, we use both direct high frequency trade-level institutional trading data from ANcerno database and proxies for institutional trading based on Thomson-Reuters 13f quarterly institutional holdings data. The use of direct and high frequency data particularly allows us to conduct a dynamic and more precise analysis of institutional trading that would not be possible with quarterly data.

We find that institutional investors react positively to liquidity shocks by increasing their holdings following positive shocks and decreasing them following negative shocks. Decile portfolios representing difference between stocks with positive and negative liquidity shocks are related to increase in institutional monthly trading by 0.07% in ANcerno database, which is 153% of the average monthly institution trading, and 0.48% in 13f, which is 103% of the average, pointing to a substantial economic significance. Moreover, the relative change in the number of all institutional shareholders is also positively related to liquidity shocks. The difference between high and low liquidity portfolio in terms of change in the number of institutional shareholders is 2.96% (69% of the average monthly change in the number of institutional shareholders). Those findings are robust to the inclusion of a number of control variables, subperiod and subsample analysis. When we partition liquidity shock into individual, stock related shock and shock due to systematic liquidity changes, the results become stronger for the portion of the shock unrelated to market changes, confirming our focus on the effects of individual stock-level shocks.

Trading in response to idiosyncratic liquidity shocks requires investors to be attentive and buy and sell stocks actively and frequently. Thus, we use the institution classification from Bushee (2001) to identify transient, short-term oriented institutions, characterized by high turnover in 13f, as well as dedicated investors with low turnover and long investment horizon and quasi-indexers who passively follow the market. The results show that the positive relation between liquidity shocks and quarterly institutional trading is mainly driven by the transient institutions.

Institutional trading is highly profitable. The amount of institutional trading induced by LIQUS differential between high and low liquidity shock decile positively predicts an annualized 5.03% return in the subsequent month. The magnitude is remarkable given that the average unconditional monthly institutional trading negatively predicts an annualized 1.01% return in the following month, likely due to the fact that institutional trades on average are liquidity demanding and as a result introduce temporary price pressure that reverts in the future.

Taken together, our analysis above supports that institutions in aggregate are attentive, sophisticated investors that help arbitrage away mispricing in the market. They appear to understand the pricing implications of liquidity shocks suggested by theory and exploit the slow adjustment of stock prices following liquidity shocks well. While they extract arbitrage profits, their trading helps reduce market's underreaction to liquidity shocks and improve price efficiency.

We further extend our analysis to see how liquidity shocks and institutional trading are endogenously related to each other. Using VAR analysis, we find institutions not only simply exploit the mispricing caused by prior liquidity shocks, but their trading also positively predicts future liquidity shocks. That is, following a positive (negative) shock, their buying (selling) activity further induces further increases (decreases) in future liquidity. Therefore, their trading in response to a liquidity shock amplifies the very shock itself.

This paper contributes to the broad literature on the relation between institutional investors' trading, liquidity, and market efficiency in several aspects. First, we introduce a dynamic stock-level liquidity dimension. Our research complements the studies on the widely researched institutional reaction to market wide liquidity changes. To our knowledge, we are the first to comprehensively study the behavior of institutions in light of idiosyncratic liquidity shocks and their asset pricing effects. Most studies find that institutions engage in trading behavior that does not help improve or can even outright damage market efficiency in crisis periods (negative systematic liquidity shocks) due to limits such as funding and performance-based constraints. In contrast, we show that in an environment when these limits to arbitrage are less likely to be binding, institutions do play the positive role of improving price efficiency regardless of positive or negative liquidity shocks.[1]

Second, we shed light on the role of institutions in market efficiency, particularly on the cause of anomalies. A large body of earlier literature posits institutions to be sophisticated investors. However, recent works provide evidence suggesting the opposite conclusion. For example, Edelen, Ince, and Kadlec (2015) show that their trading appears to cause mispricing, as proxied by several well-known anomalies, rather than taking the arbitragers' role. However, whether many anomalies are driven by risk rather than mispricing explanations is still in debate.[2] The average institution could buy (sell) the stocks in the short (long) leg of an anomaly due to a rational risk preference. In contrast, the positive relation between liquidity and price is considered a relation with a clear theoretical foundation. For example, among a set of widely documented 97 return predictors, the positive relation between liquidity and price is singled out in McLean and Pontiff (2015) as a strongly theoretically motivated relation alongside the CAPM beta-

[1] Our paper differs from the traditional fire sale literature in terms of focus. First, the fire sale literature concentrates on the temporary price impact of forced sales. In contrast, the price changes of persistent liquidity shocks are shown to be permanent. Second, a sudden sale depreciates price, but it does not necessarily change the level of liquidity. A sudden large sale may cause a large decline in price but the price decline per share (i.e., the cost per trading quantity) could be the same as in the case of a sudden small sale. More generally, even if forced buy and sell temporarily change liquidity level, they should both decrease liquidity level. While a forced sell depreciates price, a forced buy appreciates price. In contrast, a decrease in liquidity caused by a forced buy or sell always come with a depreciation in price. Therefore, forced trading and liquidity shocks are driven by different economic mechanisms and generate different price dynamics.

[2] Ali, Chen, Yao, and Yu (2008) find mutual funds in aggregate do not trade on the accrual anomaly despite its profitability after considering the transaction costs of mutual funds. Relatedly, DeVault, Sias and Starks (2014) show that institutions are sentiment traders in aggregate. However, similar to the critics to anomalies, there are no clear theoretical foundation that the widely-used sentiment indices proxy for sentiment (i.e., mispricing) or fundamental (i.e., rational pricing) either (see, e.g., Sibley, Wang, Xing, Zhang, 2015; Dong and Osambela, 2015).

return relation. Therefore, a slow price reaction to liquidity shock can be relatively easy connected to mispricing. Under this condition, our evidence supports that institutions are sophisticated and contributes to correcting anomaly-based mispricing.

Third, our result that transient institutions take a major role in exploiting mispricing suggests that organizational structures that allow institutions to be more attentive and to trade on short-term price dynamics can serve the useful social function of bringing prices to their fundamental values. The results contribute to the debate on the value of active asset management industry by supporting that active trading can bring more value (see, e.g., Pastor, Stambaugh, and Taylor, 2015).

Fourth, our paper is also related to the feedback trading literature. Several seminal papers focus on the feedback between trading and price and demonstrate feedback trading of institutions can destabilize price efficiency. For example, DeLong, Shleifer, Summers and Waldmann (1990) discuss how speculators' feedback trading leads to volatility increase. Abreu and Brunnermeier (2003) and Brunnermeier and Nagel (2004) analyze short-term amplification of mispricing by arbitrageurs. In contrast, we focus on the feedback between trading and liquidity shocks and show that although institutional trading helps correct mispricing, the feedback from their trading contributes to exacerbating the stock-level liquidity risk.

The rest of the paper proceeds as follows. Section 1 describes the sources of data and variables used. Section 2 presents the main results. Section 3 discusses robustness checks. Section 4 presents panel VAR analysis of feedback effect of institutional trading on liquidity shocks and Section 5 concludes.

1. Data and variable constructions

We use two sources of institutional trading data. Our main analysis concentrates on high frequency institutional trading as reported by ANcerno Ltd in the period from January 1999 to September 2011. In our main tests, we also use quarterly holdings data from Thomson Reuters Institutional Holdings 13f database ranging from January 1981 to December 2012.

The ANcerno Ltd (formerly a unit of Abel/Noser Corp.) is an established consulting company that analyses equity trading transaction costs of its intuitional investor clients (pension plan sponsors, money managers and brokers). According to Puckett and Yan (2011), ANcerno institutional trading accounts for a significant fraction (10%) of institutional trading volume and is representative of the financial industry trading behavior. The database presents a range of advantages (Franzoni and Plazzi, 2013):

1. Complete and detailed trade-by-trade trading data of the subscribing institution (identified by a code allowing tracking over time and in cross-section) since subscription date. The information reported includes: side of the transaction, execution price and volume, time of the transaction, costs, stock's CUSIP. Short sales are also reported albeit not identified.
2. ANcerno clients subscribe voluntarily to obtain a fair analysis of their trading costs which reduces probability of self-reporting bias.
3. The database does not suffer from survivorship bias – institutions who reported in the past remain in the data set.

There is no backfill bias as the trades are only reported from the beginning of client reporting to ANcerno.

The potential type of selection bias in ANcerno database results from the fact that possibly only the more sophisticated and careful institutions would choose to have their transaction costs analyzed by a consultant (Anand et al., 2012). These are also more likely to be actively trading institutions.

The stocks traded by ANcerno and institutions reporting with 13f filings are comparable (Puckett and Yan, 2011, Anand et al., 2012). In Table 1 we compare main characteristics of the stocks traded by institutions from the two databases. Due to different sample period, we limit the comparison to the overlapping time from January 1999 to September 2011. The stocks traded by ANcerno are on average slightly larger, more liquid, with higher beta and analyst dispersion (also more analysts following) and lower book-to-market. The differences do not appear to be very large. The overall number of stocks traded by institutions in both data sets is similar.

We aggregate trade by trade data into daily net trading by all institutions in a given stock i in a month t, scaled by shares outstanding at the end of the month t adjusted for stock splits and other distributions.

$$Trading_{i,t} = \frac{Ancerno\ aggr.buys_{i,t} - Ancerno\ aggr.sells_{i,t}}{Shares\ outstanding_{i,t}} \qquad (1)$$

The data retrieved from the Thomson Reuters Institutional Holdings 13f database (formerly CDA/Spectrum) consists of common stock holdings and transactions of institutional managers with more than USD 100 million of securities under discretionary management as reported on Form 13F filed with the SEC (this applies to equity positions greater than 10,000 shares or with fair market value of at least $200,000).

The 13f sample includes banks, insurance companies, asset management companies, hedge funds, pension funds and other. Observation of idiosyncratic liquidity shocks and trading on them requires investors to trade actively and frequently. Bushee (2001), classifies institutional investors into three types: transient, quasi-indexing and dedicated, using factor and cluster analysis based on institutions past investment behavior.[3] Transient institutions have high portfolio turnover, short-term horizon as well as highly diversified portfolio holdings, thus are most likely to exploit advantages related to noticing liquidity shocks. Two other groups of investors are less active; dedicated institutions are long-term oriented and have more concentrated holdings, while quasi-indexing firms adhere to a passive buy-and-hold strategy.

The Institutional Ownership ratio (IOR) is calculated as the sum of all stocks held by 13f reporting institutions divided by shares outstanding from CRSP. Both numbers are adjusted for stock splits and other distributions.[4] We also adjust for reporting gaps in the 13f data. Institutional ownership ratios greater than 1 are winsorised at 1 (this problem

[3] We obtain the classification information from Brian Bushee website. See also Bushee and Goodman (2007).

[4] 13f database reports two dates for each observation; RDATE (effective ownership date) and FDATE (Vintage date for which stocks are adjusted in the database) – we account for this date disparity when calculating stock adjustment. We also remove "stale" entries.

occurs for 1.9% of observations).[5] The change in IOR (DIOR), which we use to proxy for institutional trading within a quarter, is a difference between values of IOR at the beginning and end of the quarter.

$$DIOR_{i,t} = \frac{Shares\ held\ by\ 13f\ institutions_{i,t}}{Shares\ Outstanding_{i,t}} * 100 - \frac{Shares\ held\ by\ 13f\ institutions_{i,t-1}}{Shares\ Outstanding_{i,t-1}} * 100 \quad (2)$$

We perform our analysis both for all institutions included in the Thomson Reuters 13f database, as well as for different institution types as specified by Bushee (2001). We compute the change in IOR for transient, dedicated and quasi-indexing institutions as the difference in the proportion of shares outstanding held by a given type of institution. If information about ownership by a given group is missing for a given stock in quarter t, we treat it as "0%" ownership by given group of a given stock.[6] See Appendix 1 for characteristics of different Bushee investor groups.

Another variable that can be used as a proxy for institutional informed trading is the percentage change in the number of a stock's institutional investors, PC_NII. It is calculated as the difference in the number of institutions holding the stock at the beginning and the end of the quarter divided by the number of all institutions holding stock at the beginning of the quarter.

$$PC\_NII_{i,t} = \frac{\#\ of\ institutions\ holding\ stock_{i,t} - \#\ of\ institutions\ holding\ stock_{i,t-1}}{\#\ of\ institutions\ holding\ stock_{i,t-1}} * 100 \quad (3)$$

Dior may be influenced by a small number of large institutions changing holdings (Edelen, et al., 2015). In contrast, PC_NII captures entries and exits of any institutions. Entry and exit trading of a group of more active and attentive institutions who pay attention to stock liquidity changes can be more visible in PC_NII than in a DIOR

[5] We repeat the analysis in a sample excluding observations with ownership ratios greater than 100%. The results are almost identical. For discussion of Institutional Ownership Ratio greater than one see Glushow, Moussawi and Palacios, WRDS (2009).
[6] If we leave the observation as missing, the results remain quantitatively similar.

variable. Therefore, this variable accounts for institutional investor heterogeneity; Gue and Qui (2014) show that the predictive power of PC_NII for future stock returns is mainly due to the trading of high turnover institutions.

Values of ANcerno Trading, PC_NII, DIOR and DIOR for different types of investors are winsorised at 1% and 99% each quarter to avoid outliers. For firms with no institutional investors at the beginning of the quarter, the values of PC_NII and DIOR are zero.

Daily and monthly stock data comes from the Center for Research on Security Prices (CRSP), company accounting data is from Compustat and analyst forecasts are from I/B/E/S. Observations include common stocks (CRSP codes 10 and 11) listed on NYSE, AMEX and NASDAQ. Only stocks with price higher than $5 and lower than $1000 are included to mitigate market microstructure issues.

Illiquidity of the stock (ILLIQ) is measured monthly, following Amihud (2002), as the average of daily ratios of a daily return Ri,d to dollar trading volume VOLDi,d . ILLIQ is scaled by 106 and the values of ILLIQ are winsorised at 1% and 99% each quarter.

$$ILLIQ_{i,t} = Avg\left[\frac{|R_{i,d}|}{VOLD_{i,d}}\right] \quad (4)$$

ILLIQ measures the daily impact of order flow on price arising from adverse selection and inventory costs (Amihud and Mendelson, 1980; Amuhud, 2002) in the spirit of Kyle (1985).[7] Amihud's illiquidity measure is easy to calculate and based on a readily available data. Goyenko, Holden and Trzcinka (2009) show that it is an accurate measure of price impact of trade and is comparable to liquidity measures based on intraday data. According to Hasbrouk (2009), Amihud's measure's correlation with Kyle's lambda is 0.82.

Monthly liquidity shock is calculated following BPST (2014) as the negative difference between illiquidity in a given month and its past 12-month average, thus a

[7] In the Kyle (1985) model, order flow based on market orders is perceived as a signal by the market maker, from which he tries to extract information. Since he doesn't know if the flow comes from informed or uninformed investors, the price he sets is an increasing function of the order imbalance.

positive value of LIQUS signifies a positive (liquidity-improving) shock. We further standardize the liquidity measure by dividing it by the stock's past 12-month standard deviation, which allows to extract the magnitude and importance of shocks relative to security's usual liquidity variability. The values of LIQUS are winsorised at 1% and 99% each quarter.

$$LIQUS_{i,t} = \frac{-[ILLIQ_{i,t} - Avg(ILLIQ_{i|t-12,t-1})]}{Std\ Dev(ILLIQ_{i|t-12,t-1})} \quad (5)$$

As discussed in the Introduction, institutional investors are known to react to the systematic market liquidity and its changes. To address the concern that idiosyncratic liquidity shocks could coincide with market wide, much more visible, liquidity change, we also partition the illiquidity shock variable into individual shock and market shock. In particular, we first construct a market illiquidity variable, as an equal average of individual stock illiquidities, following Amihud (2002), defined as

$$MILLIQ_t = \frac{\sum_{i=1}^{N_t} ILLIQ_{i,t}}{N_t}, \quad (6)$$

where Nt is the number of stocks in a given month. Monthly systematic market liquidity shock is then defined as

$$MLIQUS_{i,t} = \frac{-(MILLIQ_{i,t} - Avg(MILLIQ_{i|t-12,t-1})}{Std\ Dev(MILLIQ_{i|t-12,t-1})} \quad (7)$$

We then run a time series rolling regression of individual stock liquidity shocks (LIQUS) on systematic market liquidity shocks (MLIQUS) over 60 month rolling window (with minimum 24 observations).

$$LIQUS_{i,t} = \alpha_{t+1} + \beta_t MLIQUS_{i,t} + \varepsilon_{i,t}, \quad (8)$$

where residuals $\varepsilon i,t$ extracted from this regression (variable INDSHOCK) proxy for individual stock related liquidity shock. Sensitivity of individual stock to systematic market liquidity in a given month (coefficient βt on systematic market liquidity from the above regression) multiplied by MLIQUS in month t (resulting in variable MKTSHOCK) proxies for market related portion of the LIQUS shock. Variables INDSHOCK and MKTSHOCK are winsorized at 1% and 99% each quarter.

Liquidity shocks, illiquidity level and control variables are measured as of the last day of the quarter (t) preceding the institutional trading quarter (t+1). If variables are calculated from daily data, they require at least 15 daily observations.

A number of stock characteristics that can potentially impact institutions' trading. Tp analyze the effect of liquidity shocks on institutional change in ownership, following Gompers and Metrick (2001) and BPST (2014), we introduce the following control variables: book-to-market ratio (LNBM), momentum (MOM, short-term return (RET), idiosyncratic stock volatility (IVOL) as well as shocks to stock volatility (IVOLU), beta (BETA) and dividend yield (DY), illiquidity measure (ILLIQ), size – logarithm of market value (LNME), standardized unexpected earnings (SUE) and analyst earnings forecast dispersion (DISP). We also include the value of lagged trading variable. The detailed descriptions of variable construction are available in Appendix 2.

Figure 1 presents time-series trend of illiquidity and liquidity shocks. Illiquidity is characterized by large variation and it fluctuated over the sample period, with peaks in 1988 (following October 1987 market crash) and 2009 (as a result of the recent financial crisis). Downward spikes in average yearly liquidity shocks (LIQUS) indicate liquidity dry-ups following 1987 crash, fall of LTCM and Russian debt crisis in 1998 and the largest drop in 2008, in the middle of financial crisis.

Table 2 presents summary statistics (Panel A for ANcerno database, Panel B for 13f). Mean and median of liquidity shock variable, LIQUS, are positive indicating an improvement of liquidity over the sample period. The variable is characterized by a large variation, with standard deviation 15 (for ANcerno, 17 for 13f) times larger than the mean.

Standard deviation of trading variable for ANcerno institutions is 32 times larger than its mean, also pointing to substantial variation. The variable is positive on average, suggesting overall increase in institutional ownership. Similar conclusions can be drawn from analyzing institutional ownership statistics from 13f data. Standard deviation of institutional ownership change is 11 times larger than its mean, especially for dedicated and transient institutions (66 and 35 times respectively).

Average institutional ownership in the 13f sample is 45%. As shown in Figure 2, institutional ownership increased over time, from 24% in 1981 to 67% in 2012 and thus both the change in the institutional ownership ratio and change in number of institutional shareholders are positive on average (0.47% and 4.17% respectively.

Table 3 presents the time series average of cross-sectional Pearson correlation matrices for both data sets. ANcerno trading as well as change in institutional ownership both for all institutions (DIOR) and for transient ones (DIOR_TRANS) only are negatively correlated with illiquidity, as expected due to institutional preference for liquid stocks. Moreover all institutional trading variables are positively correlated with liquidity shocks, suggesting that institutions observe idiosyncratic shocks and trade in their direction.

Institutional ownership and the number of institutional owners are very strongly positively correlated with log market value and thus controlling for size is crucial in this analysis. All trading variables' negative correlations with size suggest that institutions increase ownership in smaller companies, a result consistent with Blume and Keim (2014) analysis of time-series trends in institutional ownership. They show that in the period 1980-2010, institutions changed their holdings preferences from large to small stocks and in recent years underweight large market value stocks and overweight small market value stocks relative to market weights.

In both data sets liquidity shocks hold the strongest positive correlation (>13%) with size, momentum, return and earnings surprises.

2 Institutional trading and liquidity shocks

In this section, we investigate institutional trading in response to liquidity shocks.

2.1. Univariate portfolio sorts

To examine the institutions' reaction to liquidity shocks, each month we sort the stocks in the sample into ten portfolios according to liquidity shocks. The decile portfolios are based on NYSE breakpoints to mitigate the influence of the large number of small stocks from Amex and NASDAQ. We then calculate the decile average of the institutional trading as measured in the following month. In case of the quarterly 13f data, we sort based on the liquidity shocks measured in the last month of the quarter preceding the quarter of inferred institutional trading (for example, liquidity is measured in March and the institutional trading variables are inferred from the quarter from April to June). Table 4 presents the results.

The difference between the ANcerno institutional trading in the high and low liquidity shock portfolios equals 7% (153% of variable's mean) and is significant at 1%. Selling activity is only observed in two portfolios with the most negative liquidity shocks.

For 13f, the significant difference in the change in the number of institutional shareholders (PC_NII) between extreme liquidity shock portfolios equals 2.9% (that is 69% of variable's mean). As liquidity shocks increases, the increase in the value of PC_NII is almost monotonic (except the highest liquidity shock decile). Similarly, when institutional trading is measured by the change in institutional ownership ratio (DIOR), the high-low liquidity shock difference is 0.48% (103% of DIOR's mean), also significant at 1%, again with almost monotonic increase in institutional trading across deciles. These results provide evidence for the positive relation between liquidity shocks and institutional trading.

When we classify institutions into separate categories, the results show that the positive relation between liquidity shocks and quarterly institutional trading is mainly driven by the transient institutions: they sell stocks whose liquidity worsens and buy those with improvement in liquidity. The difference in DIOR across the stocks that belong to the top liquidity shock decile and those in the bottom liquidity shock decile is 0.37 (400% of its mean). The difference is negative for dedicated investors, who, with their low turnover and long investment horizon, can serve as liquidity providers. It is insignificant for quasi-indexers, who trade passively following the market.

Note that transient institutions, are the only group in the quarterly data that decreases its holdings following negative liquidity shocks (but only for the extreme negative shocks), similarly to the results we found for the higher frequency trading. The other institutions increase ownership in all deciles, but the increase in positive liquidity shock deciles is larger than the increase in the negative shock ones. The reason for this is, as mentioned before, ownership trading variables being on average positive due to the increasing institutional ownership in the past decades.

2.2. Double portfolio sorts

Institutional trading is related to a number of variables and liquidity shocks are correlated with many stock characteristics, therefore it is important to introduce a number of controls to properly assess the liquidity shocks – institutional trading dynamics. We extend our analysis by performing dependent double sorting. First we sort stocks quarterly into 5 quintiles on the value of one of the control variables at the end of the month (quarter) preceding institutional trading. Then, we sort them within those quintiles based on their liquidity shock variable into 5 groups. We then calculate the average value of the institutional trading variables in the following month (quarter) for all 25 portfolios. The control variables used for bivariate sorts are size (LNME), book-to-market ratio (LNBM), illiquidity (ILLIQ), analyst forecast dispersion (DISP), number of analysts following the stock from I/B/E/S (Num Est), institutional ownership ratio (IOR) – for 13f data, idiosyncratic volatility (IVOL), return (RET), momentum (MOM) and standardized unexpected earnings (SUE).

Table 5 presents the average institutional trading values for LIQUS portfolios averaged across the control groups. This way we create quintile portfolios with dispersion in liquidity shocks and with similar levels of control variable. The positive relation between lagged liquidity shocks and institutional trading remains significant in bivariate setting. The average difference in institutional trading from ANcerno (Panel A) ranges from 0.03% to 0.11%, all significant at 1%. Similarly, results are consistent across controls with institutional trading proxied by the change in number of institutions (Panel B, PC_NII) with differences ranging from 1.15% to 5.3%, change in ownership ratio

(Panel C, DIOR) with differences from 0.24% to 0.57% and for change in ownership by transient institutions (Panel D, DIOR TRANSIENT) with differences from 0.18% to 0.35%.

Overall, the difference in institutional trading between high and low liquidity shock portfolios remains significant (mostly at 1% level) after controlling for a number of stock characteristics, further supporting the statement that institutional investors react positively to stock-specific liquidity shocks.

Many of the characteristics we controlled for above are also correlated among each other (like institutional ownership and size or analyst coverage and illiquidity). Therefore, even though the bivariate sorts have the advantage of being a nonparametric tool, it is important to control for stock characteristics simultaneously, which we do in the next section by employing regression analysis.

2.3. Cross-sectional regressions

We now proceed to the cross-sectional regressions of institutional trading variables on lagged liquidity shocks and stock characteristics, following the Fama and MacBeth (1973) method.

$$Inst\ trading_{i,t+1} = \alpha_{t+1} + \beta_{t+1} LIQUS_{i,t} + \gamma_{t+1} X_{i,t} + \varepsilon_{i,t+1}, \qquad (9)$$

where t+1 is a month when institutional trading takes place and t is a previous month (in case of quarterly 13 f data: where t+1 is a quarter when institutional trading takes place and t is the last month of the preceding quarter). Inst tradingi,t is measured by net institutional trading from ANcerno database as well as change in institutional ownership ratio DIOR, DIOR for different Bushee institution types and change in the number of institutional shareholders PC_NII. Stock characteristics include size, book-to-market ratio, return, momentum, standardized unexpected earnings, dividend yield, volume change, risk proxies: idiosyncratic volatility and idiosyncratic volatility shocks, beta, analyst forecast dispersion, illiquidity and lagged institutional trading.

Table 6 Panel A presents the regression results where t-statistics are based on Newey-West standard errors with 4 lags (both in monthly and quarterly data sets). The coefficient for liquidity shock as a predictor of next month institutional trading equals 0.019 and is significant at 1% level. We interpret the economic significance of the average slope coefficient of LIQUS based on institutional trading portfolios. Table 4 shows that the difference in value of LIQUS for average stocks between highest and lowest deciles is 4.06. Such result implies that positive (negative) liquidity shock of that magnitude results in increase (decrease) of the number of institutions holding stock in the magnitude of 168% of institutional trading mean.[8]

Quarterly data, despite lower frequency, confirm the monthly findings. Liquidity shock coefficient in a regression with change in the number of institutional shareholders amounts to 0.396 (39% of its mean) and significant at 1% level. When the change in ownership is used to proxy for institutional trading, the coefficient of liquidity shocks is significant at 5% and equals 0.036, implying a 31% of mean change in trading following liquidity shock. The weaker significance for DIOR variable as compared with PC_NII supports the claim that change in the number of institutions could be a better measure to proxy informed trading of a small group of investors.

Next columns present results for the change in institutional ownership ratio for different institutional types. As expected, the relation between liquidity shocks and change in institutional ownership is only significant (coefficient equals 0.024) for the transient institutions that trade frequently and are short term oriented. The coefficient implies a change of 105% of its mean.

Neither dedicated nor the quasi-indexers seem to react to stock liquidity shocks in any particular direction, as they trade less frequently and actively and thus are less likely to engage in exploiting short term trends.

The coefficients for the control variables complement the description of the behavior of institutional investors. For example, coefficient on illiquidity is significant and negative for ANcerno trading, the overall ownership change and DIOR transient,

[8] The trading in reaction to liquidity shock constitutes a large proportion of trading variables' mean due to large variation of trading variables.

showing preference for more liquid stocks. Even though institutions are said to prefer large companies, they increase their ownership in the smaller (negative LNME coefficient) ones, consistently with Blume and Keim (2014) observation of overweighing of small stocks and underweighting of large stocks in institutional portfolios. Except from dedicated investors, institutions are momentum traders, both in the monthly and quarterly regressions. The quarterly regressions show especially strong reaction to short-term return of a stock. The coefficient for previous month return is negative and less significant for monthly ANcerno analysis. Finally, a positive reaction to earnings surprises is only significant in a quarterly framework.

Overall, the evidence suggests that institutions observe stock level liquidity changes and trade on them. The positive relation between liquidity shocks and institutional trading is robust after controlling for a variety of variables. The relation appears to mainly stem from the trading undertaken by transient institutions. The positive sign of the relation suggests that institutions exploit the opportunity created by the slow incorporation of liquidity shock information into the stock prices and, by doing so, contribute to the price adjustment.

2.4. Market wide shock vs. idiosyncratic shock

To verify whether the reactions of institutional investors to changes in stock liquidity are indeed driven by idiosyncratic liquidity shock instead of systematic market liquidity shock, in this section we partition liquidity shock, LIQUS, into individual, stock related shock and shock due to sensitivity to systematic market liquidity changes, as described in section *Data and variables construction,* equation (8).

Table 6 Panel B presents the estimates from the regression of different institutional trading variables on two aspects of individual liquidity shocks and controls:

$$Inst\ trading_{i,t+1} = \alpha_{t+1} + \beta_{t+1} INDSHOCK_{i,t} + \delta_{t+1} MKTSHOCK_{i,t} + \gamma_{t+1} X_{i,t} + \varepsilon_{i,t+1}, \quad (9)$$

where INDSHOCK represents liquidity change as related to individual stock characteristics and MKTSHOCK represents change in stock's liquidity resulting from systematic market liquidity change and stock's sensitivity to it.

The coefficients on INDSHOCK for all main institutional trading variables, both for monthly and quarterly data sets, are highly significant and positive. The results for individual portion of the liquidity shock are stronger than the estimates from regression using LIQUS variable for quarterly data, while coefficients on MKTSHOCK are insignificant for all specifications. This suggests that the source of institutional reactions lies in individually generated stock liquidity shocks. Systematic market liquidity shock plays little role in the reactions captured in our results. In fact, the average R2 from the equation (8) regression equals 9.7%, pointing to relatively low relation between LIQUS and market wide liquidity shocks.

2.5 Profitability of liquidity shock driven trades

The evidence in the previous sections supports that institutions trade on liquidity shocks in the direction that allow them to exploit the mispricing arising from the slow return adjustment to liquidity shocks as shown In BPST (2014). In this section, we further study the economic importance of this trading activity from an asset pricing perspective.

First, we replicate the main analysis in BPST (2014) in our sample period. We find the long-short portfolios sorted on liquidity shocks generate significant returns of 1.06% in the entire stock universe, 0.69% in 13f database, and 1.01% in ANcerno database in our sample period. The ANcerno stock universe presents a similar magnitude of the return effect as the wider stock universe. This suggests that the post liquidity shock drift in the stock universe we focus on is economically more important practically than that in the entire stock universe, as the ANcerno stocks are effectively tradable by large institutions.

We then directly test the profitability of institutions' liquidity shock driven trades. Table 7 presents the results of a two stage analysis. The first stage regression is a baseline regression of institutional trading variable on lagged liquidity shocks (see equation (9)). Based on the 1st stage regression results we construct a Predicted trading variable

$$Predicted\ trading_{i,t} = \beta * LIQUS_{i,t} \tag{10}$$

The second stage regression is a Fama and MacBeth (1973) regression of future returns on *Predicted trading* and controls

$$Return_{i,t+1} = \alpha_{t+1} + \beta_{t+1} Predicted\ Trading_{i,t} + \gamma_{t+1} X_{i,t-1} + \varepsilon_{i,t+1} \tag{11}$$

The coefficient on Predicted trading equals 5.276 and is highly significant. This means that institutional trading predicted by LIQUS differential between high and low liquidity shock decile generates a 0.407% return per month and 5.03% per year.[9] This result shows that attentive and sophisticated institutional investors' trades on monthly shocks to liquidity earn significant profit from the post shock drift in return.

Overall, the results of univariate and bivariate sorts, multivariate regressions, and profitability tests show the positive significant relation between institutional trading and liquidity shocks is economically and statistically significant, and consistent across two data sets: one using institutional trading in a monthly frequency based on direct trading data from ANcerno and spanning 11 years and the other one inferring institutional trading from quarterly holding changes and spanning 31 years. In the quarterly data, transient institutions are the main driver of the relation as the most active traders.

3 Additional analysis

In this section, we perform additional analysis on the reactions of institutional trading to understand its robustness and highlight its significance by looking into subsamples of stocks, subperiods with potentially different economic conditions, and alternative definition of subcategory of funds. Henceforth, we will concentrate on the monthly data set due to its higher precision. Quarterly analysis based on inference and not direct trading data makes it difficult to draw clear conclusions.

[9] Coefficient*first stage coefficient*LIQUS differential = 5.276*0.019*4.06=0.407% per month.

3.1. Stock Characteristics

To better understand the liquidity shock-institutional trading dynamics, we introduce into the cross-sectional regressions interactions between liquidity shock and some control variables. To make the interpretation of the coefficients meaningful, we center the liquidity and control variables with the exception of SUE for which value zero has meaningful interpretation. Because of centering, the coefficient on liquidity shock variable is the effect of liquidity shock on institutional trading for average values of a control variable (e.g. size).

Table 8 presents the results. As in previous specifications, the coefficient on liquidity shock is positive and significant in all specifications and varies from 0.015 to 0.021. The interaction between liquidity shock and size (LNME) is negative and significant, implying that the shock induced trading is more pronounced for smaller stocks, likely because the shocks are more quickly incorporated into prices in larger stocks. The institutional reaction to liquidity shocks is stronger following negative returns. Coefficient for interaction term of liquidity shock and illiquidity is significantly negative, indicating stronger reaction for liquid stocks.

In unreported results of double sorting one of the firm characteristics and liquidity shock, we further find the reaction is mostly significant in small and medium size stocks. The high-low liquidity shock differential in institutional trading is the highest in small stocks with lower analyst following, high volatility and medium liquidity – stocks that are less visible but still tradable. In those stocks the post liquidity shock return drift is likely more persistent and hence they present a better opportunity for institutions to trade on it. Taken together, the results suggest that institutional reaction is concentrated in stocks with higher chance of mispricing but are still liquid and thus easier to trade.

3.2. Positive vs. Negative Shocks

In this section, we investigate whether there is an asymmetry in the liquidity shock – institutional trading relation. We have so far established a positive reaction of institutions to individual stock liquidity shocks. In Table 9 we break down the LIQUS variable into its positive and negative portion. 66% of LIQUS observations are positive. The results indicate that the reaction to liquidity shocks is a symmetrical one; institutions react positively to both positive and negative liquidity shocks. This implies that they buy stock following its positive shock and sell it after the sudden liquidity decrease.

3.3. Market-wide liquidity shocks

We examine whether there is a difference between investor reaction to liquidity shocks when their trading coincides with positive and negative shocks to market overall liquidity. During periods of liquidity dry-ups investors can either trade less on individual shocks due to funding liquidity troubles or the opposite – market-wide liquidity issues can turn their attention towards their stock investment, which naturally increases their attention on liquidity changes of individual stocks. We perform the regression analysis for the times of positive and negative market-wide liquidity shocks at the time of institutional trading. We construct market illiquidity measure (MILLIQ) as in equation (5) and a monthly systematic market liquidity shock (MLIQUS) as in equation (6).

Table 10, Column 1 displays Fama MacBeth (1973) regressions for periods of systematic market liquidity deterioration and periods of overall liquidity improvement in the market. The positive trading reaction of institutions to liquidity shocks is significant and similar during positive and negative market shocks periods, indicating consistent investor behavior. The results support our earlier analysis that the institutional trading effect documented in this paper is mainly driven by stock-level liquidity shocks.

3.4. NBER economic cycles

We also perform the regression analysis for contractions and expansions coinciding with individual liquidity shocks, as defined by NBER. The subsample of contractions consists of 31 periods (months) and expansions – 121 periods. According to NBER *a recession is a period of falling economic activity spread across the economy, lasting* *more than a few months, normally visible in real GDP, real income, employment, industrial production, and wholesale-retail sales.*[10]

Table 10 Column 2 presents the results of the Fama MacBeth regressions for two subgroups. The coefficient on liquidity shocks is significantly higher in times of economic expansion (t statistic for the coefficient difference is 7.32). Since institutional trading decisions in crisis times are likely related to other concerns such as funding (for example sudden redemptions), as argued by Franzoni and Plazzi (2013), it is not surprising to see a stronger relation in times of economic prosperity.

3.5. Levels of VIX

In this section, we also investigate different market volatility conditions as defined by VIX (CBOE Volatility Index). VIX is a measure of implied volatility of S&P 500 index options and is considered a general proxy of market uncertainty.

We divide the sample into two groups – “high VIX” are all months above the median monthly VIX for the sample period and “low VIX” are the months below the mean. The regression result in Table 10 column 3 suggests that there is no significant difference in coefficients between periods of high and low VIX.

3.6. Early vs. Later Periods

Liquidity tends fluctuate over time (see Figure 1) thus we complement our analysis with examining the liquidity shock – institutional trading relation in the first and second half of the sample period: from January 1990 to May 2005 and from June 2005 to September 2011.

Table 10 Column 4 presents estimates of the Fama-MacBeth regressions. The reaction results are significant in both subperiods, confirming the robustness of the liquidity shock – institutional trading relation. Magnitude of the coefficient on liquidity shocks decreases slightly yet significantly over time, however remains highly significant.

[10] Announcement from the NBER's Business Cycle Dating Committee, dated 9/20/10.

3.7. ANcerno client type

We also examine the results of the regression of institutional trading on liquidity shocks for different types of ANcerno clients.

Table 11 shows the regression estimates for different client groups in ANcerno data set. The coefficient on liquidity shocks are predictors of institutional trading is 3 times larger for money managers thank for pension plan sponsors and the difference is highly significant. This supports the claim that managers tend to trade in a more informed and attentive manner as opposed to pension plans.

4 Feedback effects of institutional trading on liquidity shocks

To complement our earlier cross-sectional analysis, in this section, we perform a VAR analysis to investigate how liquidity shocks, institutional trading, and stock returns are mutually related to each other in the time series. This analysis particularly addresses whether there is a feedback effect from institutional trading to liquidity shocks. That is, instead of simply trading to exploit liquidity shock induced mispricing, whether institutional reactions have further implications on future liquidity shocks to individual stocks.

We directly account for relations between returns, liquidity shocks and institutional trading, without making assumptions on causality, by using panel vector autoregression (VAR) with fixed effects. We address the complexity of the dynamic relations between those variables by using additional lags.

Following Hendershott, Livdan and Schürhoff (2014) and Holtz-Eakin, Newey and Rosen (1988) for each stock i and month t we create a 3x1 vector yit = (Institutional Tradingit, Returnit, LIQUSit)’ and specify following system of equations:

$$y_{it} = \alpha_i + \sum_{l=1}^{L} \lambda^l y_{it-l} + \varepsilon_{it}, \tag{12}$$

where α_i is a 3x1 vector of firm specific intercepts, λ_i, l = 1, …, L, are 3x3 coefficient matrices, and ε_{it} is a 3x1 vector of innovations. Components of vector y_{it} are jointly endogenously determined and autocorrelated. Because α_i varies across firms and variance of innovations is heteroskedastic, we don't need to assume that relation between those three variables is the same for every firm. We assume that the error term satisfies following characteristics; $E[e_{it}]=0$, $E[e'_{it}e_{it}]=\Sigma$ and $E[e'_{it}e_{is}]=0$ for all $t>s$. Because of use of lags of dependent variables, fixed effects α_i are correlated with the regressors. To eliminate estimation bias, we apply the forward orthogonal deviations transformation (Helmert transform) as in Arellano and Bover (1995). We estimate the model as a system of GMM equations (which produces consistent estimates) using lagged regressors as instruments following Love and Zicchino (2006).[11]

Table 12 reports the estimates of the panel VAR regressions. Panel A uses Exret – raw return less the risk free rate as the measure of return. In Panel B we present the results with four factor alpha based on Fama-French (1993) three factor model with Carhart (1997) momentum factor. The results are consistent with the cross-sectional regressions we presented before. Trading is positively related to past liquidity shocks (middle column). The magnitude of the coefficient on the shock in month t-1 is very close to that shown in the Fama-Macbeth cross-sectional regressions.[12] The coefficient on the shock in month t-2 is even larger (more than twice larger). Institutions also chase past positive returns (middle column, institutional trading regressed on returns). Our particular interest is in the first column, in which liquidity shocks are regressed on past trading. The coefficient estimates are positive and significant (especially for the first two lags), indicating that indeed there is a feedback from trading to liquidity shocks.

The results also show institutional trading negatively predicts future returns (third column), leading to an annualized negative 1.01% return, which suggests that holding everything else constant, the temporary price pressure from intuitional buying and selling is nontrivial.[13] The results suggest that unconditional average monthly institutional trading demands liquidity. Such demand introduces temporary price pressure that reverts in the future. The results are in stark contrast to the positive return predictability of

[11] We thank Inessa Love from World Bank for providing the PVAR Stata code.

[12] PVAR estimates are multiplied by 100 for presentation purposes. Coefficient of trading regressed on liqus (t-1) is 0.019 (2.244) as compared to 0.019 (8.93) from Table 6 Panel A.

[13] Coefficient*main regression Table 6 coefficient*LIQUS differential (-1.09)*0.019*4.06=-0.084% per month and -1.01% per year.

institutional trading conditional on liquidity shocks in Table 7, thus highlighting the informativeness of institutional trading when there are liquidity shocks.

We also illustrate the dynamic relations between returns, institutional trading and liquidity shocks with the impulse response functions. Orthogonalized IRFs are based on Cholesky decomposition. We calculate standard errors for the impulse-response functions by using Monte Carlo simulations with 500 repetitions and present 5% confidence bounds on the graphs. Figure 3 shows IRF assuming following ordering of dependent variables: liquidity shocks, excess returns, institutional trading. First column shows reactions to liquidity shock, second- to return shock and the third – to trading shock. Top right graphs shows that the positive reaction of liquidity shock to institutional trading peaks in 2 months. Also the institutional trading on past liquidity shocks is the most pronounced in the 2nd month (bottom left graph). Institutional trading on past returns is short lived (bottom middle graph), as is institutional trading persistence (bottom right graph).[14]

Overall we find supporting evidence that institutions not only exploit the information from past liquidity shocks, their very trading also further amplify liquidity risk. Thus, despite the positive impact on price efficiency, institutional trading introduces a destabilizing effect on future stock liquidity.

5 Conclusion and further questions

How institutions trade and react to market liquidity is an important aspect of understanding the role that institutional investors and market liquidity jointly play in the process of achieving efficient market. In this paper, we investigate the pattern of institutions' trading following stock-level market liquidity shocks, which are much less likely to be entangled with the confounding effects that would come with systematic market liquidity shocks. This study intends to shed light on institutional investors' sophistication in response to market liquidity shocks and the impact of institutional

[14] IRFs with alternative orderings (under alternative assumptions regarding contemporaneous relations) result in similar conclusions.

trading on market efficiency and liquidity, as well as the importance of heterogeneity of institutional trading styles in the institutional trading liquidity dynamics.

Overall, the findings support that institutional investors are attentive and sophisticated when experiencing liquidity shocks. They contribute to market efficiency by reducing mispricing. On the one hand, institutions, particularly the active ones, play a positive role in helping bring price back to efficient levels following liquidity shocks. On the other hand, there is a feedback effect of the trading to future liquidity which contributes to exacerbation of stock-level liquidity risk.

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Table 1 Comparison of stocks in time-period matched 13f and Ancerno datasets

The first table summarizes yearly number of stocks traded by institutions. The second table compares the characteristics of the stocks included in the time-matched (January 1999-September 2011) Ancerno and 13f datasets. ILLIQ is Amihud illiquidity factor, LIQUS is liquidity shock, INDSHOCK and MKTSHOCK are results of partitioning LIQUS into individual and market liquidity shock-related portions, BETA is market Beta, LNME is natural logarithm of firm's market value, LNBM is natural logarithm of stock's book-to-market ratio, MOM is 11-month momentum, IVOL is idiosyncratic volatility, DISP is analyst forecast dispersion, NUMEST is numer of analysts' forecasts, SUE is standardized unexpected earnings.

Number of stocks		
Year	**Ancerno**	**13f**
1999	4781	4722
2000	4178	4667
2001	3770	3776
2002	3437	3562
2003	3829	3493
2004	3737	3743
2005	3768	3736
2006	3769	3741
2007	3629	3711
2008	3183	3419
2009	3009	2881
2010	3028	2952
2011	2604	2970

	Ancerno		**13f**			
	Mean	Std. Dev.	Mean	Std. Dev.	difference	t stat
illiq	0.13	0.65	0.26	1.10	0.12	41.68
liqus	0.10	1.45	0.14	1.31	0.05	12.26
beta	1.26	1.01	1.24	1.01	-0.02	-5.92
lnme	6.65	1.66	6.47	1.74	-0.18	-36.22
lnbm	-0.78	0.86	-0.76	0.86	0.02	9.21
mom	21.61	72.80	21.44	76.19	-0.17	-0.78
ivol	2.24	1.48	2.24	1.51	-0.01	-1.37
disp	0.09	0.26	0.09	0.24	-0.01	-8.07
numest	7.97	6.57	7.77	6.57	-0.20	-9.86
sue	-0.02	1.04	-0.03	1.04	0.00	-0.59

Table 2 Summary statistics

The table presents characteristics of variables used in the analysis. Panel A summarizes sample from Ancerno (monthly data) and Panel B from Thompson-Reuters 13f dataset (quarterly data). ILLIQ is Amihud illiquidity factor, LIQUS is liquidity shock, INDSHOCK and MKTSHOCK are results of partitioning LIQUS into individual and market liquidity shock-related portions, BETA is market Beta, LNME is natural logarithm of firm's market value, LNBM is natural logarithm of stock's book-to-market ratio, RET is the stock return in the month preceding trading quarter, MOM is 11-month momentum, IVOL is idiosyncratic volatility, IVOLU are shocks to IVOL, DISP is analyst forecast dispersion, NUMEST is numer of analysts' forecasts, SUE is standardized unexpected earnings, DY is quarterly dividend yield, Ancerno trading is the net monthly trading activity of institutions in Ancerno, IOR is the institutional ownership ratio from 13f in %. DIOR is change in IOR variable within a quarter and DIOR for specific investors types refer to changes in IOR variables for those types, INST OWNERS is the number of institutional investors holding company's stock from 13f, PC_NII is the change in the number of institutional shareholders within a quarter scaled by the lagged number of institutional holders.

Panel A Ancerno dataset

Variable	N	Mean	10thPctl	Median	90thPctl	StdDev	Skewness	Kurtosis
illiq	450,204	0.134	0.000	0.006	0.214	0.646	17.134	505.896
liqus	450,204	0.096	-1.661	0.475	1.383	1.449	-2.351	11.150
mktshock	401,335	-0.046	-0.710	0.027	0.513	0.621	-2.030	10.874
indshock	401,335	0.066	-1.544	0.261	1.437	1.334	-1.385	5.190
beta	428,808	1.256	0.226	1.063	2.537	1.012	1.577	6.158
lnme	450,204	6.651	4.669	6.464	8.927	1.662	0.565	0.221
lnbm	438,253	-0.783	-1.850	-0.700	0.161	0.858	-0.759	2.784
ret	450,204	1.750	-13.509	0.833	17.210	14.517	1.387	9.796
mom	450,188	21.613	-37.077	8.702	82.194	72.803	4.731	45.062
ivol	450,204	2.245	0.859	1.848	4.141	1.476	1.897	5.516
ivolu	450,204	-0.087	-1.210	-0.183	1.118	1.098	1.174	5.491
disp	450,204	0.091	0.000	0.023	0.185	0.258	7.138	70.208
numest	406,008	7.973	1.000	6.000	17.000	6.575	1.399	2.038
sue	397,272	-0.023	-1.464	-0.006	1.392	1.038	-0.084	-0.410
Ancerno trading	450,204	0.046	-1.089	0.019	1.207	1.462	0.143	11.910

Panel B 13f Thomson-Reuters dataset

Variable	N	Mean	10thPctl	Median	90thPctl	StdDev	Skewness	Kurtosis
illiq	383,016	0.516	0.001	0.028	1.167	1.692	7.131	78.718
liqus	383,016	0.079	-1.609	0.439	1.296	1.349	-2.003	6.717
mktshock	313,962	0.003	-0.348	0.006	0.374	0.425	-1.034	13.286
indshock	313,962	0.089	-1.513	0.309	1.404	1.293	-1.341	3.921
beta	357,204	1.284	0.307	1.146	2.397	0.941	1.614	8.741
lnme	383,016	5.937	3.769	5.777	8.305	1.768	0.493	0.055
lnbm	365,072	-0.665	-1.722	-0.577	0.270	0.846	-0.837	2.885
ret	383,016	1.783	-11.667	0.962	15.746	12.396	1.076	7.266
mom	382,989	21.150	-32.203	10.760	77.931	62.031	4.709	54.992
ivol	382,980	2.173	0.868	1.829	3.917	1.348	1.786	5.185
ivolu	382,890	-0.090	-1.082	-0.165	0.960	0.963	1.094	5.687
disp	383,016	0.095	0.000	0.025	0.198	0.260	6.862	66.302
numest	326,846	8.085	1.000	6.000	19.000	7.286	1.494	2.164
sue	295,491	-0.028	-1.477	-0.007	1.393	1.044	-0.092	-0.443
IOR	383,016	44.984	9.266	43.031	84.054	27.316	0.228	-0.998
DIOR	383,016	0.466	-4.550	0.264	5.685	4.980	0.108	4.689
DIOR QUIX	383,016	0.335	-3.573	0.217	4.380	3.761	-0.061	5.177
DIOR DED	383,016	0.028	-1.494	0.000	1.591	1.859	0.103	7.828
DIOR TRANS	383,016	0.093	-3.131	0.000	3.414	3.294	0.137	5.793
DIOR OTHER	383,016	-0.012	-0.240	0.000	0.196	0.782	-0.361	58.194
INSTOWNERS	383,016	101.741	9.000	55.000	241.000	140.399	3.722	20.858
PC_NII	382,790	4.173	-12.500	0.833	22.222	18.687	2.554	14.778

Table 3 Variable correlations

The table presents the time-series average of cross-sectional Pearson correlation matrix. The correlation values are multiplied by 100. ILLIQ is Amihud illiquidity factor, LIQUS is liquidity shock, INDSHOCK and MKTSHOCK are results of partitioning LIQUS into individual and market liquidity shock-related portions, BETA is market Beta, LNME is natural logarithm of firm's market value, LNBM is natural logarithm of stock's book-to-market ratio, RET is the stock return in the month preceding trading quarter, MOM is 11-month momentum, IVOL is idiosyncratic volatility, IVOLU are shocks to IVOL, DISP is analyst forecast dispersion, NUMEST is numer of analysts' forecasts, SUE is standardized unexpected earnings, DY is quarterly dividend yield, IOR is the institutional ownership ratio in %. DIOR is change in IOR variable within a quarter and DIOR for specific investors types refer to changes in IOR variables for those types, INST OWNERS is the number of institutional investors holding company's stock, PC_NII is the change in the number of institutional shareholders within a quarter scaled by the lagged number of institutional holders.

Panel A Ancerno dataset

	illiq	liqus	mkt shock	ind shock	beta	lnme	lnbm	ret	mom	ivol	ivolu	disp	numest	sue	Ancerno trading
illiq	100.00														
liqus	-19.53	100.00													
mkt shock	-1.96	13.17	100.00												
ind shock	-6.29	88.78	-7.34	100.00											
beta	-7.38	-3.93	8.65	-0.58	100.00										
lnme	-39.24	14.10	-1.05	-3.95	-9.10	100.00									
lnbm	16.87	0.10	4.64	7.77	-10.56	-25.60	100.00								
ret	0.24	2.41	0.41	2.22	-0.56	-1.34	1.98	100.00							
mom	-5.66	32.89	13.87	28.17	5.46	2.81	2.60	1.53	100.00						
ivol	12.45	-8.42	4.02	-0.01	34.24	-33.57	-7.07	-1.51	8.47	100.00					
ivolu	2.95	-7.24	-4.90	-7.42	-8.15	2.39	0.62	-0.45	-8.52	59.49	100.00				
disp	-5.24	-5.31	1.69	-2.58	15.86	-4.47	2.02	-1.06	-6.86	13.85	-0.67	100.00			
numest	-20.89	4.07	-1.31	-7.25	-1.90	74.38	-23.63	-0.78	-7.07	-16.90	1.90	-2.38	100.00		
sue	-0.92	13.27	5.16	11.66	-0.71	3.78	3.47	2.23	22.07	0.45	-0.50	-3.46	0.99	100.00	
Ancerno trading	-0.55	2.54	1.31	2.29	2.45	-1.33	-0.75	9.56	4.85	2.28	-1.38	0.50	-1.95	1.39	100.00

Panel B 13f Thomson-Reuters dataset

	illiq	liqus	mkt shock	ind shock	beta	lnme	lnbm	ret	mom	ivol	ivolu	disp	numest	sue	IOR	DIOR	DIOR quix	DIOR ded	DIOR trans	DIOR other	Inst owners	PC_NII
illiq	100.00																					
liqus	-25.99	100.00																				
mkt shock	-2.58	10.08	100.00																			
ind shock	-11.91	90.80	-5.93	100.00																		
beta	-3.57	-3.14	2.77	-0.46	100.00																	
lnme	-43.02	12.39	0.39	-5.36	-13.18	100.00																
lnbm	11.58	1.33	2.31	8.41	-17.47	-16.39	100.00															
ret	-1.89	14.49	0.87	14.99	-0.73	0.59	2.98	100.00														
mom	-7.52	28.75	8.04	24.57	4.61	4.30	-0.51	3.34	100.00													
ivol	26.76	-11.42	1.12	-1.06	31.99	-41.72	-12.78	10.76	0.73	100.00												
ivolu	6.68	-11.36	-3.48	-10.22	-6.83	1.74	-0.16	10.06	-12.19	56.67	100.00											
disp	-6.13	-5.35	0.50	-3.04	11.00	-0.55	3.76	-1.57	-11.29	11.09	0.04	100.00										
numest	-23.98	4.79	0.12	-7.68	-9.78	78.70	-12.72	-3.99	-4.19	-26.32	1.08	-1.33	100.00									
sue	-1.03	13.26	3.41	12.53	-1.01	2.95	3.67	6.25	25.23	-1.49	-2.80	-4.99	0.25	100.00								
IOR	-33.92	6.18	-0.02	-5.16	4.30	52.81	-5.51	-1.57	-1.57	-24.05	1.05	5.75	41.99	1.82	100.00							
DIOR	-0.97	3.97	1.44	4.08	1.47	-2.19	0.38	8.12	7.00	0.08	-4.01	-0.35	-3.98	1.72	-12.12	100.00						
DIOR quix	-1.41	2.65	0.52	1.61	1.69	0.00	-2.85	0.90	6.73	-0.20	-2.81	-1.60	-2.25	1.42	-5.71	60.97	100.00					
DIOR ded	0.12	-0.60	-0.01	-0.87	0.62	-0.72	-0.77	-1.25	-0.95	-0.20	-0.91	-0.12	-0.62	-1.55	-3.00	27.46	-4.25	100.00				
DIOR trans	-0.35	3.22	1.30	4.59	-0.47	-1.85	4.34	11.61	3.10	-0.43	-2.28	1.43	-2.42	1.75	-7.12	50.50	-6.80	-8.43	100.00			
DIOR other	0.57	0.55	0.17	0.99	-0.07	-0.54	-0.07	-0.20	-0.20	0.37	0.44	-0.15	-0.22	0.02	-1.85	7.42	-3.26	-1.77	-1.87	100.00		
Inst owners	-23.36	8.33	0.40	-4.61	-12.48	83.98	-11.79	-1.75	0.07	-31.69	1.69	-3.30	77.42	1.96	42.47	-1.53	-0.65	-0.71	-0.34	-0.49	100.00	
PC_NII	4.00	7.09	1.54	8.59	1.86	-9.49	-0.57	15.29	14.96	4.75	-3.94	-3.55	-8.94	8.01	-14.56	34.53	16.21	-0.16	29.44	0.00	-5.34	100.00

Table 4 Institutional trading for portfolios formed based on lagged liquidity shocks

Stocks listed on NYSE, Amex and Nasdaq are sorted in the last month preceding the institutional trading month (quarter) into 10 decile portoflios based on liquidity shock measure LIQUS. The table reports average values of institutional trading measures: monthly Ancerno trading data and quarterly 13f data: PC_NII - the change in the number of institutional shareholders within a quarter scaled by the lagged number of institutional holders, DIOR - change in IOR variable within a quarter and DIOR for specific investors types ; TRANS – transient, DED – dedicated and QUIX – quasi indexers, as defined by Bushee (2001). The last row reports the difference in institutional trading between high (positive shock) and low (negative shock) liquidity shock portfolios. T statistics are reported in parentheses. The table reports average decile characteristics of LIQUS in both samples. * $p<0.1$; ** $p<0.05$; *** $p<0.01$

	Ancerno monthly data		**13f quarterly data**						
LIQUS rank	**Ancerno trading**	**LIQUS**	**PC_NII**	**DIOR**	**DIOR TRANS**	**DIOR DED**	**DIOR QUIX**	**DIOR OTHER**	**LIQUS**
1	-0.04	-2.39	2.06	0.07	-0.06	0.03	0.09	-0.02	-2.44
	(-3.34)		(4.34)	(0.61)	(-0.81)	(1.57)	(1)	(-0.88)	
2	0	-0.97	2.6	0.29	0.01	0.05	0.21	-0.01	-0.91
	(-0.14)		(5.83)	(2.38)	(0.17)	(2.78)	(2.22)	(-0.53)	
3	0.01	-0.46	3.12	0.28	0.01	0.05	0.22	-0.01	-0.41
	(0.64)		(6.58)	(2.28)	(0.12)	(2.37)	(2.39)	(-0.18)	
4	0.04	-0.11	3.52	0.38	0.04	0.03	0.31	-0.01	-0.07
	(3.17)		(7.64)	(3.16)	(0.53)	(1.76)	(3.27)	(-0.26)	
5	0.04	0.16	4.18	0.46	0.01	0.05	0.37	-0.01	0.19
	(3.81)		(8.7)	(3.71)	(0.17)	(2.67)	(3.9)	(-0.33)	
6	0.07	0.4	4.81	0.5	0.08	0.04	0.39	-0.01	0.42
	(6.46)		(9.76)	(3.97)	(1)	(2.38)	(4.01)	(-0.49)	
7	0.09	0.63	5.54	0.64	0.14	0.03	0.48	-0.01	0.63
	(8.52)		(11.27)	(5.12)	(1.84)	(1.48)	(5.05)	(-0.56)	
8	0.09	0.86	5.67	0.68	0.21	0.02	0.43	0	0.86
	(8.48)		(11.77)	(5.47)	(2.79)	(0.84)	(4.44)	(-0.09)	
9	0.08	1.14	5.82	0.69	0.26	0	0.4	-0.01	1.12
	(8.1)		(12.19)	(5.46)	(3.29)	(-0.17)	(4.15)	(-0.18)	
10	0.04	1.67	4.96	0.56	0.31	-0.02	0.23	0	1.62
	(3.57)		(11.38)	(4.19)	(3.96)	(-0.85)	(2.31)	(0.03)	
H-L	**0.07*** **		**2.9*** **	**0.48*** **	**0.37*** **	**-0.05*** **	**0.16**	**0.02**	
	(5.93)		**(9.95)**	**(8.33)**	**(10.69)**	**(-2.85)**	**(1.47)**	**(1.35)**	

Table 5 Bivariate portfolio sorts

Stocks listed on NYSE, Amex and Nasdaq are sorted in the last month preceding the institutional trading month – in Ancerno data (quarter, in 13 f data) into 5 quintile portfolios based on control variables and then into five portoflios based on liquidity shock measure LIQUS. The table reports average values of monthly Ancerno trading and quarterly PC_NII, DIOR and DIOR_TRANS averaged across the control groups so that there are quintile portfolios with dispersion in liquidity shocks and with similar levels of control variable. The (H-L) row reports the difference in institutional trading between high (positive shock) and low (negative shock) liquidity shock portfolios. LNME is natural logarithm of firm's market value, LNBM is natural logarithm of stock's book-to-market ratio, RET is the stock return in the month preceding trading quarter, MOM is 11-month momentum, IVOL is idiosyncratic volatility, DISP is analyst forecast dispersion, NUMEST is numer of analysts' forecasts, ILLIQ is Amihud (2002) monthly illiquidity, IOR is institutional ownership ratio, SUE is standardized unexpected earnings. T statistics are reported in parentheses. * p<0.1; ** p<0.05; *** p<0.01

PANEL A Ancerno trading

liquidity shock rank	lnme	lnbm	mom	ret	ivol	disp	numest	illiq	sue
1	-0.03	-0.02	0.01	-0.01	-0.02	-0.02	-0.02	-0.03	-0.02
	(-2.54)	(-2.33)	(1.42)	(-1.58)	(-2.44)	(-2.29)	(-2.2)	(-2.91)	(-2)
2	0.02	0.02	0.05	0.02	0.02	0.02	0.02	0.01	0.02
	(1.57)	(2.06)	(5.1)	(2.57)	(1.95)	(2.21)	(1.73)	(1.19)	(2.15)
3	0.05	0.06	0.05	0.06	0.05	0.06	0.06	0.05	0.06
	(5.26)	(6.26)	(6)	(5.79)	(5.24)	(6.17)	(6.18)	(4.98)	(6.38)
4	0.09	0.09	0.06	0.08	0.09	0.08	0.09	0.08	0.09
	(9.77)	(10.14)	(7.55)	(9.61)	(9.82)	(8.99)	(10.16)	(8.6)	(9.42)
5	0.07	0.06	0.04	0.06	0.07	0.06	0.06	0.08	0.06
	(8.77)	(7.37)	(4.9)	(7.23)	(8.33)	(8.07)	(7.86)	(10.04)	(7.08)
H-L	0.09***	0.08***	0.03***	0.08***	0.09***	0.09***	0.08***	0.11***	0.08***
	(8.82)	(7.92)	(4.06)	(7.95)	(9.73)	(8.45)	(8.15)	(10.23)	(7.83)

Panel B PC_NII

liquidity shock rank	lnme	lnbm	mom	ret	ivol	disp	numest	illiq	ior	sue
1	2.01	2.38	3.32	2.7	2.31	2.36	2.19	1.52	2.18	2.35
	(4.61)	(5.2)	(7.16)	(5.81)	(5.11)	(5.19)	(4.89)	(3.71)	(4.95)	(5.16)
2	2.99	3.34	4.12	3.72	3.22	3.24	3.27	2.53	3.28	3.33
	(6.6)	(7.14)	(8.86)	(8.09)	(7.09)	(7.11)	(7.1)	(6.01)	(7.06)	(7.15)
3	4.17	4.57	4.58	4.73	4.39	4.38	4.38	3.64	4.42	4.48
	(8.84)	(9.63)	(9.77)	(9.77)	(9.35)	(9.33)	(9.46)	(8.25)	(9.44)	(9.43)
4	5.47	5.55	4.82	5.17	5.43	5.57	5.62	5.34	5.69	5.57
	(11.65)	(11.74)	(10.4)	(11.42)	(11.19)	(11.74)	(11.85)	(10.91)	(11.81)	(11.69)
5	6.21	5.41	4.47	4.86	5.71	5.68	5.79	6.82	5.58	5.44
	(12.57)	(12.04)	(10.42)	(10.93)	(12.35)	(12.12)	(12.1)	(12.7)	(11.83)	(12.07)
H-L	4.21***	3.03***	1.15***	2.16***	3.4***	3.32***	3.59***	5.3***	3.4***	3.09***
	(17.81)	(12.98)	(6.6)	(9.71)	(14.58)	(15.1)	(15.49)	(18.94)	(15.08)	(13.26)

PANEL C DIOR

liquidity shock rank	lnme	lnbm	mom	ret	ivol	disp	numest	illiq	ior	sue
1	0.17	0.17	0.28	0.23	0.19	0.18	0.17	0.16	0.21	0.17
	(1.42)	(1.46)	(2.33)	(1.99)	(1.61)	(1.49)	(1.38)	(1.24)	(1.69)	(1.44)
2	0.31	0.34	0.44	0.4	0.33	0.34	0.33	0.27	0.35	0.34
	(2.54)	(2.8)	(3.66)	(3.23)	(2.74)	(2.83)	(2.7)	(2.17)	(2.83)	(2.83)
3	0.43	0.48	0.5	0.51	0.45	0.46	0.47	0.38	0.47	0.48
	(3.49)	(3.88)	(4)	(4.13)	(3.66)	(3.79)	(3.88)	(3.05)	(3.83)	(3.83)
4	0.62	0.65	0.57	0.59	0.62	0.65	0.66	0.62	0.65	0.65
	(5.1)	(5.31)	(4.6)	(4.87)	(4.92)	(5.22)	(5.31)	(5.06)	(5.3)	(5.25)
5	0.71	0.64	0.51	0.55	0.67	0.65	0.67	0.72	0.61	0.64
	(5.75)	(5.01)	(4.12)	(4.25)	(5.26)	(5.11)	(5.31)	(6.12)	(4.79)	(5.06)
H-L	0.54***	0.47***	0.24***	0.31***	0.48***	0.47***	0.5***	0.57***	0.4***	0.47***
	(12.97)	(10.58)	(6.2)	(7.16)	(10.57)	(10.56)	(11.69)	(13.25)	(8.63)	(10.39)

PANEL D DIOR TRANS

liquidity shock rank	lnme	lnbm	mom	ret	ivol	disp	numest	illiq	ior	sue
1	-0.03	-0.03	-0.02	0.01	-0.02	-0.03	-0.03	-0.05	-0.02	-0.03
	(-0.46)	(-0.41)	(-0.33)	(0.16)	(-0.26)	(-0.47)	(-0.45)	(-0.63)	(-0.29)	(-0.46)
2	-0.01	0.02	0.03	0.07	0.02	0.02	0.02	-0.03	0.02	0.03
	(-0.14)	(0.25)	(0.42)	(1.04)	(0.29)	(0.24)	(0.26)	(-0.44)	(0.31)	(0.36)
3	0.03	0.05	0.1	0.07	0.04	0.03	0.03	-0.01	0.05	0.06
	(0.36)	(0.7)	(1.35)	(0.99)	(0.49)	(0.47)	(0.39)	(-0.08)	(0.66)	(0.76)
4	0.16	0.17	0.15	0.14	0.15	0.18	0.19	0.15	0.18	0.16
	(2.07)	(2.33)	(2.07)	(1.86)	(2.05)	(2.39)	(2.49)	(1.97)	(2.34)	(2.24)
5	0.32	0.29	0.23	0.19	0.29	0.29	0.29	0.31	0.27	0.28
	(4.14)	(3.7)	(3.18)	(2.41)	(3.71)	(3.75)	(3.73)	(4.24)	(3.4)	(3.53)
H-L	0.35***	0.32***	0.26***	0.18***	0.31***	0.33***	0.32***	0.36***	0.29***	0.31***
	(12.68)	(11.28)	(11.01)	(6.05)	(10.56)	(11.78)	(11.76)	(13.3)	(10.89)	(10.58)

Table 6 Cross-sectional regressions for different institutional trading measures

The table presents the results of a stock-level Fama and MacBeth (1973) type regression of institutional trading variable on lagged liquidity shocks and controls. In Panel A, the regression is specified as $Inst\ trading_{i,t+1} = \alpha_{t+1} + \beta_{t+1} LIQUS_{i,t} + \gamma_{t+1} X_{i,t} + \varepsilon_{i,t+1}$ and lagged liquidity shocks are measured by LIQUS.
In Panel B, the regression is specified as $Inst\ trading_{i,t+1} = \alpha_{t+1} + \beta_{t+1} INDSHOCK_{i,t} + \delta_{t+1} MKTSHOCK_{i,t} \gamma_{t+1} X_{i,t} + \varepsilon_{i,t+1}$ and lagged liquidity shocks are partitioned into liquidity individual shock (INDSHOCK) and market-related shock (MKTSHOCK).
T+1 is a month when institutional trading takes place and *t* is a previous month (in case of quarterly 13 f data: where *t+1* is a quarter when institutional trading takes place and *t* is the last month of the preceding quarter). $Inst\ trading_{i,t}$ is measured by net institutional trading from Ancerno database as well as change in institutional ownership ratio from 13f - DIOR for different Bushee institution types and change in the number of institutional shareholders PC_NII. Stock characteristics: BETA is market Beta, LNME is natural logarithm of firm's market value, LNBM is natural logarithm of stock's book-to-market ratio, MOM is 11-month momentum, RET is the stock return in the previous month (in the last month of preceding quarter), IVOL is idiosyncratic volatility, IVOLU are shocks to IVOL, DISP is analyst forecast dispersion, SUE is standardized unexpected earnings, DY is quarterly dividend yield, lag trading is the previous month (quarter) value of the trading variable. T statistics are based on Newey-West standard errors, 4 lags. * $p<0.1$; ** $p<0.05$; *** $p<0.01$.

Panel A Liquidity shock measured by LIQUS

	Ancerno trading	PC_NII	DIOR	DIOR TRANS	DIOR DED	DIOR QUIX	DIOR OTHER
liqus	0.019	0.396	0.036	0.024	-0.004	0.012	0.001
	(8.93)***	(7.59)***	(2.42)**	(2.89)***	(0.92)	(1.11)	(0.31)
lnme	-0.012	-0.984	-0.100	-0.034	-0.012	-0.041	0.022
	(3.99)***	(5.38)***	(5.37)***	(3.06)***	(1.82)*	(2.51)**	(2.98)***
lnbm	-0.011	-0.286	0.039	0.153	-0.014	-0.123	-0.003
	(2.73)***	(2.60)**	(1.17)	(6.42)***	(1.51)	(6.51)***	(0.90)
mom	0.001	0.053	0.008	0.002	-0.000	0.005	-0.000
	(6.88)***	(14.57)***	(10.56)***	(3.85)***	(1.78)*	(11.85)***	(2.50)**
ret	-0.001	0.219	0.039	0.036	-0.002	-0.000	-0.000
	(1.80)*	(28.18)***	(13.03)***	(15.71)***	(3.10)***	(0.11)	(2.19)**
sue	0.002	0.529	-0.010	0.012	-0.017	-0.006	-0.001
	(0.56)	(11.79)***	(0.92)	(1.59)	(4.36)***	(0.78)	(0.81)
dy	0.365	-3.714	-3.072	-0.987	-1.232	-0.608	-0.439
	(0.82)	(0.57)	(2.39)**	(0.90)	(2.19)**	(0.56)	(1.71)*
ivol	0.013	0.022	-0.045	-0.025	-0.003	-0.018	0.009
	(2.66)***	(0.27)	(1.41)	(1.42)	(0.38)	(0.75)	(1.99)**
ivolu	-0.004	-0.668	-0.178	-0.069	-0.013	-0.056	-0.005
	(0.65)	(6.78)***	(5.40)***	(2.76)***	(1.28)	(2.59)**	(1.47)
beta	0.008	-0.143	0.087	0.004	0.021	0.056	-0.000
	(1.63)	(0.92)	(2.18)**	(0.15)	(1.43)	(3.10)***	(0.01)
disp	0.005	-0.913	0.054	0.264	-0.043	-0.178	-0.001
	(0.36)	(4.17)***	(0.78)	(5.56)***	(2.01)**	(3.98)***	(0.13)
illiq	-0.025	0.281	-0.115	-0.044	-0.013	-0.062	0.007
	(2.71)***	(2.27)**	(3.25)***	(2.19)**	(2.42)**	(2.92)***	(1.82)*
lag trading	0.224	-0.062	-0.146	-0.026	0.020	-0.084	-0.374
	(45.12)***	(7.02)***	(17.43)***	(2.92)***	(1.47)	(6.49)***	(16.07)***
_cons	0.044	8.031	0.923	0.366	0.102	0.368	-0.115
	(1.68)*	(6.07)***	(6.52)***	(3.78)***	(2.32)**	(2.62)***	(2.66)***
R^2	0.06	0.10	0.07	0.05	0.03	0.05	0.18
N	375,262	287,480	287,552	287,552	287,552	287,552	287,552

Panel B Liquidity shock partitioned into individual stock and market sensitivity portion

	Ancerno trading	PC_NII	DIOR	DIOR TRANS	DIOR DED	DIOR QUIX	DIOR OTHER
indshock	0.016	0.377	0.050	0.055	-0.007	-0.003	-0.000
	(6.87)***	(8.21)***	(3.45)***	(6.23)***	(2.15)**	(0.26)	(0.15)
mktshock	-0.006	9.036	-0.385	-1.370	0.300	-1.476	0.599
	(0.07)	(1.18)	(0.54)	(0.96)	(0.69)	(0.85)	(0.97)
lnme	-0.011	-0.912	-0.096	-0.032	-0.012	-0.038	0.022
	(3.71)***	(5.06)***	(5.01)***	(2.95)***	(1.79)*	(2.29)**	(2.99)***
lnbm	-0.013	-0.283	0.035	0.144	-0.013	-0.121	-0.003
	(2.90)***	(2.57)**	(1.10)	(6.10)***	(1.35)	(6.93)***	(0.86)
mom	0.001	0.052	0.008	0.002	-0.000	0.005	-0.000
	(7.44)***	(14.55)***	(10.15)***	(4.07)***	(1.85)*	(12.45)***	(2.17)**
ret	-0.001	0.217	0.039	0.036	-0.002	-0.000	-0.000
	(1.87)*	(27.93)***	(12.66)***	(15.55)***	(3.09)***	(0.11)	(2.06)**
sue	0.001	0.529	-0.009	0.010	-0.017	-0.005	-0.001
	(0.47)	(11.73)***	(0.86)	(1.37)	(4.25)***	(0.60)	(1.04)
dy	0.363	-6.413	-2.723	-1.005	-1.318	-0.180	-0.441
	(0.81)	(1.09)	(2.00)**	(0.90)	(2.18)**	(0.16)	(1.68)*
ivol	0.013	-0.022	-0.054	-0.034	-0.003	-0.018	0.009
	(2.56)**	(0.27)	(1.59)	(1.83)*	(0.29)	(0.72)	(1.87)*
ivolu	-0.003	-0.667	-0.171	-0.057	-0.014	-0.058	-0.006
	(0.52)	(6.51)***	(4.92)***	(2.18)**	(1.24)	(2.64)***	(1.43)
beta	0.005	-0.140	0.060	-0.014	0.021	0.052	-0.000
	(1.11)	(0.93)	(1.59)	(0.65)	(1.36)	(2.81)***	(0.00)
disp	0.001	-0.891	0.057	0.266	-0.044	-0.171	-0.001
	(0.08)	(4.24)***	(0.85)	(5.54)***	(2.01)**	(3.77)***	(0.06)
illiq	-0.033	0.205	-0.124	-0.044	-0.017	-0.064	0.009
	(3.34)***	(1.74)*	(3.33)***	(2.14)**	(3.06)***	(2.81)***	(1.97)*
lag trading	0.225	-0.063	-0.147	-0.027	0.020	-0.084	-0.377
	(43.53)***	(7.20)***	(17.59)***	(3.00)***	(1.47)	(6.46)***	(16.45)***
_cons	0.042	7.567	0.894	0.333	0.107	0.366	-0.119
	(1.56)	(5.74)***	(5.90)***	(3.25)***	(2.35)**	(2.60)**	(2.64)***
R^2	0.07	0.11	0.07	0.06	0.03	0.05	0.18
N	364,475	276,568	276,629	276,629	276,629	276,629	276,629

Table 7 Profitability of liquidity shock-driven trades

The table presents the results of a two stage analysis. The first stage regression is a baseline stock-level Fama and MacBeth (1973) regression of institutional trading variable on lagged liquidity shocks (LIQUS) and controls $Inst\ trading_{i,t+1} = \alpha_{t+1} + \beta_{t+1} LIQUS_{i,t} + \gamma_{t+1} X_{i,t} + \varepsilon_{i,t+1}$, where *t+1* is a month when institutional trading takes place and *t* is a previous month. *Inst trading*$_{i,t}$ is measured by net institutional trading from Ancerno database. Based on the 1st stage regression results we construct a predicted trading variable $Predicted\ trading_{i,t} = \beta * LIQUS_{i,t}$. The second stage regression is a Fama and MacBeth (1973) regression of future returns on predicted trading and controls $Return_{i,t+1} = \alpha_{t+1} + \beta_{t+1} Predicted\ Trading_{i,t} + \gamma_{t+1} X_{i,t-1} + \varepsilon_{i,t+1}$.
Stock characteristics: BETA is market Beta, LNME is natural logarithm of firm's market value, LNBM is natural logarithm of stock's book-to-market ratio, RET is the stock return in the month preceding trading quarter, MOM is 11-month momentum, IVOL is idiosyncratic volatility, IVOLU are shocks in IVOL, DISP is analyst forecast dispersion, SUE is standardized unexpected earnings, DY is quarterly dividend yield, LAG is the previous month value of the trading variable. T statistics are based on Newey-West standard errors (4 lags). * p<0.1; ** p<0.05; *** p<0.01.

1st stage	Ancerno trading	2nd stage	ret (t+1)
liqus	0.019	Predicted Trading	5.276
	(8.93)***		(2.74)***
lnme	-0.012	lnme	-0.138
	(3.99)***		(2.64)***
lnbm	-0.011	lnbm	0.003
	(2.73)***		(0.03)
mom	0.001	mom	-0.001
	(6.88)***		(0.27)
ret	-0.001	ret	-0.005
	(1.80)*		(0.72)
sue	0.002	sue	0.102
	(0.56)		(2.83)***
dy	0.365	dy	-2.802
	(0.82)		(0.61)
ivol	0.013	ivol	-0.225
	(2.66)***		(1.23)
ivolu	-0.004	ivolu	0.050
	(0.65)		(0.32)
beta	0.008	beta	-0.019
	(1.63)		(0.11)
disp	0.005	disp	-0.363
	(0.36)		(1.71)*
illiq	-0.025	illiq	-0.080
	(2.71)***		(0.46)
lag trading	0.224	lag	-0.089
	(45.12)***		(4.10)***
_cons	0.044	_cons	1.821
	(1.68)*		(2.71)***
R^2	0.06	R^2	0.09
N	375,262	N	375,182

Table 8 Cross-sectional regressions with interaction terms (Ancerno database)

The table presents the results of a stock-level Fama and MacBeth (1973) type regression of institutional trading variable on lagged liquidity shocks (LIQUS), controls and interaction between a given control variable and liquidity shock: $Inst\ trading_{i,t+1} = \alpha_{t+1} + \beta_{t+1} LIQU_{i,t} + \delta_{t+1}(LIQU_{i,t} * Contr_{i,t}) + \kappa_{t+1} Contr_{i,t} + \gamma_{t+1} X_{i,t} + \varepsilon_{i,t+1}$ where *t+1* is a month when institutional trading takes place and *t* is a previous month. $Inst\ trading_{i,t}$ is measured by net institutional trading from Ancerno database. Stock characteristics included in the interactions are: LNME is natural logarithm of firm's market value, RET is the stock return in the previous month, LNBM is natural logarithm of stock's book-to-market ratio, IVOL is idiosyncratic volatility, SUE is standardized unexpected earnings. The liquidity and control variables used in interactions have been centered with the exception of SUE for which value zero has meaningful interpretation. T statistics are based on Newey-West standard errors, 4 lags. * $p<0.1$; ** $p<0.05$; *** $p<0.01$.

	1	2	3	4	5	6
liqus	0.017 (6.97)**	0.015 (6.10)**	0.019 (9.16)**	0.021 (7.48)**	0.018 (8.67)**	0.019 (8.33)**
lnme*liqus	-0.008 (4.18)**					
ret*liqus		-0.001 (4.66)**				
lnbm*liqus			-0.000 (0.02)			
ivol*liqus				0.014 (5.58)**		
illiq*liqus					-0.030 (4.09)**	
sue*liqus						-0.002 (0.72)
lnme	-0.012 (4.20)**	-0.012 (4.06)**	-0.012 (4.03)**	-0.012 (3.87)**	-0.013 (4.09)**	-0.012 (4.00)**
lnbm	-0.012 (2.84)**	-0.011 (2.63)**	-0.009 (1.90)	-0.012 (2.81)**	-0.011 (2.62)**	-0.011 (2.72)**
mom	0.001 (7.29)**	0.001 (6.85)**	0.001 (7.00)**	0.001 (6.72)**	0.001 (6.79)**	0.001 (6.89)**
cret	-0.001 (1.82)	-0.001 (1.29)	-0.001 (1.80)	-0.001 (1.97)	-0.001 (1.80)	-0.001 (1.80)
sue	0.002 (0.55)	0.002 (0.61)	0.002 (0.57)	0.002 (0.58)	0.002 (0.55)	0.001 (0.43)
dy	0.319 (0.72)	0.394 (0.88)	0.349 (0.79)	0.400 (0.90)	0.379 (0.85)	0.380 (0.85)
ivol	0.013 (2.65)**	0.014 (2.89)**	0.013 (2.58)*	0.011 (2.10)*	0.014 (2.85)**	0.014 (2.75)**
ivolu	-0.004 (0.62)	-0.004 (0.71)	-0.004 (0.63)	-0.004 (0.61)	-0.005 (0.77)	-0.004 (0.70)
beta	0.008 (1.68)	0.008 (1.67)	0.008 (1.67)	0.008 (1.61)	0.007 (1.53)	0.008 (1.58)
disp	0.007 (0.45)	0.005 (0.35)	0.006 (0.38)	0.007 (0.49)	0.004 (0.29)	0.005 (0.32)
illiq	-0.013 (1.39)	-0.028 (2.99)**	-0.025 (2.60)*	-0.021 (2.24)*	-0.048 (3.95)**	-0.025 (2.80)**
lag trading	0.224 (45.08)**	0.224 (45.08)**	0.224 (45.04)**	0.224 (45.06)**	0.224 (45.12)**	0.224 (45.16)**
_cons	-0.033 (2.88)**	0.045 (1.70)	0.055 (2.03)*	0.072 (3.11)**	0.043 (1.69)	0.046 (1.74)
R^2	0.07	0.07	0.07	0.07	0.06	0.06
N	375,262	375,262	375,262	375,262	375,262	375,262

Table 9 Cross-sectional regression with positive and negative individual liquidity shocks (Ancerno database)

The table presents the results of a stock-level Fama and MacBeth (1973) type regression of institutional trading variable on lagged positive and negative liquidity shocks (LIQUS) and controls:

$$Inst\ trading_{i,t+1} = \alpha_{t+1} + \beta_{t+1} LIQUS\ Pos_{i,t} + \theta_{t+1} LIQUS\ Neg_{i,t} + \mu_{t+1} Ret\ Pos_{i,t} + \pi_{t+1} Ret\ Neg_{i,t} + \gamma_{t+1} X_{i,t} + \varepsilon_{i,t+1}$$

where *t+1* is a month when institutional trading takes place and *t* is a previous month. $Inst\ trading_{i,t}$ is measured by net institutional trading from Ancerno database. Stock characteristics: BETA is market Beta, LNME is natural logarithm of firm's market value, LNBM is natural logarithm of stock's book-to-market ratio, MOM is 11-month momentum, RET Pos and RET Neg are the positive and negative stock return in the previous month, IVOL is idiosyncratic volatility, IVOLU are shocks in IVOL, DISP is analyst forecast dispersion, SUE is standardized unexpected earnings, DY is quarterly dividend yield, LAG is the previous month value of the trading variable. T statistics are based on Newey-West standard errors, 4 lags. * p<0.1; ** p<0.05; *** p<0.01.

	Ancerno
liqus positive	0.014 (2.06)**
liqus negative	0.017 (2.70)***
lnme	-0.012 (3.93)***
lnbm	-0.011 (2.75)***
mom	0.001 (7.05)***
ret	-0.001 (1.76)*
sue	0.002 (0.57)
dy	0.353 (0.79)
ivol	0.014 (2.74)***
ivolu	-0.004 (0.66)
beta	0.008 (1.63)
disp	0.006 (0.40)
illiq	-0.024 (2.62)***
lag trading	0.224 (45.03)***
_cons	0.048 (1.90)*
R^2	0.06
N	375,262

Table 10 Cross-sectional regressions for institutional trading in subperiods

The table presents the results of a stock-level Fama and MacBeth (1973) type regression of institutional trading variable on lagged liquidity shocks (LIQUS) and controls $Inst\ trading_{i,t+1} = \alpha_{t+1} + \beta_{t+1} LIQUS_{i,t} + \gamma_{t+1} X_{i,t} + \varepsilon_{i,t+1}$, where *t+1* is a month when institutional trading takes place and *t* is a previous month. *Inst* $trading_{i,t}$ is measured by net institutional trading from Ancerno database. Stock characteristics: BETA is market Beta, LNME is natural logarithm of firm's market value, LNBM is natural logarithm of stock's book-to-market ratio, RET is the stock return in the month preceding trading quarter, MOM is 11-month momentum, IVOL is idiosyncratic volatility, IVOLU are shocks in IVOL, DISP is analyst forecast dispersion, SUE is standardized unexpected earnings, DY is quarterly dividend yield, lag trading is the previous month value of the trading variable. T statistics are based on Newey-West standard errors, 2 lags. The analysis is performed for the periods of positive and negative values of the average market liquidity shocks (column 1), the times of contraction and expansion, as defined by NBER (column 2), the times of high and low VIX - below and above the monthly VIX median in the sample period (column 3), the first and second half of the time-period studied (column 4). * $p<0.1$; ** $p<0.05$; *** $p<0.01$

	1		2		3		4	
	Positive mkt shock	Negative mkt shock	Contraction	Expansion	High VIX	Low VIX	01.1990-05.2005	06.2005-09.2011
liqus	0.019	0.018	0.015	0.020	0.019	0.018	0.020	0.018
	(5.69)***	(6.39)***	(4.68)***	(6.97)***	(6.77)***	(5.19)***	(5.85)***	(5.97)***
lnme	-0.017	-0.005	-0.004	-0.014	-0.001	-0.023	-0.009	-0.015
	(4.44)***	(1.51)	(0.81)	(4.64)***	(0.17)	(10.28)***	(2.12)**	(4.58)***
lnbm	-0.019	-0.002	-0.002	-0.014	-0.001	-0.022	-0.011	-0.012
	(3.55)***	(0.42)	(0.20)	(3.48)***	(0.11)	(4.48)***	(1.80)*	(2.29)**
mom	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001
	(7.76)***	(3.83)***	(1.35)	(9.00)***	(4.00)***	(7.26)***	(6.89)***	(4.13)***
ret	-0.001	-0.001	0.001	-0.001	0.000	-0.002	-0.001	-0.001
	(2.32)**	(0.78)	(0.64)	(2.67)***	(0.15)	(3.13)***	(1.97)*	(1.03)
sue	-0.004	0.008	0.006	0.001	0.002	0.001	-0.005	0.008
	(1.13)	(1.85)*	(0.91)	(0.20)	(0.48)	(0.40)	(1.24)	(2.34)**
dy	0.145	0.637	1.144	0.165	-0.060	0.779	-0.167	0.897
	(0.23)	(1.01)	(1.58)	(0.30)	(0.09)	(1.21)	(0.24)	(1.49)
ivol	0.018	0.008	0.020	0.012	0.018	0.009	0.016	0.011
	(2.80)***	(1.04)	(1.69)	(2.11)**	(2.71)***	(1.13)	(1.96)*	(1.78)*
ivolu	-0.008	0.001	0.020	-0.010	-0.000	-0.007	-0.022	0.014
	(1.23)	(0.12)	(1.34)	(1.69)*	(0.05)	(0.97)	(2.92)***	(1.94)*
beta	0.015	-0.001	0.012	0.007	0.007	0.008	0.009	0.007
	(2.55)**	(0.16)	(0.96)	(1.36)	(1.07)	(1.29)	(1.29)	(1.04)
disp	0.021	-0.014	0.014	0.003	-0.007	0.017	0.011	0.000
	(1.29)	(0.49)	(0.49)	(0.17)	(0.30)	(0.73)	(0.42)	(0.00)
illiq	-0.044	-0.001	-0.007	-0.029	0.001	-0.051	-0.023	-0.027
	(3.93)***	(0.09)	(0.34)	(3.03)***	(0.12)	(3.87)***	(2.48)**	(1.59)
lag trading	0.223	0.225	0.200	0.230	0.213	0.234	0.227	0.221
	(34.77)***	(32.79)***	(29.47)***	(44.02)***	(32.41)***	(39.21)***	(34.46)***	(32.36)***
_cons	0.070	0.013	-0.025	0.062	-0.047	0.133	0.027	0.062
	(2.01)**	(0.40)	(0.57)	(2.33)**	(1.45)	(5.80)***	(0.75)	(1.95)*
R^2	0.07	0.06	0.05	0.07	0.06	0.07	0.07	0.06
N	211,151	164,111	70,839	304,423	174,123	201,139	190,962	184,300
*Difference**		0.000		-0.005		0.001		0.002
		(0.786)		(-7.32)***		(1.35)		(3.65)***

**T-test for a difference in coefficients on liqus between two subperiods*

Table 11 Cross-sectional regressions for different Ancerno client types

The table presents the results of a stock-level Fama and MacBeth (1973) type regression of institutional trading variable on lagged liquidity shocks (LIQUS) and controls

$$Inst\ trading_{i,t+1} = \alpha_{t+1} + \beta_{t+1} LIQUS_{i,t} + \gamma_{t+1} X_{i,t} + \varepsilon_{i,t+1}$$

where $t+1$ is a month when institutional trading takes place and t is a previous month. $Inst\ trading_{i,t}$ is measured by net institutional trading from Ancerno database by institutions assigned to different Ancerno database clients – pension plan sponsors, managers and brokers. Stock characteristics: BETA is market Beta, LNME is natural logarithm of firm's market value, LNBM is natural logarithm of stock's book-to-market ratio, MOM is 11-month momentum, RET is the stock return in the previous month (in the last month of preceding quarter), IVOL is idiosyncratic volatility, IVOLU are shocks to IVOL, DISP is analyst forecast dispersion, SUE is standardized unexpected earnings, DY is quarterly dividend yield, lag trading is the previous month (quarter) value of the trading variable. T statistics are based on Newey-West standard errors, 4 lags. * $p<0.1$; ** $p<0.05$; *** $p<0.01$.

	pension plan sponsor	manager	broker	missing	difference PPS and manager
liqus	0.003	0.010	-0.000	0.006	0.007
	(6.46)***	(6.25)***	(0.78)	(4.65)***	(47.9***)
lnme	-0.002	-0.009	0.000	-0.001	
	(2.34)**	(3.93)***	(0.95)	(1.45)	
lnbm	-0.002	-0.010	-0.000	0.001	
	(2.67)***	(2.66)***	(1.11)	(0.39)	
mom	0.000	0.001	0.000	0.000	
	(6.69)***	(5.95)***	(1.47)	(1.98)**	
ret	0.001	-0.002	0.000	0.001	
	(7.09)***	(4.88)***	(1.01)	(3.53)***	
sue	0.001	-0.001	-0.000	0.002	
	(3.18)***	(0.56)	(1.02)	(2.07)**	
dy	0.096	0.287	0.025	-0.010	
	(1.19)	(0.69)	(2.16)**	(0.07)	
ivol	0.004	0.008	-0.000	-0.001	
	(3.93)***	(2.01)**	(0.98)	(0.39)	
ivolu	-0.005	0.003	0.000	-0.002	
	(3.91)***	(0.46)	(0.62)	(0.64)	
beta	0.001	0.008	-0.000	0.000	
	(1.48)	(1.71)*	(0.54)	(0.05)	
disp	-0.001	0.003	0.000	0.006	
	(0.44)	(0.21)	(0.73)	(1.05)	
illiq	-0.001	-0.028	-0.000	0.002	
	(0.23)	(3.73)***	(0.82)	(0.98)	
lag trading	0.007	0.178	0.000	0.032	
	(12.10)***	(32.92)***	(2.19)**	(6.56)***	
_cons	-0.002	0.050	-0.001	0.008	
	(0.33)	(2.50)**	(1.16)	(0.75)	
R^2	0.02	0.06	0.02	0.02	
N	375,262	375,262	375,262	375,262	

Table 12 Panel vector autoregression analysis – monthly, Ancerno database

The table reports estimates from panel vector autoregression with firm fixed effects following equation $y_{it} = \alpha_i + \sum_{l=1}^{L} \lambda^l y_{it-l} + \varepsilon_{it}$, where vector yit = (Institutional Trading$_{it}$, Return$_{it}$, LIQUS$_{it}$)' , α_i is a 3x1 vector of firm-specific intercepts, λ_i, l = 1, …, L, are 3x3 coefficient matrices, and ε_{it} is a 3x1 vector of innovations. The model is estimated using system GMM with three lags. The number of observations is 448,511. T-statistics are reported next to coefficient estimates. In Panel A Return is measured by Excess Return – stock return less the risk-free rate. In Panel B, we measure the four-factor alpha (based on Fama-French (1993) three factor model with Carhart (1997) momentum factor). * p < 0:1, ** p < 0:05, *** p < 0:01.

Panel A

	Liqus			**Trading**			**Exret**		
	(coef)	(t)		(coef)	(t)		(coef)	(t)	
Liqus t-1	40.454	129.639	***	1.991	2.244	**	73.058	29.759	***
Liqus t-2	7.342	31.316	***	4.724	4.018	***	-26.993	-10.489	***
Liqus t-3	9.223	46.924	***	1.682	1.517		8.740	3.779	***
Trading t-1	0.072	2.964	***	10.942	5.753	***	-1.090	-3.696	***
Trading t-2	0.092	5.017	***	2.809	1.876	*	-0.577	-2.173	**
Trading t-3	0.046	1.759	*	3.050	1.207		-1.349	-3.500	***
Exret t-1	2.136	131.493	***	0.398	5.291	***	0.307	1.242	
Exret t-2	0.778	54.902	***	0.087	1.243		-4.219	-17.340	***
Exret t-3	0.487	34.932	***	0.043	0.533		0.062	0.272	

Panel B

	Liqus			Trading			4f alpha		
	(coef)	(t)		(coef)	(t)		(coef)	(t)	
Liqus t-1	4.743	146.211	***	2.940	3.297	***	0.337	5.322	***
Liqus t-2	8.180	33.732	***	4.556	3.760	***	-0.322	-4.244	***
Liqus t-3	7.489	37.451	***	1.250	1.079		-0.312	-5.126	***
Trading t-1	0.174	7.032	***	11.869	6.219	***	-0.003	-0.436	
Trading t-2	0.094	5.110	***	2.675	1.760	*	-0.003	-0.554	
Trading t-3	0.026	0.979		4.262	1.733	*	-0.001	-0.107	
4f alpha t-1	28.253	49.910	***	9.713	4.368	***	94.625	360.846	***
4f alpha t-2	-13.463	-18.447	***	-5.546	-2.032	*	1.079	3.283	***
4f alpha t-3	-10.814	-20.491	***	2.883	1.410		1.596	6.994	***

Figure 1 Time-series trend in average stock illiquidity and standardized liquidity shocks
The figure presents yearly averages of stock-level illiq (Amihud illiquidity level) and liqus (standardized liquidity shock) variables

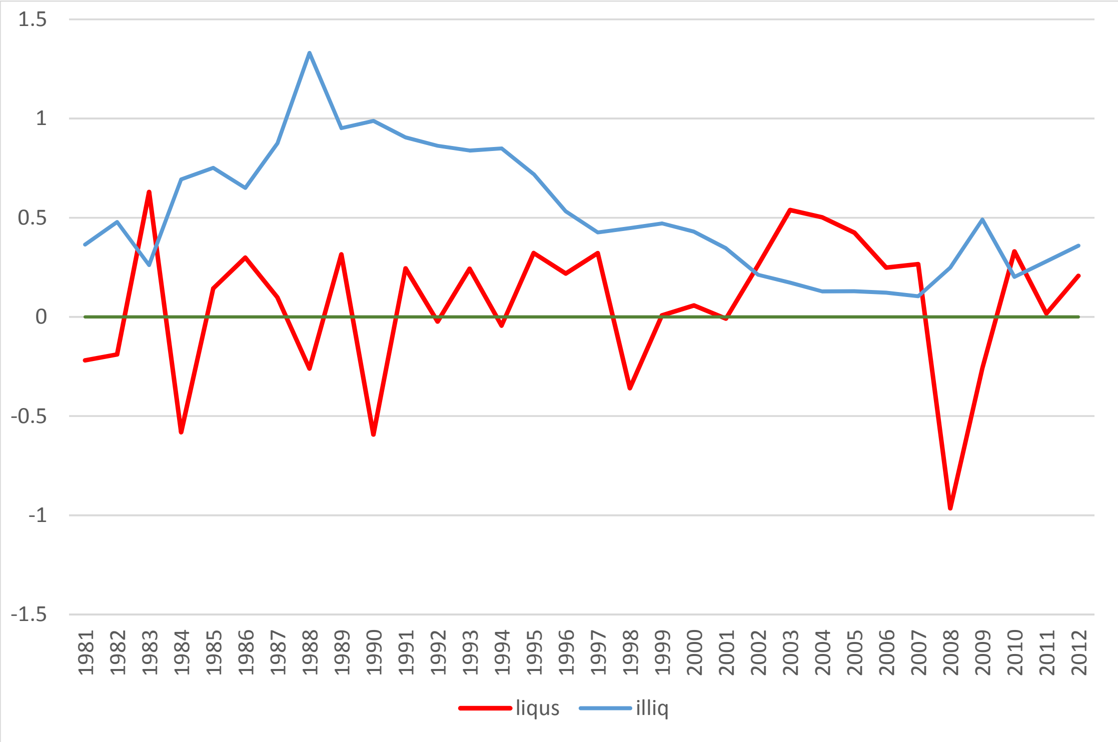


Figure 2 Time-series trend in institutional ownership ratio
The figure presents yearly averages of stock-level institutional ownership ratio

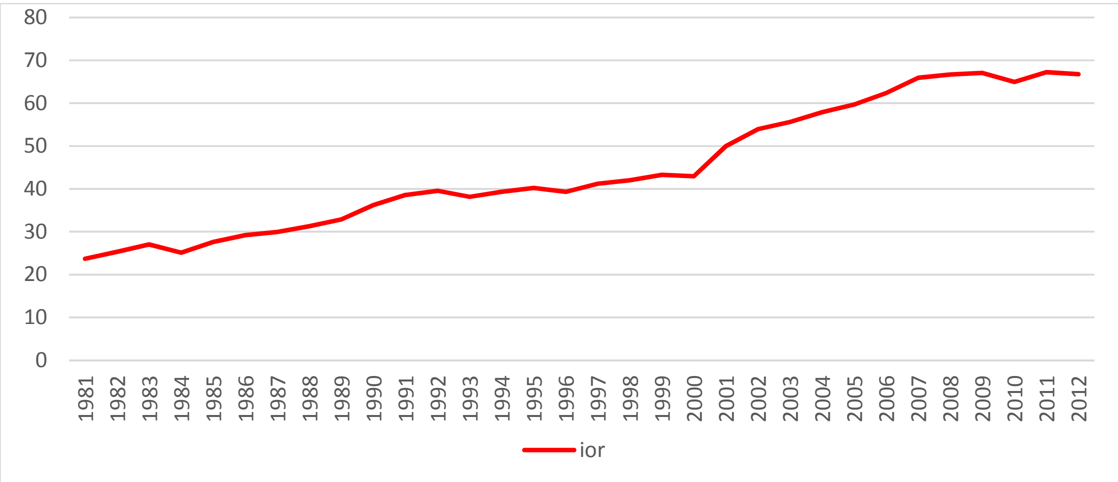
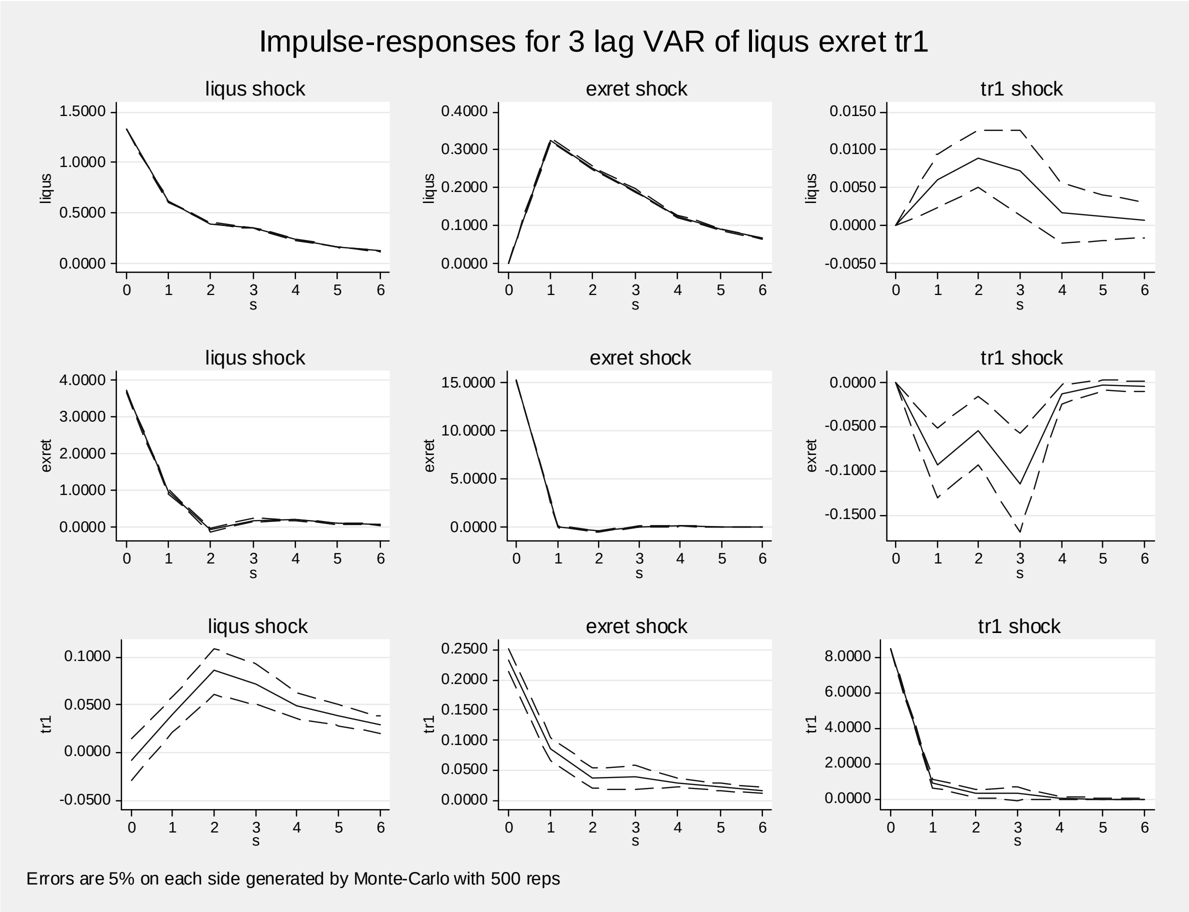


Figure 3



Impulse-responses for 3 lag VAR of liqus exret tr1
liqus shock
exret shock
tr1 shock
liqus
exret
tr1
s
Errors are 5% on each side generated by Monte-Carlo with 500 reps

Appendix 1 Bushee investor groups characteristics

Table A1 presents some characteristics of Bushee (2001) investors groups. Transient institutions are characterized by the highest turnover among classified institutions both by using Carhart turnover measure and the measure incorporating net flows. Dedicated investors have on average largest individual assets under management, however quasi-indexers is a dominating group in terms of assets managed by the whole group which is related to the popularity of index funds (Ke and Ramalingegowda, 2005).[15] Quasi-indexers are also characterized by the highest ownership ratio of 27%. Transient institutions as a group manage on average 13.2% of assets managed by institutions and their mean ownership ratio is 10%. The institutions unclassified by Brian Bushee are characterized by small holdings and low assets under management and their behavior likely has small impact on the market.

[15] The managed assets are based on the equity holdings as listed in the 13(f) statements prepared by institutions. Thus, this number does not include international equity holdings, bond holdings, and other derivatives. Short positions are not included either.

Table AI Characteristics of different Bushee (2001) investor types

Table presents average quarterly measures for investor types following Bushee (2001) investor classification in the sample period 1981-2012. The managed assets are based on the equity holdings as listed in the 13(f) statements prepared by institutions. Thus, this number does not include international equity holdings, bond holdings, and other derivatives. Short positions are not included either.Turn_1 is Carhart (1997) turnover measure – the minimum of buys and sells divided by average quarterly assets. Turn_2 is the minimum of buys and sells added to the absolute value of net flows, divided by lagged assets. Turn_3 is the sum of buys and sells less the absolute value of net flows, divided by lagged assets. Buys and sells are measured with end-of-quarter $q - 1$ prices, where "buy" ("sell") is an increase (decrease) in the adjusted number of shares of a given stock held by the institution in a given quarter q. Net flows are the difference between portfolio assets at the end of quarter t and assets at the end of quarter t-1 increased by the portfolio return. For methodology, see WRDS Research Applications http://wrds-web.wharton.upenn.edu/wrds/research/applications/ownership/Institutional%20Trades/

Investors class	QUASI-IDEXERS	DEDICATED	TRANSIENT	NOT CLASSIFIED
Average Turn_1	0.069	0.072	0.210	0.149
Average Turn_2	0.205	0.145	0.671	1.973
Average Turn_3	0.142	0.151	0.441	0.319
Average portfolio assets per manager $m	27,935	67,140	12,252	3,311
Average managed assets per investor group $m	6,768,605,003	1,020,554,815	1,187,122,729	16,342,877
Avg assets per group as % of all avg assets	75.3%	11.3%	13.2%	0.2%
Number of institutions classified	2,624	262	1,608	4,477
Mean ownership ratio	26.897	6.363	10.084	0.321
Mean change in ownership ratio	0.328	0.045	0.102	-0.011

Appendix 2 Variable definitions

Below we provide detailed definitions of control variables.

Size (LNME) – natural logarithm of the stock's market value (price per share multiplied by shares outstanding) each quarter.

Book-to-market ratio (LNBM) – natural logarithm of the ratio of book to market value, where book value is the book value of stockholders' equity, plus deferred taxes and investment tax credit (if available), minus the book value of preferred stock for the last fiscal year end in t -1; the market value is calculated at the end of December of t -1.[16]

Return (RET) – stock return over a month preceding the institutional trading quarter, the variable is winsorized quarterly at 1 and 99%.

Momentum (MOM) - the cumulative return of a stock over 11 months ending one month prior to the portfolio formation month (the month preceding the quarter of institutional trading), as in Jegadeesh and Titman (1993), the variable is winsorized quarterly at 1 and 99%.

Standardized unexpected earnings (SUE) - stock's quarterly unexpected earnings (UE) scaled by its standard deviation over the preceding eight quarters (minimum four). Following Ball and Brown (1968) and Bernard and Thomas (1989, 1990), unexpected earnings are defined as the difference between stock's basic EPS excluding extraordinary items in quarters q and q-4:

$$UE_{i,q} = EPS_{i,q} - EPS_{i,q-4} \tag{A1}$$

Dividend yield (DY) is measured as cash dividends in a given quarter divided by the price at the end of the quarter.

Stock idiosyncratic volatility (IVOL) is measured monthly as the standard deviation of the residuals from the following regression of daily excess stock returns on market excess returns and size and book-to-market factors of Fama and French (1993). Risk free rate used to compute

[16]For the book value of preferred stock, redemption, liquidation or par value are used depending on availability.

excess returns is the rate of one-month treasury bills and market return is the CRSP value-weighted index; the rates and factors are downloaded from Kenneth French's website.[17]

$$R_{i,d} - R_{f,d} = \alpha_i + \beta_i(R_{m,d} - R_{f,d}) + \gamma_i SMB_d + \varphi_i HML_d + \varepsilon_{i,d} \quad \text{(A2)}$$

The variable is winsorized quarterly at 1 and 99%.

Unexpected shocks to idiosyncratic volatility (IVOLU) are measured monthly as:

$$IVOLU_{i,t} = (IVOL_{i,t} - AVGIVOL_{i|t-12,t-1}), \quad \text{(A3)}$$

where $AVGIVOL_{i|t-12,t-1}$ is the past 12-months mean of idiosyncratic volatility. The variable is winsorized quarterly at 1 and 99%.

Market beta of the stock (BETA) is estimated based on time-series regression of monthly excess stock returns on current and lagged market excess returns over 60 months (minimum 24). The beta is calculated as a sum of coefficients of current and lagged excess stock returns. Risk free rate used to compute excess returns is the rate of one-month treasury bills and market return is the CRSP value-weighted index.

Analyst earnings forecast dispersion (DISP) is computed as the standard deviation of annual EPS forecasts divided by the absolute value of the average outstanding forecast (Diether, Malloy, Sherbina, 2002), the variable is winsorized quarterly at 1 and 99%.

[17] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html