You can only lend what you own: Inferring daily institutional trading from lendable equity inventory[*]

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Abstract

Institutions make their holdings lendable, allowing us to use changes in lendable equity to track stock-specific daily net institutional trading. Our proxy better tracks quarterly changes in institutional ownership than alternatives, including a subset of actual institutional trades, especially if we allow the corresponding sensitivity to vary across stocks. Using this proxy, we document (1) institutions unwind holdings before earnings announcements and re-establish them afterwards, contributing to the earnings announcement premium; (2) negative short-term return predictability, reflecting institutional price pressure; (3) price momentum anomaly obtains only if institutional trading opposes intraday returns during the portfolio formation period, consistent with under-reaction.

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1 Introduction

In the U.S., almost 80% of publicly traded equity is held by institutions (Blume and Keim (2012)), raising many important questions regarding the role of institutional investors in equity markets. However, researchers face challenges performing analyses that require high frequency data on institutional trading activity. This is because institutions are only required to disclose their equity positions quarterly (via 13-F filings). One possibility is to examine actual institutional trades from databases like ANcerno. However, these data account for a modest fraction of overall institutional trading and are only available until 2015 (Hu et al., 2018). The second alternative is to resort to proxies of such activity. For example, some infer institutional buy and sell trades using transaction sizes and trade directions inferred by Lee and Ready's (1991) algorithm (Lee and Radhakrishna, 2000; Campbell et al., 2009). However, in modern equity markets, the accuracy of such trade and quote based algorithms diminishes as institutions increasingly rely on sophisticated dynamic order splitting strategies, which render identifying their trades via algorithms difficult (O'Hara, 2015). We propose a new proxy for daily net institutional trading that addresses these concerns.

Our proxy is based on the simple premise that changes in the total amount of equity holdings that institutions make available for lending tracks changes in institutional ownership (IO). Institutions routinely make some of their holdings available for lending to potential borrowers of security loans in order to earn lending fees.[1] S&P Global Insights (formerly Markit) estimates the total number of lendable shares ("lendable quantity") for each stock on a daily basis—see Section 2 for details—and makes them commercially available. For emphasis, lendable equity is the *inventory* of shares that can be lent and is an upper bound for the number of shares that are lent out to facilitate short selling. Empirically, the latter divided by the former, i.e., utilization rate, is below 10% for a typical stock. According to IHS Markit's Quant Summary, lendable equity "*can be used as a high-frequency proxy for*

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[1] According to an Office of Financial Research Survey, the majority of these lending assets are provided by investment firms, pension funds, and endowment funds.

institutional ownership." Thus, our proxy is not subject to measurement complications due to trade execution strategies or limitations on actual institutional trade data.[2]

lendable equity underestimates IO because each institution may not lend more than one-third of its total holdings.[3] Empirically, lendable equity, on average, accounts for 35% of institutionally held shares, and this ratio, denoted *Lratio*, varies across stocks.[4] For example, the ratio tends to be lower for growth and volatile stocks, as well as stocks with concentrated institutional ownership. Importantly, *Lratio* is highly persistent at the stock level, with an average quarterly autocorrelation of 86%, and is barely related to security lending fees and short interest.[5] These observations lead us to use the daily change in lendable equity (*dLend*), divided by *Lratio* at the end of the previous quarter, to proxy daily changes in IO, i.e., net institutional trading activity. Indeed, we confirm that *dLend*/*Lratio*'s ability to track institutional trading is similar across stocks with different *Lratio*s.

We caution that our proposed measure is imperfect, as is any other proxy. Relying on insights from the security lending literature and our own empirical analysis, we flag days around or at dividend-distribution and voting record dates as instances where a change in the inventory of lendable equity likely reflects the strategic considerations of owners, rather than a change in institutional ownership. We also show that the ability of our proxy in tracking changes in IO varies with some stock characteristics (see Table 4). We remedy this by constructing out-of-sample (OOS) *estimated* changes in IO using a parsimonious model that accounts for such variation. Thus, when employing our proxy, researchers can either use *dLend*/*Lratio* and directly control for these stock characteristics or use our estimated IO change that accounts for them. Lastly, our measure does not capture the trading volume

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[2] A small fraction of lendable equity reflects holdings of individual investors made available for lending by retail brokers as custodians. Even though quantifying this fraction is difficult, it introduces noise to our proxy of net daily IO change. Hence, it's effects attenuate our findings, rather than drive them.

[3] Investment companies typically do not have more than one-third of the value of their portfolio on loan at any given point in time. This limitation stems from the asset coverage requirements in section 18 of the Investment Company Act.

[4] Aggarwal et al. (2015) report that average share of lendable equity to market-cap is about 28%. Dividing 28% by 35% implies an approximate 80% institutional ownership as expected.

[5] This is consistent with the literature documenting the modest price elasticity of lending supply to price changes, especially over shorter horizons (Sikorskaya, 2024; Dong and Zhu, 2024; Kolasinski et al., 2013).

due to institutional trading, rather it reflects the sign and quantity of net changes in institutionally held shares in each security. Importantly, despite these potential sources of error, our measure outperforms common alternatives by large margins, making it the preferred measure of net daily institutional trading during our sample period.

We compare the ability of $dLend/Lratio$ as a proxy of net change in IO to those of three alternative proxies of institutional trading. Since true institutional holdings are only observable quarterly, we use quarterly changes in IO as the benchmark. We aggregate $dLend/Lratio$ and three alternative proxies to the quarterly level before examining their associations with quarterly changes in IO. In the spirit of Lee and Radhakrishna (2000) and Campbell et al. (2009), the first alternative is the net amount of signed large trades whose values exceed \$50,000.[6] Another proxy is the imbalance in retail trading volume identified using Boehmer et al. (2021)'s (BJZZ's) algorithm multiplied by -1, with the premise that most non-retail trades capture institutional trades.[7] Finally, we utilize a subset of actual institutional trades available from ANcerno, which are limited to a shorter sample period from 2007 through 2014.

Following the standard practice, we first compare the in-sample abilities of these four proxies to track the actual quarterly changes in IO. Specifically, we quantify goodness of fit using the slope coefficients from panel regressions of quarterly changes in institutional trading on each proxy, aggregated and standardized quarterly. The change in lendable equity has the strongest association with the actual change in IO. Concretely, one standard deviation increase in $dLend/Lratio$ is associated with 0.35 to 0.41 units increase in the standardized actual change in IO, depending on the combination of quarter and stock fixed effects used. ANcerno trades yield the second best fit, with analogous estimates between 0.20 to 0.23. The proxies based on large trades and BJZZ trades perform poorly, with slope coefficients

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[6] We find similar results using other cutoff points such as \$20,000.

[7] This is consistent with the negative association between BJZZ retail imbalances and institutional trade imbalances documented by Barardehi et al. (2024) using ANcerno data from 2007-2014. Barber et al. (2023) reports that a retail trades comprise a subset of trades that remain unidentified by by BJZZ's algorithm, this will add noise to minus BJZZ retail imbalances as a proxy fo institutional trading. We find similar results using the improvements that Barber et al. (2023) propose on BJZZ's algorithm.

under 0.02. Similar results hold when all four proxies enter multivariate regressions.

Our baseline analysis involving $dLend/Lratio$ basically assumes the sensitivity of IO with respect to lendable equity is equal to $1/Lratio$ from the previous quarter end. However, we find that while $dLend/Lratio$'s ability to track contemporaneous IO changes does not strongly vary with the composition of institutional investors holding a stock—classified as in Bushee (1998) or Aggarwal et al. (2015)— it varies more with stock characteristics. The goodness of fit is stronger among stocks with higher lending activity, as reflected by higher utilization rates or lower average loan tenure. It is also stronger among stocks with less concentrated institutional ownership, larger stocks, growth stocks, more volatile stocks, and recent winners. Again, these stocks likely feature higher lending activity than others. Thus, the sensitivity of IO to lendable equity tends to vary across stocks, motivating us to consider out-of-sample exercises where we model the sensitivity as a function of stock characteristics using recent data. We can then compute *estimated* daily changes in IO using the estimated function and stock characteristics that are updated more frequently.

We conduct the out-of-sample analyses during 2013-2021. In this shorter sample, we find an average R-squared of 13.8% using $dLend/Lratio$, which remarkably exceeds the analogues obtained using the other three proxies, i.e., only 4.99% for ANcerno trades, 0.34% for BJZZ trades, and 0.29% for large transactions. We then allow the sensitivity of changes in IO to changes in lendable equity to vary with stock characteristics and over time in a mutli-variate OLS approach. Specifically, each quarter, we use data from the prior 20 quarters to estimate the OLS. We then skip one quarter before computing *estimated* daily IO changes. To examine out-of-sample fit, we run cross-sectional regressions of the actual quarterly IO change on the estimated IO change in each quarter, averaging the resulting R-squareds across quarters. The OLS approach elevates the average R-squared from the 13.8% baseline to 17.7%.

Observing that the sensitivity of IO with respect to lendable equity can be a complex function of stock characteristics, we also employ several machine learning (ML) methods, including Random Forest, Gradient Boosting, and various Ensamble methods, to predict quarterly changes in IO using our proxy. However, we find that these ML methods underperform our mutli-variate OLS approach when evaluated based on the out-of-sample R-squareds. This likely reflects machine learning algorithms' tendencies to overfit outliers. Consistent with this conjecture, the average out-of-sample R-squared from ML methods marginally surpasses the 17.7% from OLS estimates, when we trim the most extreme 10% of $dLend/Lratio$ observations. Given this negligible improvement from ML methods obtains only after trimming a significant fraction of data, we recommend that researchers rely on a parsimonious OLS approach if they need a daily institutional trading proxy that accounts for heterogeneity across stocks and over time.

We use our simple proxy in several applications, documenting institutional trading dynamics around corporate events and on its ability to predict stock returns. First, we examine $dLend/Lratio$ around earnings announcements, showing that institutions unwind their holdings before earnings announcements and re-establish them afterwards. Our findings align with Di Maggio et al.'s (2023) based on actual institutional trades from ANcerno data. Johnson and So (2018) report a similar tendency among financial intermediaries, leading to increased trading costs for sellers prior to earnings announcements. That is, institutional investors tend to unwind positions prior to announcements, when market makers also limit liquidity provision to sellers. These two effects, together, may drive negative transitory institutional price impacts prior to announcements that are then followed by positive price impacts as institutions re-establish holdings. Thus, our findings complement Di Maggio et al. (2023) by offering suggestive evidence that institutional trading can contribute to the earnings announcement premium, well documented by Beaver (1968) and Frazzini and Lamont (2007), among many others.[8]

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[8] Investigating the economics behind these patterns falls outside the scope of our study. The literature offers different economic explanations for this premium. For example, while Patton and Verardo (2012) and Savor and Wilson (2016) offer explanations based on information spillovers and the resulting changes in systematic risk; Barber et al. (2013) and Yang et al. (2020) provide evidence of increased idiosyncratic risk around announcements. However, Di Maggio et al. (2023) attribute institutional trading behavior around earnings announcements to post-announcement fund flow sensitivity, using data from 331 mutual funds that they match between ANcerno and CRSP. They argue that such flow sensitivity discourages institutions from taking advantage of earnings announcement premium and therefore constitutes a source of limits to arbitrage

Second, we document that *dLend/Lratio*'s short-term return predictability aligns with price reversals that follow price pressures created by institutional liquidity consumption (Campbell et al., 1993; Hendershott and Menkveld, 2014). Daily long-short strategies buying stocks in *dLend/Lartio*'s top decile—strong institutional buying—and selling stocks in *dLend/Lartio*'s bottom decile—strong institutional selling—are associated with negative short-term future returns. For example, using equally-weighted returns from portfolios formed based on NYSE breakpoints, we find -22 bps of cumulative 20-day returns, adjusted for five Fama-French, momentum, and short-term reversals risk factors.[9] Such a negative return predictability is consistent with transitory institutional price impacts. Notably, such a price reversal is most statistically significant when our proxy is used to measure daily net institutional trading.

Third, we use *dLend/Lratio* to provide new evidence consistent with a link between the momentum anomaly and price under-reaction, building on the premise that institutional trading incorporates long-lived information into prices (Sias et al., 2006). Barardehi et al. (2025) show the momentum anomaly reflects investor under-reaction to price signals associated with trading by showing that momentum strategies only work when portfolios are formed using past intraday returns, but not past overnight returns. We refine this result by highlighting the role of institutional investors in driving it.

Observing that institutional investors primarily trade intraday (Lou et al., 2019), we show momentum strategies are only profitable when portfolios are formed based on past intraday returns whose signs *oppose* those of the corresponding daily *dLend*. Reinforcing this result, similar patterns obtain when we decompose past intraday signals based on whether the underlying intraday returns agree in sign with the corresponding *actual* institutional flow obtained from ANcerno. Our findings suggest that when most institutional trade aligns with the information, reflected by intraday price changes, then prices adjust correctly and there is no under-reaction. If, however, the sign of net institutional trading opposes those of

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for institutional investors.

[9] The use of CRSP breakpoints or value-weighting returns leaves our qualitative findings unaffected.

intraday returns, e.g., suggesting liquidity timing by institutions, then momentum strategies are profitable, consistent with price under-reaction.

We contribute to the literature by proposing an effective proxy of *daily* changes in institutional ownership that addresses limited availability of high-frequency data on actual institutional trading activity. We motivate our proxy based on an extensive discussion of the current institutional details of security lending markets, informing researchers interested in studying these markets. Our proxy is simple, intuitive, and unaffected by methodological challenges that render existing proxies based on transaction sizes and inferred trade directions inaccurate in today's electronic order-driven markets. Moreover, reflecting its accessibility, our proxy comes from a commercially available database that covers securities listed in the U.S. and abroad. Recognizing that no proxy is perfect, we highlight several caveats and security characteristics that researchers should consider when employing our measure.

2 Institutional Details

2.1 U.S. Securities Lending Markets

A securities loan is a transaction where the owner of a security, often referred to as the beneficial owner, temporarily transfers legal ownership of a security to a borrower in an over-collateralized transaction.[10] In the equities market securities, lending exists largely to facilitate short selling.[11] The compensation that the lender receives depends on the type of collateral used to secure the loan. For cash collateralized loans, the most common form of collateral for U.S. equity loans, the lender re-invests the cash and earns interest. The lender rebates a predetermined fixed rate back to the borrower, earning as their fee the

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[10] This transfer includes voting rights and the rights to dividends. See Aggarwal et al. (2015) for additional discussion of the role of securities lending on corporate voting actions. With respect to dividends, securities lending agreements generally require that lenders be reimbursed for any dividends received while the stock is on loan by receiving a substitute dividend. See Blocher et al. (2013) and Dixon et al. (2021) for additional discussion of securities lending and dividends.

[11] This is not true in the fixed income market where securities lending and repo markets exist largely interchangeably and are used for other functions such as managing liquidity ratios on balance sheets.

difference between the interest earned on the securities and the rebate rate.[12] For non-cash collateralized loans, the borrower pays a cash fee that is generally a fraction of the loan value.

The securities lending market is divided into two segments often referred to as the wholesale and retail segments. The term "retail" does not refer to non-institutional participants. It simply refers to loans from broker dealers to their customers to facilitate specific short selling transactions. The terms of these loans are often spelled out in the prime brokerage agreement.[13] In the retail segment of the market securities seldom actually exchange hands. This is because broker-dealers usually facilitate clearing and settlement for their customers, and in doing so, their obligation is netted across all accounts.

For broker dealers, the profit associated with lending to their customers and facilitating short sales is the difference between what they charge their customers for 'loans' and what it costs them to deliver on their net share obligation at clearing and settlement. When a broker-dealer faces a delivery obligation, they will typically source shares in the following order. First they will use their own inventory or from customer margin accounts, because these are the least expensive source of shares since there is no fee involved to acquire the shares. Next, they tap into the holdings of their own customers with fully paid lending agreements which allow the broker-dealer to lend their shares. If they still cannot source sufficient shares they will turn to the wholesale market to borrow shares.

The wholesale market comprises all "non-retail" loans. The primary purpose for loans

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[12] If the security is in high demand, the rebate rate may be negative implying that the lender keeps all of the re-invested interest plus the borrower must provide additional compensation to the lender equal to the rate of the negative rebate. Borrowing costs for cash collateralized loans are often converted from rebate rates to lending fees, which can be more easily compared to non-cash collateralized loans. This is done by subtracting the rebate rate from the federal funds rate or the overnight bank funding rate (OBFR). It is also possible for the lender to lose money on the loan if their investment returns do not cover the rebate rate. This reality played a significant role in the downfall of AIG during the 2008 financial crisis when AIG reinvested cash collateral from securities loans into risky assets which ultimately did not pay off leaving AIG responsible to return the cash from securities loans plus the agreed upon rebate rate. See Peirce (2014).

[13] Retail loans often have a pre-determined fixed rate associated with borrowing shares that are easy to borrow, and cost-plus model to price loans for securities that are harder to borrow. For harder to borrow stock, the cost to borrow is often benchmarked off of a reference rate, which is frequently the prevailing wholesale market rate plus a markup.

in this market is to facilitate the clearing and settlement obligations of various market participants—mostly broker dealers.[14] A market participant, usually a broker-dealer, who needs to borrow shares in the wholesale market will maintain relationships with one or more lending programs and will negotiate bilaterally with the lending program for the loan of the shares. Sometimes these negotiations occur with a phone call, although electronic negotiations are increasingly common. High search costs characterize this market (Kolasinski et al., 2013; D'avolio, 2002; Duffie et al., 2002). While supply and demand forces are key determinants of lending rates, other factors, e.g., high search costs, can drive significant variation in rates, even for similar loans on the same day.[15]

The primary suppliers of shares in this market are institutional investors such as investment firms, pension and endowment funds, banks, insurance companies, and government entities (Baklanova et al., 2016).[16] However, pursuant to SEC Staff guidance with regards to compliance with Section 18(f)1 of the Investment Company Act, "a fund may not have on loan at any given time securities representing more than one-third of its total assets."[17] Institutional investors make their shares available to loan by either offering the shares to a lending agent who runs a lending program, or if they are large enough, by running their own lending program. By far the largest lending programs are the major custodian banks who typically offer a reduction in their custodian fees and a share of the lending revenue to

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[14] An OFR Pilot Survey indicated that approximately 85% of all wholesale loans went to broker dealers. The remainder generally went to large entities like exceptionally large hedge funds or pension and sovereign wealth funds that are large enough to bypass broker-dealers in the borrowing process and maintain their own relationships with lending programs and facilitate clearing and settlement internally (Baklanova et al., 2016).

[15] As discussed in the comment file for the SEC's recently adopted Rule 10c-1a, rates for wholesale loans are affected by myriad factors including: the difficulty a broker-dealer might face in finding an alternate source of shares, the length of the loan, the collateral used, the creditworthiness of the counterparty, the relative bargaining power of the two parties, the size and stability of the lender's position, the lender's propensity to recall the loan, interest rate stability, supply concentration, and idiosyncratic factors such as capital and opportunity costs, whether a borrower has access to the lenders portfolio, the volume of the borrower, and other services offered by the prime broker. See SEC Rule 10c-1a Adopting Release at FN 723.

[16] While shares from non-institutional traders are sometimes lent in the wholesale market they play a reduced role. This is because non-institutional traders are less likely to make their shares available for lending and when they do, their shares are often used to facilitate the net clearing and settlement obligations of their own broker-dealer rather than the wholesale market in general.

[17] See Brinson No-Action letter November 25, 1997.

customers who allow their shares to be lent by the custodian bank.

2.2 Security Lending Data Sources

The securities lending market is opaque. There is limited transparency in the retail segment of the market.[18] In the wholesale market, data primarily comes from three main data providers: S&P Global Insights (formerly Markit), FIS, and Datalend. These companies obtain data via a give-to-get model, whereby participants in the wholesale securities lending market are required to give data to the vendor in exchange for the right to buy the aggregated data from the vendor, and usually only those with data to contribute can purchase concurrent access to the data.[19] Relevant for our study, participants often report the quantity of shares they have on loan along with the associated utilization rate, measuring the on-loan fraction of all shares a participant would make available as lendable equity—however, participants may or may not directly report the lendable equity.

Additional data aggregation details highlight the challenging nature of inferring lendable equity from the aggregate quantities of shares on loan and utilization rates. Each data provider has its own proprietary process for collecting, cleaning, and aggregating the data it receives. Key variables offered by the major wholesale market data providers include information about the distribution of loan fees and the quantity of shares on loan, e.g., average and standard deviation of these variables across participants, at the *stock-day* level. Major data providers often do not provide direct estimates of the lendable quantity (equity), but instead provide estimates of the utilization rate. This variable is computed by surveying multiple lending programs about their own utilization rates and then using a proprietary process to compute an *average* utilization rate. However, dividing average shares on loan

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[18] There are some data providers that survey asset managers in the retail segment of the market about their lending experiences in order to gain insight into the retail segment of the market, but the coverage of these datasets is relatively small.

[19] The quality and comprehensiveness of the data provided by these three companies is comparable. The give-to-get model limits access to the data and is designed to maximize participation since many participants would be unwilling to contribute data if they knew that it was being offered to, e.g. hedge funds and HFTs, that could potentially use the data form trading strategies that could harm them. Some providers make exceptions and allow academics and regulators to purchase the data.

by average utilization rate produces a highly noisy estimate of lendable quantity at the daily frequency for several reasons: (1) the data received from participants are aggregated using proprietary processes, which may weight observations based on undisclosed factors; (2) the estimate reflecting the ratio of two averages will be biased reflecting the likely non-zero cross-participant correlations between shares on loan and utilization rate; and (3) the lending programs providing utilization rate information to the data providers are not necessarily the same as those providing shares on loan information.[20]

S&P Global Insights (Markit), stands out among peer data providers as it provides users with direct measures of lendable quantity. We rely on these measures to develop our estimates of directional institutional trading in equity markets. Plausibly, these lendable quantity measures are based on a proprietary aggregation process that is consistent with those that Markit employs to construct their reported metrics of shares on loan and utilization rates. Moreover, Markit's lendable quantity estimates can benefit from the aggregator's access to the distributional properties of shares on loan and utilization rates across contributing participants. Our empirical findings are supportive of these conjectures: for example, quarterly changes in lendable quantity reported by Markit are strongly correlated with changes in quarterly changes in 13F institutional ownership measures; whereas, a weak analogous association obtains when we back out lendable quantity as the ratio of shares on loan to utilization rates reported by FIS.

2.3 Security Lending vs. Equity Trade Settlement Gap

Securities loans have same-day settlement and occur in Depository Trust Company (DTC). This is different from equities transactions which settle $t+1$ for transactions on or after May 28, 2024, $t+2$ for transactions between September 5, 2017 and May 27, 2024, and

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[20] Some reported utilization rates can be extremely close to zero, consequently dividing shares on loan by the utilization rate can result in absurd values. Some researchers address this by estimating shares available using the formula SharesAvaliable = min(IO,SharesOnLoan/Utilization) were IO is the most recent institutional ownership based on 13F filings (Dixon et al. (2021)). We cannot use this approach since we aim to estimate daily IO using lendable equity.

$t+3$ for transactions occurring between June 7, 1995 and September 4, 2017. The resulting settlement differences are important to researchers because they mean that the securities loans that facilitate short sales occur on the settlement day for that transaction, and not on the transaction day.[21] Further, a beneficial owner cannot make their shares available for lending until they have them in custody which occurs on the settlement day and not the transaction day.

The differing settlement cycles have implications for the recall of loans. The typical lending agreement allows a lender to recall shares at any time, but provides the borrower with "the normal settlement cycle" to return the shares. Thus, for a transaction occurring after May 28, 2024, a beneficial owner who on day t sells shares that were previously lent out issues a recall to the borrower also on day t. That borrower must deliver shares on day $t+1$ to close out the loan. The beneficial owner uses the returned shares to meet their settlement obligation for the shares they sold that same day. A borrower facing a recall can either buy the shares on day t and deliver shares $t+1$ to the lender after they take custody of the shares via the equity settlement cycle, or they can borrow new shares on $t+1$ and return the newly borrowed shares, transferring their loan to a new beneficial owner.[22]

Figure 1 provides an illustrative example of the effect of the different lending cycles, where we rely on non-informational institutional trading triggered in common stocks by Russell 1000/2000 index reconstitutions from 2010 through 2016. We show that one must account for settlement misalignments to accurately proxy the net change in institutional ownership using changes in lendable equity. Our example compares three outcomes across

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[21] Rule 203(b)(1) of Reg SHO requires that when facilitating short sales, broker-dealers must have reasonable grounds to believe that a stock is available for borrowing when settlement is due. This is known as the "locate" requirement, which is intended to help ensure that they will be able to deliver the shares on the settlement date. In order to facilitate their own and their customer's short sales, a broker dealer obtains the 'locate' from a lending program on the day of the transaction. A 'locate' is an assurance from a lending program that shares will be available to borrow on the settlement date. Lending programs frequently offer locates for free for easy to borrow stocks by posting a list of easy to borrow stocks. For stocks that are harder to borrow, a lending program may charge a fee, in addition to whatever lending fee is charged, to provide a locate.

[22] Because shares can only be transferred after custody has been received, and because settling loans is separate from settlement for stock transactions, sometime this process bleeds into the late hours of $t+1$. But, so long as all transactions settle by midnight $t+1$ no fail to deliver charges accrue to any party.

index-switcher stocks and the otherwise similar stocks in the indexes: (1) absolute changes in lendable equity, itself; (2) absolute estimated changes in institutional ownership; and (3) the true institutional trading volume obtained from ANcerno. We only shift dates associated with quantities of (1) and (2) to account for settlement differences, since (3) is a direct measure of institutional trading activity.

Each year, index-switching stocks between Russell-1000 and Russell-2000 indexes on the last Friday of June are selected as "treatment" stocks. For each index-switching (treated) stock, the two stocks whose Russell-1000/2000 rankings in the preceding May fall immediately above and below the treated stock are used as control stocks. Panel A in Figure 1 plots the medians of $|dLend_{jt}|$ for treated and control firms in 30-day event windows around reconstitution dates, documenting patterns consistent with the findings of von Beschwitz et al. (2025). Panel B plots the medians of absolute estimated changes in institutional ownership, reflecting $dLend_{j,t+3}$ divided by the share of $Lend$ three days after the previous-quarter's end in institutionally held shares, IO, at the end of the previous quarter. Panel C plots the median share of actual institutional trading volume, observed in ANcerno data, in total number of shares outstanding with *no adjustments for settlements*. The alignments of the spikes in three panels support our approach to account for the settlement gaps. In the analysis that follows, we account for the gap between security lending versus equity trade settlement periods by shifting the date for a given change in lendable equity backward by three business days before September 5, 2017, and by two business days after that date as our sample period ends in 2021.[23]

2.4 Caveats

The core assumption of our proposed measure is that directional changes in lendable equity are driven by changes in institutionally owned equity that occur in the same direction. However, we caution about some caveats that may violate this assumption. Two of these

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[23] For additional institutional details regarding the structure of the securities lending market see the Economic Baseline section of recently adopted SEC Rule 10c-1a.

violations can be easily identified and avoided. We address the third caveat based on institutional details.

Institutional investors have an incentive to temporarily cut back the inventory of shares they make available for lending in anticipation of dividend distributions. Dividend distribution process features three key dates: (1) on the "declare" date, the firm announces dividends will be paid to stockholders; (2) on the "record" date, stockholders eligible to receive dividends are identified; and (3) on the "distribution" date, cash dividends are paid. Crucially, security lending contracts transfer dividend rights from the lender to the borrower. If a stock is on loan over a dividend record date, the borrower is obligated to return to the lender a substitute dividend. However, in some situations these substitute dividends may be taxed differently from regular dividends (Dixon et al., 2021). Thus, to ensure they will collect dividends, instead of substitute dividends, institutional investors may remove shares from the pool of lendable shares prior to a dividend record date and then reestablish the inventory immediately after the record date passes. Consistent with these incentives, Dixon et al. (2021) document a significant decrease in shares available to loan on dividend record dates. This reduction in supply likely has very little to do with institutional investors systematically buying or selling the respective stocks on these days.

Institutions also tend to reduce the inventory of lendable equity in anticipation of shareholder voting events. In addition to dividend rights, security lending contracts transfer voting rights from the owner (lender) to the borrower. Eligibility to vote on an upcoming proposal is established on voting "record" dates. As a result, prior to record dates, we expect to see reductions in lendable equity inventory that are then reversed after record dates. This is exactly what we find using the data on voting record dates compiled by Fos and Holderness (2021). Figure 2 documents negative changes in lendable equity prior to voting record dates that are then followed by large positive changes in lendable equity immediately after record dates. Our findings suggest that daily changes in lendable equity are noisy measures of net changes in institutional ownership in the 2-week periods that end on the second day after voting record dates.

In the situation where an institutional investor purchases a stock from an institutional short seller, our measure may overestimate net institutional trading. The true net institutional trading is zero in this case, but our measure indicates a net buy when the institutional investor makes the purchased stock lendable. Note that this issue also applies to using the true quarterly institutional holding change. In practice, such a transaction is not very prevalent as many institutional investors are constrained from shorting (see, e.g., Nagel (2005)). Indeed, our attempts to correct for this upward bias by assuming that all observed short sales are done by institutions weakens the ability of our measure.

3 Data and Sample Construction

3.1 Sample construction

Our sample includes all NMS-listed common shares between January 2007 through December 2021, merging data from 13F, Markit, Daily TAQ, CRSP, and I/B/E/S. From 13F, we collect quarterly information on institutional ownership. We obtain estimates of lendable equity and other security loan characteristics, including security loans tenure and utilization rates, from Markit data that covers over between 80% to 94% of NMS-listed common stocks across different quarters in our sample period. From WRDS Intraday Indicators, we obtain the volumes of buyer- and seller-initiated trades (identified by Lee and Ready's (1991) algorithm) whose transaction values exceed \$50,000[24] as well as the volumes of buyer- and seller- initiated "retail" trades identified by the BJZZ algorithm. We obtain daily and monthly trading and price information, as well as risk-factor returns, from CRSP. Earning announcement dates, analyst forecast statistics, and earnings surprise scores come from I/B/E/S. Finally, for the period 2007 through 2014, we construct trading volumes of actual institutional buy and sell trades at the stock-day level using ANcerno.

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[24] We use a \$20,000 cutoff to examine robustness.

We then apply the following filters to the data: First, we exclude observations where institutional holdings and lendable equity are either missing or exceed the total shares outstanding, or where lendable shares surpass institutional holdings. Such data points represent 2.1% of the initial sample. Second, we exclude observations with missing firm characteristics such as size, book-to-market value, Amihud illiquidity, volatility, turnover ratio, average return over the past year, institutional holdings, and idiosyncratic volatility. These observations account for 3.2% of the initial sample. Third, we require institutional holdings and lendable quantities over consecutive quarters, in order to compute quarterly changes. This requirement excludes 11.4% of the initial sample. Fourth, we trim the data by removing observations with quarterly turnover ratios in the lowest 1% (0.7%) of the remaining (initial) sample. Stocks with exceptionally low turnover ratios are unlikely to experience substantial changes in institutional holdings. Fifth, we exclude observations with extreme changes in split-adjusted total shares outstanding, where the share outstanding at quarter q is smaller than 50% or larger than 200% of the share outstanding at $q-1$. These observation account for 0.2% of the initial sample. Finally, we remove any observation with a Lend-to-IO ratio ($Lratio$) of less than 5%, trimming 1.3% of observations in the initial sample. Collectively, these filters reduce the number of observations by 19%.

3.2 Variable definitions

Our key variables include quarterly and daily (when possible) changes in insitutional ownership, lendable equity, as well as three existing proxies of institutional trading activity.

Quarterly measures for each stock are constructed as follows. The change in institutional holdings is:

$$dIO_q = \frac{IO_q - IO_{q-1}}{Shrout_{q-1}} \, ,$$

where, IO_q is the split-adjusted institutional holdings at the end of quarter q from 13-F, and $Shrout$ is the number of shares outstanding at the end of the previous quarter. Hence, dIO_q

represents the change in the number of institutional shares normalized by the total shares outstanding. The change in lendable equity is defined similarly:

$$dLend_q = \frac{Lend_q - Lend_{q-1}}{Shrout_{q-1}} \, ,$$

where $Lend_q$ is the Markit's estimate for the quantity of lendable shares at the end of quarter q. The quarterly imbalance in

$$Non\text{-}retail\_Trade_q = -1 \times \frac{Retail\_Buy\_Shares_q - Retail\_Sell\_Shares_q}{Shrout_{q-1}} \, ,$$

where $Retail\_Buy\_Shares$ and $Retail\_Sell\_Shares$, respectively, are the total amounts by buy and sell BJZZ share volumes, obtained from TAQ data and aggregated at the stock-quarter level. The quarterly imbalance in actual institutional activity using ANcerno data is

$$Institution\_Trade_q = \frac{Institution\_Buy\_Shares_q - Institution\_Sell\_Shares_q}{Shrout_{q-1}} \, ,$$

where, $Institution\_Buy\_Shares_q$ and $Institution\_Sell\_Shares_q$ are, respectively, the total share volumes of institutional buy and sell trades. Lastly, the quarterly imbalance in trades with values exceeding $50,000$ is

$$Trade{>}50K_q = \frac{Trade50K\_Buy\_Shares_q - Trade50K\_Sell\_Shares_q}{Shrout_{q-1}} \, ,$$

where, $Trade50K\_Buy\_Shares_q$ and $Trade50K\_Sell\_Shares_q$ are, respectively, the total share volumes of large trades classified and buy and sell by the Lee-Ready algorithm.

We construct daily versions of these measures, with the exception of dIO. To maintain consistency, the daily version of $dLend$ is scaled by $Lend$ at the end of the previous calendar quarter. Similarly, the other three measures also scale daily changes by shares outstanding at the end of preceding calendar quarter.

We also construct the following stock characteristics at each quarter-end: (1) the number of institutional investors holding shares of a give stock obtained from 13F data, denoted #Owners; (2) the Herfindahl index of institutional ownership concentration calculated using 13F data, denoted IOC_HHI; (3) the natural log of firm size, measured by the product of closing price and the number of shares outstanding obtained from CRSP, denoted log(Market Cap); (4) the book-to-market ratio reflecting the most recently observed book value and share price obtained from COMPUSTAT, denoted BtoM; (5) Past_Year_Return, calculated as the compound return of each stock stock over the preceding twelve months using CRSP; and (6) idiosyncratic volatility, which is the standard deviation of residuals of a market model estimated by WRDS Beta Suite using weekly data over the previous quarter, denoted Id_Vol. Moreover, for each stock-quarter, we obtain the utilization rate, i.e., the ratio of shares lent divided by shares available averaged across lending programs, and average tenure, i.e., the average tenure across all outstanding security loans (in days), from Markit.

3.3 Summary statistics

Table 1 presents key summary statistics for the main variables of interest. The mean and median of the fraction of institutionally-owned shares in total shares outstanding (IO) are 0.64 and 0.7, respectively. The average fraction of lendable equity in total shares outstanding ($Lend$) is 0.22. The lendable-to-IO ratio ($Lend/IO$) has a mean of 0.35, and a standard deviation of 0.14—indicative of its temporal and cross-sectional variation. The quarterly changes in both IO and Lend are close to zero on average. Their standard deviations are 0.06 and 0.03, respectively.

[Insert Table 1 here]

In terms of loan characteristics, on average, 17.42% of the lendable shares are lent out, for an average tenure of 88.73 days. We also find the institutional ownership to be quite dispersed in our sample with an average stock held by about 192 different institutions, with an average Herfindahl index of ownership concentration as little as 0.09. Table 1 also includes common stock characteristics such as the logarithm of market capitalization, the book-to-market ratio, average return over the past year, and idiosyncratic volatility.

The last three rows of Table 1 report the summary statistics of the alternative quarterly institutional trading proxies. The last column shows a much smaller number of observations when we examine actual institutional trading from ANcerno, which covers a shorter sample period from 2010 through 2014.

3.4 Lendable-to-IO ratio

Table 1 suggests that the lendable-to-IO ratio (*Lratio*) varies across stocks. Table 2 relates this variation to key stock characteristics.

[Insert Table 2 here]

Column (1) of Table 2 shows that *Lratio* is a persistent stock characteristic. Regressing *Lratio* on its own lag from the prior quarter yields a slop coefficient of 0.86 and an adjusted-R^2 of 0.76, suggesting that *Lratio* is highly persistent from one quarter to the next for the same stock. This remarkable persistence in *Lratio* means that the change in *Lend* is highly correlated with the change in the underlying IO, even though institutions can make no more than 35% of their overall holdings available for lending.

Reinforcing this conclusion are our findings that neither the heterogeneity in institutional investors owning a stock nor stock characteristics can explain the cross-sectional variation in *Lratio* nearly as well as lagged *Lratio*. In columns (2) and (3) of Table 2, we control for the heterogeneity in institutional investors along two dimensions independently: (1) legal institution types, including banks, insurance companies, investment corporations, independent advisors, and other investors (Aggarwal et al., 2015); and (2) institutional-investor style categories reflecting their investment strategies, i.e., dedicated, quasi-indexer, and transitory (Bushee, 1998). For each stock, we measure the extent pf participation/importance of each institution type/category using the fraction of institutionally-owned shares by that particular type/category in the previous quarter. The adjusted-R^2 of 0.18 and 0.11, respectively, in column (2) and (3) show that, even though the heterogeneity in investor composition meaningfully correlates with next-quarter *Lratio*, it fails to absorb much of its variation. Similarly, column (4) shows that a host of key stock characteristics explain only 15% of the variation of *Lratio*.

To further highlight the incremental importance of *Lratio*'s temporal persistence in driving its variation, column (5) includes all investor and stock characteristic measures, in addition to lagged *Lratio*, while column (6) includes investor and stock characteristics only. The difference in the corresponding adjusted-R^2s, i.e., 0.79 in column (5) and only 0.29 in column (6), is striking. Of note, we do not find *Lratio* to respond significantly to the lending fee except when all other variables are included in column (5). Nevertheless, the coefficient of 0.004 indicates a very modest economic magnitude: even among stocks in the highest fee decile, their *Lratio* is only 0.4% higher, relative to a mean *Lratio* of 35%. Collectively, our analysis demonstrates that *Lratio*, i.e., the *inventory* of lenadable equity, strongly persists over time and is inelastic to security lending fees.

4 Tracking Quarterly Institutional Trading

In this section, we validate the ability of our proxy of institutional trading by showing that it successfully tracks the changes in true institutional ownership. Since true institutional trading is difficult to observe at high frequencies, we use the quarterly changes in IO—obtained from 13F filings—as the benchmark. We show that our simple proxy is far superior to several alternatives in tracking institutional trading in terms of both in-sample association and out-of-sample predictive power. Our results obtain based on parsimonious uni- and multi-variate OLS estimates, as well as sophisticated machine learning algorithms.

4.1 In-Sample Performance

We first evaluate the in-sample ability of the four proxies of institutional trading in tracking the actual quarterly change in IO, denoted dIO_q. We estimate

$$dIO^s_{jq} = a + bX^s_{jq} + u_{jq}, \tag{1}$$

where dIO^s is the standardized change in actual institutional ownership, i.e., dIO, and X^s is the standardized proxy $X \in \{dLend_q/Lratio_{q-1}, Institution\_Trade_q, Retail\_Trade_q, Trade50K_q\}$. In our baseline analysis, we simply scale $dLend_q$ by $Lratio$ from the previous quarter—later we show that directly modeling the sensitivity of dIO to $dLend$ as a function of stock characteristics only improves our results. Moreover, the use of both standardized dependent and independent variables in equation (1) facilitates straight forward comparisons slope coefficients (b) across the alternative proxies. These estimated slope coefficients capture the change in standardized dIO as a given proxy rises by one standard deviation. Hence a larger slope coefficient indicates the respective proxy's stronger ability to capture actual institutional trading. We examine specifications with or without firm fixed effects, and/or quarter effects, clustering standard errors by firm.

[Insert Table 3 here]

Table 3 shows that our proxy, $dLend/Lratio$, possesses the strongest association with actual changes in IO. Panel A, shows that when used as the sole explanatory variable, a one standard deviation increase in $dLend/Lratio$ is associated with 0.345 to 0.384 units of increase in standardized dIO depending on the set of fixed effects included. Moreover, the baseline adjusted-R^2 in the exercise is 15%. Panels B, C, and D report analogous results when standardized $Retail\_Trade_q$, $Institution\_Trade_q$, and $Trade50K_q$ are, respectively, used to explain standardized dIO. The b coefficient estimates for all of these proxies have the expected signs. However, their magnitudes are much smaller that those obtained for $dLend/Lratio$. In fact, the second best performing alternative is that constructed based on actual institutional trades obtained from ANcerno data, yielding b coefficients no greater than 0.210 and a baseline adjusted-R^2 of only 4%. The b coefficients for proxies based on BJZZ-identified and large trades never surpass 0.015 and are associated with negligible baseline adjusted-R^2. Panel E verifies that $dLend/Lratio$ maintains the strongest association with dIO when the other three proxies are also included as independent variables.[25]

The weak performance of alternatives relative to $dLend/Lratio$ should not surprise. First, ANcerno institutional volume accounts for 8-12% of the total trading volume (Hu et al., 2018). Assuming that institutional volume accounts for 70% of the the total volume, it follows that ANcerno data covers only less than 20% of all institutional trades. Thus, as institutions can lend up to 30% of their holdings, our proxy likely offers a more accurate picture of overall institutional trading.

Second, trade sizes and inferred trading directions cannot effectively identify institutional trades. In today's order-driven fragmented markets, institutional investors employ sophisticated trade execution algorithms that split their intended (parent) orders dynamically and across trading venues and order types. As such institutional trades often appear in the form of small trades. Moreover, the frequent use of limit orders, low-latency, and prevalent trading at the quote midpoints renders the Lee-Ready unable to accurately sign errors. As such, classification of large trades into buy and sell becomes a challenge. See O'Hara (2015) for discussion of these issues.

Third, even though the imbalance in -1 times BJZZ-identified trades explains dIO with the expected positive sign, its explanatory power is minimal. This is consistent with Barardehi et al. (2024)'s finding that BJZZ-identified trades are inversely related to institutional trading only when institutional investors with pressing liquidity demand have difficulty locating institutional trade counterparties. In such conditions, wholesalers internalize unequal amounts of retail buy and sell trades to provide liquidity to institutions, and the BJZZ algorithm picks up this imbalance. In normal times, however, institutions trade with

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[25] Of note, the sample period for this analysis is from 2010 through 2014, reflecting limited ANcerno data.

other institutional counterparties at the midpoint, without a need to purchase liquidity from wholesalers. As a result, the inverse link between the imbalance in BJZZ-identified trades and institutional trading interest should not be strong in normal market conditions.

4.2 In-Sample Conditional Performance

We first condition equation (1) estimates on stock characteristics. Specifically, in each quarter, we sort firms into two equally-large groups based on each of the following firm or security loan characteristics: Lend/IO, i.e.; *Lratio*, Utilization, which is the average ratio of shares on loan to lendable shares across security loans; Average Tenure, i.e., the average time duration for which loans were outstanding; #Owners; IOC_HHI; log(MarketCap); BtoM; Past_Year_Return; log(Inst_Holding), i.e., the natural log of the number of shares held by institutional investors; and Id_Vol. In each subsample, we fit Fama-Macbeth estimates of equation (1) using standardized $dLend/Lratio$ as the independent variable and adopting Newey-West standard errors with 3 lags.

[Insert Table 4 here]

Panel A in Table 4 suggests that the association between our proxy and the actual quarterly changes in IO change is stronger among stocks with more active security lending activity, reflected in higher utilization rates or lower average loan tenure. However, this association does not appear to significantly vary with *Lratio*. Since *Lratio* is highly persistent characteristic (see Table 2), this finding highlights the validity of our proxy regardless of the "economic importance" of security lending at the individual stock level. Panel B shows stronger association between our proxy and dIO for stocks with less concentrated institutional ownership, where the lendable equity is unlikely driven by the lending policies of a small number institutions holding a stock. Finally, Panel C reports stronger associations in large stocks, growth stocks, volatile stocks and recent winners, i.e., stocks that are likely to be associated with greater lending turnover.

We next establish that the association between dIO_q and $dLend_q/Lratio_{q-1}$ varies modestly with compositions of institutional investors holding a stock. Similar to Subsection 3.4, We control for the heterogeneity in institutional investors based on legal institution types, i.e., banks, insurance companies, investment corporations, independent advisors, and other investors (Aggarwal et al., 2015); and institutional-investor categories, i.e., dedicated, quasi-indexer, and transitory (Bushee, 1998). Thus, we split the sample of stocks in each quarter q into stocks with low versus high participation by a given investor type/category in the preceding quarter, before fitting equation (1). Our findings in Table 5 suggest that the association and goodness of fit metrics, captured by equation (1), vary minimally with institutional-investor composition.

[Insert Table 5 here]

4.3 Out-of-Sample Performance: OLS

In our baseline proxy $dLend/Lratio$, the sensitivity of IO to lendable equity is assumed to be equal to $1/Lratio$, measured at the end of the previous quarter. Conditional performance analyses show that this sensitivity could vary across stocks and over time, a feature that we incorporate in this subsection using OLS regressions.

In each quarter q^*, using data from quarters $q^* - 20$ through $q^* - 1$, we fit

$$dIO_{jq} = a_0 + \sum_{k \in K} a_k \left[dLend_{jq} \times Var^k_{j,q-1} \right] + u_{jq}, \tag{2}$$

where Var^k_{q-1} denotes the stock characteristics, used in Table 4, or participation by investors with different legal types or styles, used in Table 5. The estimated coefficients, combined with stock characteristics observed at the end of quarter q^* and the observed $dLend$ in quarter $q^* + 1$, generates the estimated daily IO change, $\widehat{dIO_{q^*+1}}$. To examine the out-of-sample fit, we regress the actual dIO_q on the estimated $\widehat{dIO_q}$ for each quarter where both quantities are available and then average the R^2_q's across quarters.

Since our sample spans 2007-Q1 through 2021-Q4, employing 20 quarters to "train" equation (2) and skipping one quarter before making an out-of-sample estimation mean that our estimated dIO's are available as of 2013-Q2.

[Insert Table 6 here]

In Panel A in Table 6, we first report the in-sample performance of the four proxies in this shorter out-of-sample period. As in Table 3, our baseline proxy $dLend/Lratio$ outperforms the other three alternatives by a large margin. Its R^2 averages at 13.8%, which is far greater than the analogues for existing alternatives—the second best predictive power belongs to *Institution_Trade* (ANcerno), with a R^2 averages of only 4.99%.

In Panel B in Table 6, we report the performance of $\widehat{dIO_{q^*+1}}$, which models the sensitivity of IO to lendable equity as a linear function of observable stock characteristics. Consistent with the links between $dLend/Lratio$'s goodness of fit for dIO and stock characteristics, the more flexible equation (2) that augment these characteristics in the estimation procedure notably improves the average R^2 to 17.7%. In contrast, consistent with the much weaker links between $dLend/Lratio$'s goodness of fit for dIO and investor type/style participation, documented in Table 5, augmenting these metrics improves the average R^2 only marginally to 15.06%. Further reinforcing the limited role of investor heterogeneity, augmenting the prediction procedure with both stock characteristics and investor heterogeneity metrics yields a R^2 to 17.55%. Thus, the use of stock characteristics as additional observables leads to the best predictive power in an OLS setting.

4.4 Out-of-Sample Performance: Machine Learning

In this subsection, we address the possibility that equation (2) is too parsimonious to capture the potentially complex and non-linearities in the relationships between IO's sensivity with respect to *Lend* and stock characteristics. We employ machine learning (ML) algorithms to determine the "best" functional form governing these links. That is, we use

$$dIO_{jq} = Sensitivity(Char^1_{j,q-1}, \ldots, Char^k_{j,q-1}, Lratio_{j,q-1}) \times dLend_{jq}, \tag{3}$$

where stock characteristics ($Char$) used are lendable equity, utilization rate, average tenure, number of institutional owners, institutional ownership concentration, market cap, book-to-market ratio, past year return, and idiosyncratic volatility, all obtained from the previous quarter. With the exception of changes in lendable equity, the remaining characteristics are categorized into ten deciles each quarter and assigned values ranging from 1 to 10. Again, we use data from the preceding 20 quarters to train the model, skip one quarter, and then estimate dIO one quarter ahead.

For a quarter q^*, we first use standalone nonlinear models, Elastic Net, Random Forest and Gradient Boosting to to train and validate $\mathit{Sensitivity}(., q) \equiv dIO_{jq}/dLend_{jq}$ using the above stock characteristics and date spanning $q^* - 20$ through $q^* - 1$.[26] We then use the product of the estimated $\mathit{Sensitivity}(., q^* + 1)$ and $dLend_{q^*+1}$ to obtain $\widehat{dIO_{q^*+1}}$. We also employ an ensemble of Elastic Net and Random Forest as well as an ensemble of Elastict Net, Random Forest, and Gradient Boosting. Ensemble methods involve averaging the out-of-sample estimates generated by the underlying standalone models. For instance, the ensemble of Elastic Net, Random Forest, and Gradient Boosting averages the outputs of these three models for estimated $\mathit{Sensitivity}(., q^* + 1)$. As before, the second step involves fitting quarterly cross-sectional regressions of dIO on $\widehat{dIO}$ and averaging the resulting R^2s across quarters. Panel C in Table 6 summarizes our findings.

Reflecting the tendency of ML algorithm to over-fit outliers, we trim the most extreme top *and* bottom 0.5%, 1%, 2.5%, and 5% of the sensitivity estimates from the training sample—but not from the validation and out-of-sample periods. Consistent with the sensitivity of ML algorithms to inclusion of outliers, Panel C in Table 6 documents the beneficial effects of outlier exclusions on the out-of-sample performance of our proxy.

A more general observation, however, is that the use of machine learning does not appear to be decisively superior to the OLS-regression approaches reported in Panel B of Table 6. Specifically, average R^2's reported in Panel C of Table 6 indicate that the use of ML would

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[26] Training data covers quarters from $q^* - 20$ to $q^* - 2$, with quarter $q^* - 1$ reserved for validation.

lead to minimal improvements in the out-of-sample performance of our proxy—average R^2s are only slightly larger than the 17.7% figure reported in Panel B of Table 6 *only if* we remove at least 10% of observations with most extreme sensitivity estimates. We therefore recommend that researchers interested in a measure that accounts for heterogeneity across stocks and over time to follow our parsimonious OLS approach with stock characteristics.

5 Daily IO Changes: Determinants and Applications

In this section, we first document the association between our proxy of daily changes in IO and several firm characteristics, as well as market conditions. We then apply our proxy to study daily *net* institutional trading in different contexts. Unless stated otherwise, throughout this section, we shift $dLend_{jt}$ backward by 2 or 3 days to account for settlement gaps between equity and security lending markets discussed in Subsection 2.3. Our findings from these applications align with the existing literature and uncover new patterns consistent with strategic institutional investor trading and price under-reaction.

5.1 Determinants of Daily IO Changes

We relate our proxy of daily net changes in IO and its absolute values to several observable stock characteristics and market outcomes. For $Y_{jt} \in \{dLend_{jt}/Lratio_{j,q-1}, |dLend_{jt}/Lratio_{j,q-1}|\}$ on day t of month m, with $Lratio$ recorded at the end of the previous quarter, we estimate

$$\begin{aligned} Y_{jt} &= \sum_{i=1}^{5} a_i Y_{j,t-i} + b_1 \times cret_{j,t-5}^{t-1} + b_2 \times cret_{j,t-10}^{t-6} + b_3 \times cret_{j,t-30}^{t-11} + b_4 \times cret_{j,t-125}^{t-31} \\ &+ b_5 \times cret_{j,t-250}^{t-126} + c_1 \times SIZE_{j,m-1} + c_2 \times BM_{j,m-1} + c_3 \times TO_{j,m-1} \\ &+ c_4 \times OCAM_{j,m-1} + c_5 \times Volatility_{j,m-1} + c_6 \times MISP_{jm} + Y_0 + u_{jt}, \end{aligned} \tag{4}$$

where $Y_{j,t-i}$ denotes stock j's lagged Y quantities from days $t-1$ to $t-5$; $cret_l^h$ is the cumulative returns from day l to h; $SIZE$ is the natural log of market-capitalization; BM

is the book-to-market ratio; TO is share turnover; $OCAM$ is the open-to-close Amihud illiquidity measure (Barardehi et al., 2021); $Volatility$ is the daily return standard deviation; and $MISP$ is Stambaugh et al. (2012)'s monthly mis-pricing factor. We estimate the model using Fama-MacBeth regressions of daily cross sections, applying the Newey-West correction with 30 lags to standard errors.

Panel A in Table 7 shows that, consistent with institutional investors' market-making activities (Anand et al., 2012), $dLend_{jt}/Lratio_{j,q-1}$ displays a rapidly decaying negative auto-correlation—Subsections 5.4 provides additional suggestive evidence of institutional market making. Moreover, consistent with Griffin et al. (2003), net daily changes in institutional holdings tend to be higher in stocks with past higher returns. Lastly, $dLend_{jt}/Lratio_{j,q-1}$ tend to be higher in less liquid and more volatile stocks, and institutions appear to be expanding net positions in undervalued stocks as reflected by the loading on Stambaugh et al. (2012)'s factor. Panel B in Table 7 reports on an analogous analysis for $|dLend_{jt}/Lratio_{j,q-1}|$, suggesting that the magnitudes of the net changes in IO holdings persists over time, tend to be higher in recent loser stocks, value stocks, less liquid stocks, and undervalued stocks.

5.2 Institutional Trading around Earnings Announcements

A natural starting point to apply our daily proxy is to examine it around major corporate events to shed light on how institutional investors behave in such settings. Thus, we begin by exploring the behavior of our measure around earnings announcements. In Panel A of Figure 3, we plot daily means and 95% confidence intervals of $dLend_{jt}/Lratio$ in 21-day event windows around earnings announcement dates.[27]

[Insert Figure 3 here]

Panel A shows that institutions tend to unwind their holdings before earnings announcements and re-establish them afterwards. These patterns suggest that Di Maggio et al. (2023)'s findings using actual trades of institutional investors in ANcerno data pre 2015,

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[27] Qualitatively similar patterns obtain if we use $\widehat{dIO_{jt}}$ estimated using equation (2).

which we replicate in Panel E, are generalizable to a much broader sample. To the extent that *Non-retail_Trade* is an inverse measure of institutional trading, Panel D, which replicates Laarits and Sammon's (2025) results—i.e., that BJZZ flow spikes in days prior to earnings announcements but drops immediately after them before rebounding to its normal levels—further reinforces our findings. Of note, Panel F documents that *Trade>50K* displays no clear pattern around earnings announcements.

Relatedly, Johnson and So (2018) report that trading costs, especially cost of selling, also rise prior to earnings announcements and attribute the effect to financial intermediaries' tendencies to reduce their exposure to announcement risk. That is, an increased liquidity demand by institutions is coupled by a reduction in liquidity supply prior to earnings announcements. As such, price impacts of institutional trading prior and after the announcement could contribute to the increased return commonalities around earnings announcements, as well as the well-known earnings announcement premium (see, e.g., Beaver, 1968; Yang et al., 2020).

Uncovering the the economics roots of these patterns is outside the scope of our paper. The literature offers a number economic explanations for this premium. For example, Patton and Verardo (2012) and Savor and Wilson (2016) offer explanations based on information spillovers and the resulting changes in systematic risk, while Barber et al. (2013) and Yang et al. (2020) document that idiosyncratic risk rises around announcements. Di Maggio et al. (2023) use data from 331 mutual funds that that can be matched between ANcerno and CRSP to attribute institutional trading behavior around earnings announcements to post-announcement fund flow sensitivity. They argue that such flow sensitivity constitutes a source of limits to arbitrage for institutional investors that discourages institutions from taking advantage of earnings announcement premium.

Panels B and C plot estimates conditional on, respectively, negative and positive earnings surprises as reflected by by SUE scores obtained from I/B/E/S. We observe more persistent institutional buying post-announcement when the earnings surprise is positive. In this case, the institutional trading measure is positive and significant during the entire 10-day window after the announcement. In contrast, in the event of negative earnings surprise, it quickly becomes indistinguishable from zero.

5.3 Short-term return predictability

We next examine the short-term return predictability of net changes in IO by conducting simple tradable portfolio sorts. On each day t, we sort stocks into 10 portfolios of institutional trading, captured by each of the four proxies, based on NYSE breakpoints. Beginning on day $t + 2$ (or $t + 3$), reflecting the settlement gaps discussed in 2.3, and continuing through the next 20 days, we implement a strategy that goes long the highest (most positive) institutional-trading portfolio and short the lowest (most negative) portfolio. We accumulate the resulting returns and risk-adjust them using the Fama-French five, momentum, and short-term reversals factors.

[Insert Figure 4 here]

Figure 4 presents point estimates and 95% confidence intervals of the short-term return predictability of institutional trading measures. We find that directional institutional trading is followed by significant negative returns, consistent with price reversals followed by directional institutional trading (Campbell et al., 1993; Hendershott and Menkveld, 2014). Our results are especially pronounced for $dLend/Lratio$. Of note, Boehmer et al. (2021) attribute *Non-retail_Trade*'s predictability to informed retail trading, while Barardehi et al. (2024) attribute it to price reversals following institutional price pressure in markets with unusually high institutional demand for liquidity. Our findings using $dLend/Lratio$ seem consistent with the latter.

5.4 Long-term return predictability

Finally, we apply our proxy of daily IO changes in the context of the momentum anomaly, highlighting the role of net institutional trading for momentum. We motivate this analysis by the premise that institutional trading reveals fundamental information (Sias et al., 2006) and therefore leads prices to reflect fundamental asset values more precisely. Thus, market participants put some weight on net changes in institutional holdings when assessing whether associated price movements reflect information about fundamental asset values. Our daily proxy allows us to separate past price movements that align with changes in IO from those that oppose them to examine whether these two types of price signals have different return predictability in the context of the momentum anomaly.

Since institutional investors primarily trade intraday (Lou et al., 2019), we focus on the alignment of *intraday* returns, denoted IDR, and proxied daily changes in IO, $dLend/Lratio$. Following Barardehi et al. (2025), we examine month-m's 3-factor alphas of trading strategies that buy past winners and sell past losers according to compound intraday returns from months $m-12$ to $m-2$.[28] However, before compounding past intraday returns, we split them into those that align with the corresponding daily change in IO, i.e., $\text{sign}(IDR) = \text{sign}(dLend)$, and those that do not, i.e., $\text{sign}(IDR) \neq \text{sign}(dLend)$. Table 8 reports portfolio sort results using NYSE breakpoints.[29] We find that momentum strategies based on past intraday signals are only profitable when the signs of past intraday returns oppose those of daily changes in IO. The 3-factor alphas (t-statistics) of momentum strategies based on signals with $\text{sign}(IDR) = \text{sign}(dLend)$ and $\text{sign}(IDR) \neq \text{sign}(dLend)$ are 0.28% (0.84) and 0.78% (2.52), respectively, equivalent to a statistically significant difference of 0.50% (2.57). Importantly, these findings are not driven by the variation in the distribution of days with $\text{sign}(IDR) = \text{sign}(dLend)$ versus those with $\text{sign}(IDR) \neq \text{sign}(dLend)$. In fact, the number of trading days entering the constructions of portfolio formation signals is evenly distributed across the two cases and remains roughly stable across portfolios.

[Insert Table 8 here]

We find that momentum strategies become unprofitable when positive (negative) past

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[28] Our qualitative findings extend if we instead use signals from months $m-7$ to $m-2$. Moreover, not only are past overnight signals irrelevant for our analysis, but Barardehi et al. (2025) show that momentum strategies based on past overnight signals are not profitable.

[29] Qualitatively similar results obtain using CRSP breakpoints.

intraday return signals are associated with expansions (contractions) of institutional positions. When sign(IDR) = sign($dLend$), average compound intraday return in the formation period rises from −58.50% at the bottom portfolio to 45.34% at the top portfolio (a spread of 103.84%), and aggregate $dLend/Lratio$ rises from 0.00 at the bottom portfolio to 0.14 at the top, with a statically insignificant holding-period 3-factor alpha. Of note, aggregate overnight returns that follow intraday signals, denoted $FONR$, indicate nearly no immediate overnight price reversals at the top portfolios during the formation period, i.e., in the top portfolio intraday returns revers by only 0.42/45.34 = 0.92%. This lack of reversals suggests that the expansions of institutional positions that are associated with large positive intraday returns are likely motivated by information that is impounded in prices in the form of permanent price impacts.

By contrast, when sign(IDR) $\neq$ sign($dLend$), average compound intraday return rises from −61.82% at the bottom portfolio to only 35.05% at the top (a spread of 96.85%), with aggregate $dLend/Lratio$ falling from 0.08 at the bottom portfolio to 0.03 at the top—that is, institutions tend to expand positions across all portfolios, just less so as we go from the bottom portfolio to the top. The smaller spread between intraday signals at the top and bottom portfolios is then followed by a statistically significant holding-period 3-factor alpha of 0.78%. Of note, aggregate $FONR$ suggests that institutions selling when intraday returns are at the top portfolio enjoy a 5.78/35.05 = 16.5% immediately subsequent price reversal. This is consistent with institutional investors timing their liquidity consumption to save on trading costs.

We implement the same decomposition of momentum signals using the three alternative proxies of daily institutional trading. Consistent with the second best performance of ANcerno-reported actual institutional trades in tracking daily institutional trading, established in Panel A of Table 6, $Institution\_Trade$ is the only proxy that yields momentum results similar to the analogous strategies based on $dLend$. Concretely, the 3-factor alphas (t-statistics) of momentum strategies based on signals with sign(IDR) = sign($Institution\_Trade$)

and sign(IDR) $\neq$ sign(*Institution_Trade*) are -0.63% (-1.07) and 0.98% (2.26), respectively, equivalent to a statistically significant difference of 1.61% with a t-statistic of 4.56. The difference in analogous alpha obtained using *Non-retail_Trade* is -0.40 with a t-statistic of -1.61, i.e., this difference is statistically insignificant. Moreover, consistent with the very different behavior of *Trade>50K* in our several other tests, the difference in analogous alphas obtained using this measure is -0.78, with a t-statistic of -3.24.

Our collective findings are consistent with under-reaction theories of the momentum anomaly. To the extent that changes in net institutional holdings facilitate incorporation of information into prices, the alignment of these changes with intraday price signals may shed light on the sources of momentum. Specifically, market participants may place a weaker weight on price signals that are not associated with net institutional activity in the same direction, and this leads participants to under-react to intraday price signals when these signals do not align with the corresponding changes in institutional ownership. This under-reaction manifests itself in the form of momentum as future prices adjust.

6 Conclusion

Institutions can only lend what they currently own. Based on this simple intuition and the empirical fact that the ratio between lendable equity and institutional ownership (IO) is persistent, we propose to use the (scaled) daily change in lendable equity to track net daily changes in IO at the stock level. We highlight corporate events around which this measure likely reflects factors other than changes in IO. We also show the performance of our measure is related to certain stock characteristics, leading us to construct a metric that accounts for this conditional performance. Overall, we provide guidance on how researchers should utilize our proposed measure.

At the quarterly frequency and during a more recent 2007-2021 sample period, we find the change in lendable equity performs much better in tracking IO change than alternatives based on large trades, non-retail trades, and a subset of actual institutional trades. For example, a one standard deviation increase in lendable equity is associated with a 0.4 unit increase in the standardized actual change in IO. In out-of-sample estimation exercises, we allow the sensitivity of IO to lendable equity to be a linear function of stock characteristics. This approach uses only past data to fit parameters, which we then use to estimate the change in IO using the observed change in lendable equity. With this approach, we find that the change in lendable equity outperforms alternatives, in tracking IO changes, even by greater margins than those found in our baseline tests.

Importantly, lendable equity change at the daily frequency allows us to track daily net institutional trading. Daily analyses reveal three findings. First, institutions unwind their holdings before the earnings announcement and re-establish them afterwards. The resulting price pressure contributes to the well-known earnings-announcement premium. Second, daily institutional trading measures negatively and significantly predict future returns, consistent with the notion of a transitory price impact. Third, we find price momentum anomaly to only exist if institutional trading and intraday returns oppose during the portfolio formation period, consistent with under-reaction.

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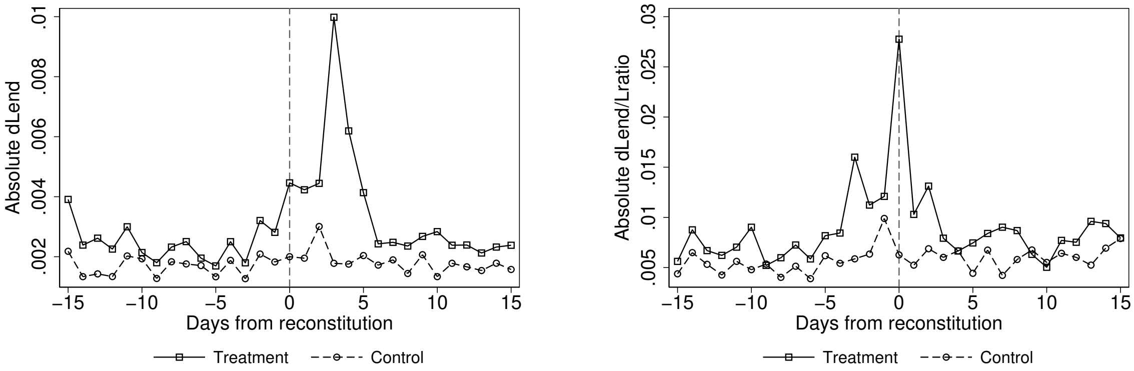
Figures and Tables

Figure 1. Changes in Lendable Equity, Changes in Scaled Lendable Equity Adjusted for Settlement Gaps, and Institutional Trading Volume around Index Reconstitution Dates. This figure reports on the variation in absolute changes in the number of lendabel shares, the absolute value of our proxy of net daily change in institutional ownership, and the actual institutional trading volume around stock index reconstitution dates. Each year, index-switching stocks between Russell-1000 and Russell-2000 indexes on the last Friday of June are selected as "treatment" stocks. For each index-switching stock, the two stocks whose Russell-1000/2000 rankings in the preceding May fall immediately above and below the treated stock are used as control stocks. Panel A plots the medians of $|dLend_{jt}|$ for treated and control firms in 30-day event windows around reconstitution dates. Panel B plots the medians of absolute values of our proxy of net institutional trading, i.e., $|dLend_{j,t+3}/Lratio|$, where $Lratio$ divides $Lend$ three days after the previous-quarter's end to IO at the end of the previous quarter. $dLend$ is shifted by three days reflecting the three-day gap between actual trade and settlement days in the security lending market. Panel C plots the median share of actual institutional trading volume, observed in ANcerno data, in total number of shares outstanding. The sample includes Russell-1000 and Russell-2000 common stocks from 2010 through 2016, with ANcerno data limited to 2010 through 2014.



Panel A: Change in lendable shares

Panel B: Estimated change in institutional ownership

Panel C: Institutional trading volume (ANcerno)

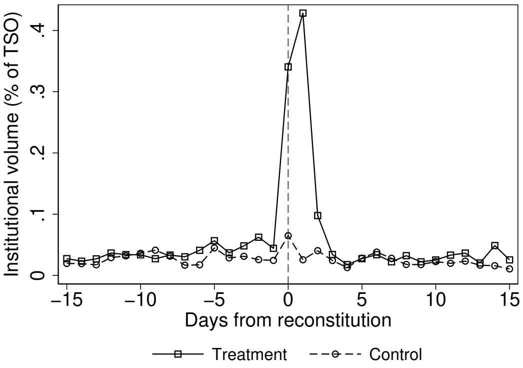


Figure 2. Changes in Lendable Equity around Voting "Record" Dates. This figure reports on average net changes in $dLend_{jt}/Lratio$ around voting record dates. The figure plots daily means and 95% confidence intervals of $dLend_{jt}/Lratio$ in 21-day event windows around 19,462 voting record dates that occurred among common NMS-listed stocks from January 2008 though February 2019. The data on voting record dates is similar to the that compiled by Fos and Holderness (2021). To account for settlement gaps between equity and security lending markets, $dLend_{jt}/Lratio$ observations shifted backward three days prior to September, 6, 2017 and are shifted backward two days as of September, 6, 2017. Daily $dLend_{jt}/Lratio$ observations are winsorized at 1% and 99%. Confidence intervals reflect standard errors that are clustered by date.

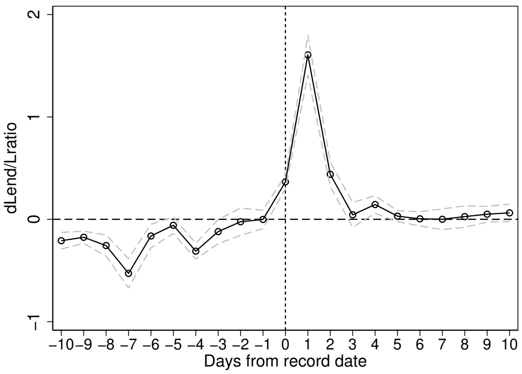
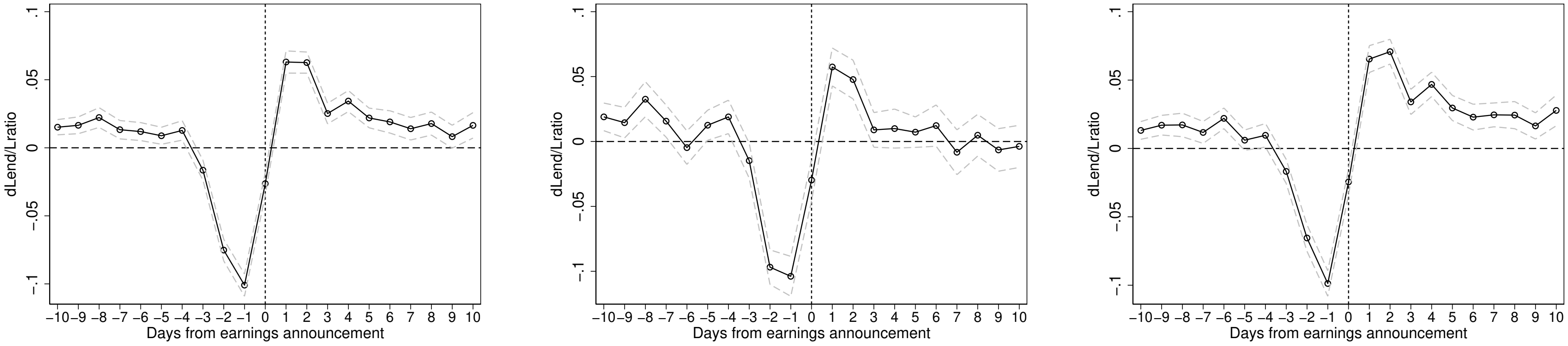


Figure 3. Daily Institutional Trading around Earnings Announcements. This figure reports on daily institutional trading around earnings announcements, using different proxies. Panel A plots daily means and 95% confidence intervals of $dLend_{jt}/Lratio$ in 21-day event windows around earnings announcement dates. Panels B and C plot analogues of Panel A estimates for, respectively, negative and positive earnings surprises. Panels, D, E, and F plot daily means and 95% confidence intervals of *Institution_Trade*, *Non-retail_Trade*, and *Trade>50K*, respectively. Earnings announcement dates and SUE scores for earnings surprises are obtained from I/B/E/S. To account for settlement gaps between equity and security lending markets, $dLend_{jt}/Lratio$ observations are shifted backward three days prior to September, 6, 2017 and two days as of September, 6, 2017. Daily $dLend_{jt}/Lratio$ observations are winsorized at 1% and 99%. Confidence intervals reflect standard errors that are double-clustered by stock and date. The sample includes all NMS-listed common shares in 2007-Q4 through 2021-Q4 for *dLend/Lratio*, 2007-Q1 through 2021-Q4 for *Trade>50K*, 2010-Q1 through 2021-Q4 for *Non-retail_Trade*, and 2007-Q1 through 2021-Q4 for *Institution_Trade* (ANcerno).



Panel A: All announcements

Panel B: Announcements with SUE< 0

Panel C: Announcements with SUE> 0

Panel D: ***Institution_Trade***, all announcements

Panel E: ***Non-retail_Trade***, all announcements

Panel F: ***Trade>50K***, all announcements

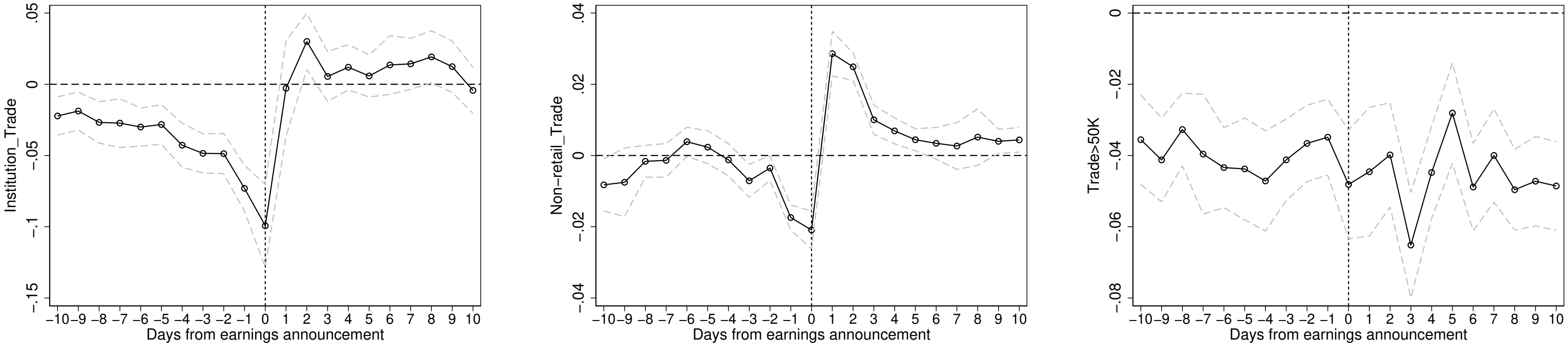
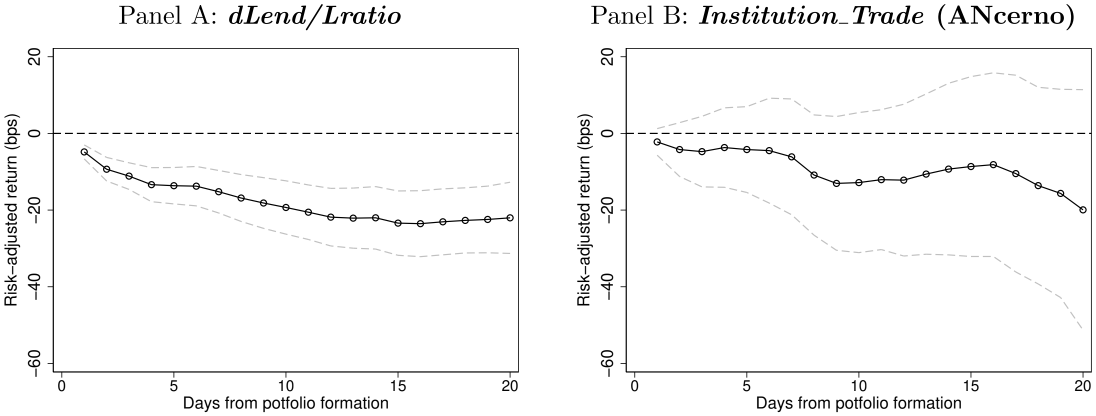
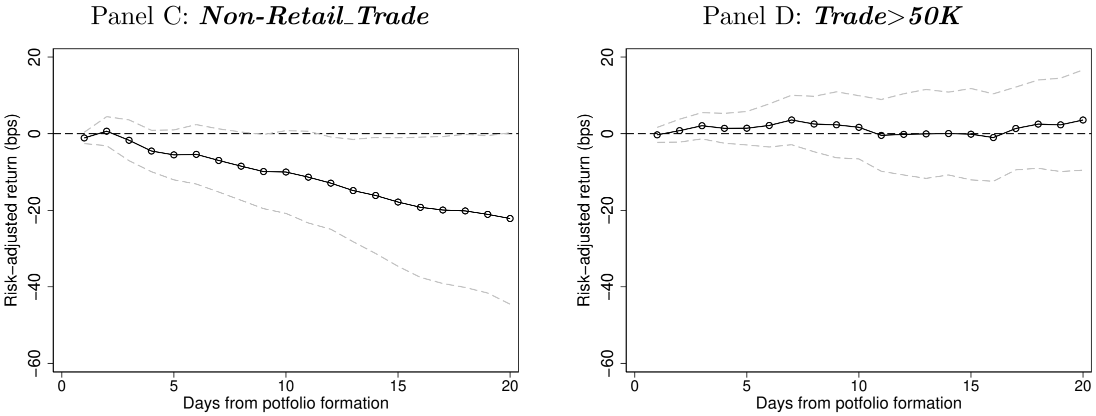


Figure 4. Short-term Return Predictability of Daily Institutional Trading. This figure plots the cumulative sum of risk-adjusted daily returns over the 20 trading days following portfolio formation. On day t, stocks are sorted into ten portfolios for each of the four institutional-trading proxies. Beginning on day $t+2$ (or $t+3$), reflecting the settlement gaps discussed in 2.3, and continuing through the next 20 days, a strategy that goes long the highest (most positive) institutional-trading portfolio and short the lowest (most negative) portfolio is implemented. Portfolios are constructed using NYSE breakpoints, and the strategy's profits reflect equally-weighted cumulative future returns. Long–short returns are adjusted using the daily Fama–French five factors, the momentum factor, and the short-term reversal factor. The 95% confidence bands are computed using Newey–West standard errors with 60 lags. The sample includes all NMS-listed common shares in 2007-Q4 through 2021-Q4 for *dLend/Lratio*, 2007-Q1 through 2021-Q4 for *Trade>50K*, 2010-Q1 through 2021-Q4 for *Non-retail_Trade*, and 2007-Q1 through 2014-Q3 for *Institution_Trade* (ANcerno).



Panel A: ***dLend/Lratio***

Panel B: ***Institution_Trade* (ANcerno)**



Panel C: ***Non-Retail_Trade***

Panel D: ***Trade>50K***

Table 1. Summary Statistics. This table reports mean, median, standard deviation, the 5th and 95th percentiles, skewness, kurtosis, and the number of observations of the key variables, constructed quarterly. *IO* is the split-adjusted institutional holdings normalized by the total share outstanding; *Lend* is the split-adjusted lendable shares normalized by the total share outstanding; Change in *IO* is the split-adjusted change in institutional holdings normalized by the total share outstanding; Change in *Lend* is the split-adjusted change in lendable shares normalized by the total share outstanding; Utilization measures the average ratio of shares on loan to lendable shares across security loans,; Average_Tenure measures the average time duration for which loans were outstanding; **#Owners** is the number institutional owners; IOC_HHI is the Herfindahl index of institutional ownership concentration; log(MarketCap) is the natural log of the product of closing price and the number of shares outstanding; BtoM is the book-to-market ratio based on the most recently observed book value and share price; Past_Year_Return is calculated by the average return of the stocks over past one year; Id_Vol is the idiosyncratic volatility is the standard deviations of residuals of market model estimated using weekly data over the previous quarter; *Non-retail_Trade* is −1 times the imbalance between buyer- vs. seller- initiated internalized retail trades identified by the BJZZ algorithm in TAQ; *Institution_Trade* is the institutional order flow obtained from ANcerno; *Trade>50K* is imbalance between buyer- vs. seller- initiated trades with dollar volumes of at least $50,000 obtained from TAQ; and *Lend/IO* is the ratio of lendable share and institutional holdings. The sample includes all NMS-listed common shares in 2007-Q1 through 2021-Q4 for *Trade>50K*, 2010-Q1 through 2021-Q4 for *Non-retail_Trade*, and 2007-Q1 through 2014-Q3 for *Institution_Trade* (ANcerno), and 2007-Q4 through 2021-Q4 for other variables.

	Mean	**Median**	**Std**	**p5**	**P95**	**skew**	**kurt**	**N**
IO	0.64	0.70	0.26	0.12	0.96	−0.66	−0.66	105169
Lend	0.22	0.22	0.12	0.03	0.42	0.20	−0.25	105169
Lend/IO	0.35	0.34	0.14	0.13	0.56	3.53	116.82	105169
Change in *IO*	0.01	0.00	0.06	−0.06	0.09	2.81	32.50	105169
Change in *Lend*	0.00	0.00	0.03	−0.03	0.05	0.08	46.12	105169
Utilization (%)	17.42	9.55	19.81	1.45	64.43	1.86	3.12	105169
Average Tenure (days)	88.73	70.23	77.26	17.14	217.97	3.82	31.11	105167
#Owners	191.81	124.00	221.06	21.00	606.00	3.43	17.83	105169
IOC_HHI	0.09	0.06	0.09	0.03	0.26	3.60	17.78	105169
log(MarketCap)	20.47	20.36	1.83	17.55	23.63	0.15	−0.03	105169
BtoM	3.14	3.02	1.34	1.13	5.58	0.58	0.68	105169
Past_Year_Return	0.15	0.12	0.64	−0.70	1.05	4.51	83.73	105167
Id_Vol	0.06	0.05	0.05	0.02	0.13	9.44	296.05	103559
Institution_Trade	0.00	0.00	0.02	−0.02	0.02	5.21	434.31	46936
Non-retail_Trade	0.00	0.00	0.02	−0.01	0.01	−19.16	1244.01	85368
Trade>50K	−0.02	−0.01	0.22	−0.37	0.30	−3.18	154.95	96977

Table 2. Impact of Stock/Security Loan Characteristics on the Ratio of Lendable Quantity to Institutional Ownership. This table presents the associations between the ratio of quarterly lendable shares to institutional ownership and security loan and stock characteristics as defined in Table 1 along with the composition of institutional investors holding a stock. Each quarter, the dependent variable (*Lend/IO*) divides the quantity of lendable shares, obtained from Markit, by the split-adjusted number of shares owned by institutional investors, obtained from 13F filings—both quantities are first scaled by shares outstanding. Institutional investor compositions are measured using the fraction of shares owned by institutional investors of each legal type, i.e., Bank, Insurance Corp, Investment Corp., and Independent Advisor, (Aggrawal et al., 2015) or investment categories, i.e., dedicated, quasi-indexer, and transitory (Bushee, 2004), in all institutionally held shares. Lending Fee Score takes two values: it equals 1 when the Markit value is 1, and 2 when the Markit value is in between 2 and 10; higher scores indicate more expensive security loans. Short Interest comes from COMPUSTAT. #Owners is the number of institutional investors holding the stock. IOC_HHI is the Herfindahl ownership concentration index among institutions. IO/Shrout is the number of shares held by institutions divided by the number of outstanding shares. log(MarketCap) is the log of the product of closing price and the number of shares outstanding. BtoM is the book-to-market ratio based on the most recently observed book value and share price. Past_Year_Return is calculated by the average return of the stocks over past one year; **Id_Vol**, the idiosyncratic volatility, is the standard deviation of residuals of a market model estimated using weekly data over the previous quarter. Specification (1) regresses *Lend/IO* on *Lend/IO* in previous quarter; Specification (2) regresses *Lend/IO* on the fractions of shares held by different legal types; specification (3) regresses *Lend/IO* on the fractions of shares held by different investor categories; specification (4) regresses *Lend/IO* on stock characteristics; Specification (5) includes *Lend/IO* in previous quarter and all controls; and specification (6) includes all controls. The sample includes all NMS-listed common shares covered by Markit in 2007-Q4 through 2021-Q4. Standard errors are Newey-West adjusted with 3 lags. The numbers in parentheses are *t*-statistics with ***, **, and * identifying statistical significance at the 1%, 5%, and 10% levels, respectively.

	Dependent Variable = *Lend/IO*					
	(1)	(2)	(3)	(4)	(5)	(6)
Lagged *Lend/IO*	0.857***				0.803***	
	(54.07)				(44.38)	
Legal Investor Type:						
Banks		0.670***			0.115***	0.515***
		(8.48)			(4.05)	(7.15)
Insurance Corp		0.417***			0.108***	0.456***
		(7.86)			(6.71)	(17.98)
Investment Corp		0.694***			0.125***	0.473***
		(3.85)			(3.08)	(3.12)
Independent Advisor		0.052			0.009	0.049
		(1.02)			(0.70)	(1.05)

Continued on next page

Table 2 – *continued from previous page*

Investor Style Category:						
Dedicated			−0.087		0.006	−0.055
			(−1.54)		(0.52)	(−1.34)
Quasi−Indexer			0.181**		0.038***	0.106**
			(2.68)		(3.04)	(2.33)
Transitory			0.154**		0.027**	0.099**
			(2.67)		(2.26)	(2.27)
Stock Characteristic:						
Lending Fee Score				0.005	0.004**	0.005
				(1.00)	(2.18)	(0.97)
Short Interest				−0.003	−0.004	−0.009
				(−0.37)	(−1.10)	(−1.28)
#Owners				−0.000	−0.000	−0.000**
				(−0.62)	(−1.58)	(−2.13)
IOC_HHI				−0.469***	−0.067***	−0.270***
				(−18.16)	(−9.36)	(−7.83)
IO/Shrout				−0.121***	−0.024***	−0.072***
				(−12.92)	(−6.42)	(−7.97)
log(MarketCap)				0.000	0.000	−0.004
				(0.07)	(0.06)	(−1.13)
BtoM				0.010***	0.002***	0.008***
				(10.99)	(6.34)	(10.54)
Past_Year_Return				0.004	0.004***	0.004
				(1.34)	(3.20)	(1.32)
Id_Vol				−0.186***	0.033*	0.020
				(−2.81)	(1.71)	(0.41)
Observations	69,847	69,847	69,847	69,847	69,847	69,847
Adjusted R−squared	0.76	0.18	0.11	0.15	0.79	0.29

Table 3. Correlations Between Changes in actual IO and its Proxies. This table presents the associations between the quarterly changes in institutional ownership (dIO) and measures of institutional flow aggregated at the stock-quarter level, using estimates of equation (1). IO is the split-adjusted number of shares owned by institutional investors, obtained from 13F filings, divided by the number of outstanding shares. Panel A through D report pairwise correlations between dIO and, respectively, *dLend/Lratio*, *Institution_Trade*, *Non-retail Trade*, and *Trade>50K*. Panel D includes all four proxies on the left-hand-side. In each panel, Columns 1-3 report results from panel regressions with different sets of fixed effects and Column 4 presents results from a Fama-MacBeth regression. All variables are standardized each quarter to feature a mean of 0 and standard deviation of 1. The sample includes all NMS-listed stocks covered by Markit in 2007-Q4 through 2021-Q4 for *dLend/Lratio* and *Trade>50K*, 2007-Q1 through 2014-Q3 for *Institution_Trade* (ANcerno), and 2010-Q1 through 2021-Q4 for *Non-retail Trade*. Standard errors are clustered by firm in panel regressions and Newey-West corrected using 3 lags in Fama-MacBeth regressions. The numbers in parentheses are t-statistics with ***, **, and * identifying statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Change in IO vs. *dLend/Lratio*

	(1)	(2)	(3)	(4)
dLend/Lratio	0.384***	0.345***	0.386***	0.406***
	(29.48)	(26.25)	(28.24)	(14.35)
Firm FE	No	Yes	No	N/A
Time FE	No	No	Yes	N/A
Observations	105,169	105,169	105,169	105,169
Adj-R^2	0.15	0.19	0.19	0.16

Panel B: Change in IO vs. *Institution_Trade*

	(1)	(2)	(3)	(4)
Institution Trade	0.210***	0.204***	0.199***	0.226***
	(9.49)	(9.71)	(9.21)	(7.55)
Firm FE	No	Yes	No	N/A
Time FE	No	No	Yes	N/A
Observations	46,936	46,936	46,936	46,936
Adj-R^2	0.04	0.10	0.13	0.05

Panel C: Change in IO vs. *Non-retail Trade*

	(1)	(2)	(3)	(4)
Non-retail Trade	0.005	0.012	0.005	0.105***
	(0.75)	(1.48)	(0.76)	(3.52)
Firm FE	No	Yes	No	N/A
Time FE	No	No	Yes	N/A
Observations	85,368	85,368	85,368	85,368
Adj-R^2	0.00	0.09	0.04	0.00

Panel D: Change in IO vs. *Trade>50K*

	(1)	(2)	(3)	(4)
Trade>50K	0.007	0.015***	0.011**	0.014**
	(1.36)	(3.08)	(2.32)	(2.30)
Firm FE	No	Yes	No	N/A
Time FE	No	No	Yes	N/A
Observations	98,143	98,143	98,143	98,143
Adj-R^2	0.00	0.08	0.05	0.00

Panel E: Change in IO vs. different measures of institutional flow

	(1)	(2)	(3)	(4)
dLend/Lratio	0.278***	0.234***	0.302***	0.340***
	(12.19)	(10.23)	(12.31)	(12.58)
Institution_Trade	0.158***	0.168***	0.151***	0.157***
	(8.80)	(8.11)	(8.58)	(12.35)
Non-retail Trade	0.036*	0.057	0.039*	0.217***
	(1.84)	(1.60)	(1.91)	(3.49)
Trade>50K	−0.003	0.002	−0.003	−0.001
	(−0.30)	(0.18)	(−0.35)	(−0.07)
Firm FE	No	Yes	No	N/A
Time FE	No	No	Yes	N/A
Observations	30,700	30,700	30,700	30,700
Adj-R^2	0.12	0.15	0.21	0.18

Table 4. Correlations Between Changes in IO and Changes in Lendable Equity: Conditional on Stock Characteristics. This table presents Fama-MacBeth estimation results of equation (1), with X^s being the standardized *dLend/Lratio*, conditional on previous-quarter-end's security loan and stock characteristics defined in Table 1. For each characteristic and in each quarter, the sample is sorted into two equally-large subsamples. The sample includes all NMS-listed common shares covered by Markit in 2007-Q4 through 2021-Q4. Standard errors are Newey-West adjusted with 3 lags. The numbers in parentheses are t-statistics with ***, **, and * identifying statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Correlations Conditional on Loan Characteristics

	Lend/IO		**Utilization**		**Average Tenure**	
	High	Low	High	Low	High	Low
dLend/Lratio	0.408***	0.419***	0.426***	0.376***	0.313***	0.449***
	(16.06)	(13.69)	(16.40)	(10.28)	(13.76)	(13.99)
Observations	52,599	52,570	52,599	52,570	52,597	52,570
Adj-R^2	0.16	0.17	0.17	0.13	0.09	0.19

Panel B: Correlations Conditional on Institutional Characteristics

	#Owners		**IOC_HHI**		**log(Inst_Holding)**	
	High	Low	High	Low	High	Low
dLend/Lratio	0.431***	0.399***	0.368***	0.464***	0.425***	0.398***
	(15.89)	(12.20)	(11.05)	(15.24)	(12.92)	(14.76)
Observations	52,595	52,574	52,599	52,570	52,599	52,570
Adj-R^2	0.18	0.16	0.13	0.21	0.17	0.15

Panel C: Correlations Conditional on Firm Characteristics

	log(MarketCap)		**BtoM**		**Past_Year_Return**		**Id_Vol**	
	High	Low	High	Low	High	Low	High	Low
dLend/Lratio	0.454***	0.386***	0.371***	0.433***	0.445***	0.357***	0.410***	0.364***
	(15.08)	(12.45)	(12.98)	(13.28)	(14.05)	(13.18)	(13.38)	(13.73)
Observations	52,599	52,570	52,599	52,570	52,599	52,568	51,796	51,763
Adj-R^2	0.20	0.14	0.13	0.18	0.19	0.12	0.16	0.13

Table 5. Correlations Between Changes in Institutional Ownership and Changes in Lendable Equity: Conditional on Investor Type/Style. This table presents Fama-MacBeth estimation results of equation (1), with X^s being the standardized $dLend/Lratio$, conditional on the fraction of shares owned by institutional investors of each legal type according to (Aggrawal et al., 2015) or categories according to (Bushee, 1998) at the end of the previous quarter in a given stock. The sample of stocks is sorted into two equally-large subsamples using each type or category in each quarter. The sample includes all NMS-listed common shares covered by Markit in 2007-Q4 through 2021-Q4. Standard errors are Newey-West adjusted with 3 lags. The numbers in parentheses are t-statistics with ***, **, and * identifying statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Correlations Conditional on Investor Legal Type Participation

	Bank		**Insurance Company share**		**Investment Company**		**Independent Advisor**		**Other**	
	High	**Low**	**High**	**Low**	**High**	**Low**	**High**	**Low**	**High**	**Low**
dLend/Lratio	0.400***	0.405***	0.415***	0.397***	0.437***	0.383***	0.442***	0.379***	0.403***	0.412***
	(11.37)	(12.76)	(14.51)	(11.50)	(13.64)	(11.34)	(14.28)	(9.69)	(10.51)	(13.94)
Observations	39,995	39,972	39,995	39,972	39,995	39,972	39,995	39,972	39,995	39,972
Adj-R^2	0.16	0.16	0.17	0.16	0.19	0.15	0.19	0.15	0.16	0.17

Panel B: Correlations Conditional on Investor Category Participation

	Dedicated		**Quasi-Indexer**		**Transitory**	
	High	**Low**	**High**	**Low**	**High**	**Low**
dLend/Lratio	0.394***	0.386***	0.361***	0.391***	0.425***	0.319***
	(11.51)	(13.57)	(10.87)	(13.88)	(14.32)	(10.85)
Observations	49,639	30,328	49,648	30,319	49,648	30,319
Adj-R^2	0.16	0.15	0.14	0.15	0.18	0.11

Table 6. Goodness of Fit of Institutional Flow Measures for Changes in Institutional Ownership: Out-of-sample Power of Changes in Lendable Equity. This table presents the performance of various proxies of institutional trading to estimate the cross-section of actual institutional trading. Each quarter, the change in institutional ownership ($\widehat{dIO}$) is estimated using *Non-retail_Trade*, *Institution_Trade*, *Trade>50K*, or *dLend/Lratio*, along with firm characteristics and the legal types and investment styles of institutional investors. The actual change in institutional ownership is then regressed on the estimated change ($\widehat{dIO}$) to obtain R^2 for the quarter. Average R^2 of each proxy is calculated across quarters. Panel A presents average R^2's assuming $\widehat{dIO}$ is equivalent to *Non-retail_Trade*, *Institution_Trade*, *Trade>50K*, or *dLend/Lratio*, fitting equation (1) each quarter from 2013-2021. Panel B presents the average out-of-sample R^2 when $\widehat{dIO}$ is constructed using equation (2), interacting *dLend* with (a) stock characteristics characteristics, used in Table 4, (b) participation by institutional investors with different legal types and styles, used in Table 5, and (c) all variables in (a) and (b). Panel C presents average out-of-sample R^2s when machine learning algorithms are used to construct $\widehat{dIO}$ based on *dLend* and stock characteristics, as in equation (3). The models are trained using Elastic Net, Random Forest, and Gradient Boosting algorithms, along with an ensemble approach that integrates Elastic Net with Random Forest, and another ensemble method that combines all three learning algorithms. In the training samples machine learning methods, the top *and* bottom $y\%$ of $dLend_{jq}/Lratio_{q-1}$ are excluded, with $y \in \{0.5, 1, 2.5, 5\}$

Panel A: Correlations between dIO_q and four proxies of daily change in IO

Change in IO proxy	**Average R^2 (%)**
***dLend*/Lratio**	13.80
Institution_Trade	4.99
Non-retail_Trade	0.34
Trade>50K	0.29

Panel B: Correlations between dIO_q and $\widehat{dIO}_q$ estimated using equation (2)

Interaction variables	**Average R^2 (%)**
Stock characteristics	17.70
Type-category participation	15.06
Stock characteristics + Type-category participation	17.55

Panel C: Correlations between dIO_q and $\widehat{dIO}_q$ estimates using equation (3)

	Average R^2 (%)			
	Trim the highest and lowest y percent elasticities			
Estimation method	$y = 5\%$	$y = 2.5\%$	$y = 1\%$	$y = 0.5\%$
Elastic Net (Enet)	15.98	16.29	16.39	14.91
Random Forest (RF)	18.45	17.60	15.93	13.94
Gradient Boosting (GBRT)	18.19	17.69	16.32	15.04
Ensemble of Enet and RF	18.46	17.80	16.37	14.54
Ensemble of Enet, RF, and GBRT	18.12	17.82	17.05	15.37

Table 7. Determinants of Daily Institutional Trading. This table documents the association between daily institutional trading activity and past daily outcomes. Panel A and B examine these associations for $dLend_t/Lratio_{q-1}$ and $|dLend_t/Lratio_{q-1}|$, respectively, reporting estimates of equation (4). Each institutional trading variable from day t, scaled by 100, is regressed on its lags from days $t-5$ through $t-1$; as well as a combination of the following variables: compound returns over the preceding 5 trading days, $cret_{t-5}^{t-1}$, the 5 days before them, $cret_{t-10}^{t-6}$, the 20 days before them, $cret_{t-30}^{t-11}$, the 95 days before them, $cret_{t-125}^{t-31}$, and the 125 trading days before them, $cret_{t-250}^{t-126}$; previous month-end's log market-capitalization (SIZE) and the book-to-market ratio (BM); previous month's open-to-close Amihud liquidity measure (OCAM) of Barardehi et al. (2021) and daily return standard deviation (Volatility); and the current month's aggregate mispricing factor (MISP) of Stambaugh et al. (2012). Estimates reflect Fama-MacBeth regressions of daily cross-sections with Newey-West standard errors based on 30 lags. Each variable is winsorized at percentiles 1 and 99 daily. The numbers in parenthesis reflect t-statistics, and symbols ***, **, and * identify statistical significance at the 1%, 5%, and 10% type one errors, respectively. The sample includes all NMS-listed common shares in 2007-Q4 through 2021-Q4, but—reflecting the availability of MISP—-limited to 2007-Q4 through 2013-Q4 when MISP is used.

	Panel A: Dependent variable: $Y = dLend/Lratio$				Panel B: Dependent variable: $Y = \|dLend/Lratio\|$			
Constant	0.048***	0.038***	0.085***	−0.027	0.38***	0.35***	0.36***	0.65***
	(8.03)	(6.06)	(2.70)	(−0.36)	(47.13)	(55.34)	(8.75)	(8.37)
Y_{t-1}	−0.46***	−0.47***	−0.47***	−0.44***	0.34***	0.33***	0.33***	0.30***
	(−83.57)	(−80.95)	(−81.23)	(−43.94)	(99.07)	(98.11)	(94.81)	(45.51)
Y_{t-2}	−0.21***	−0.23***	−0.23***	−0.20***	0.060***	0.057***	0.049***	0.046***
	(−40.48)	(−37.61)	(−37.36)	(−22.18)	(26.15)	(24.95)	(22.09)	(10.85)
Y_{t-3}	−0.10***	−0.12***	−0.12***	−0.11***	0.097***	0.094***	0.087***	0.078***
	(−22.51)	(−24.79)	(−24.62)	(−14.66)	(58.54)	(58.57)	(50.31)	(40.52)
Y_{t-4}	−0.049***	−0.057***	−0.055***	−0.050***	0.079***	0.076***	0.068***	0.064***
	(−15.19)	(−16.61)	(−17.16)	(−10.95)	(35.38)	(33.47)	(29.66)	(33.78)
Y_{t-5}	−0.017***	−0.020***	−0.019***	−0.017***	0.10***	0.099***	0.088***	0.079***
	(−8.11)	(−9.62)	(−9.78)	(−4.86)	(73.09)	(70.43)	(64.96)	(36.78)
$cret_{t-5}^{t-1}$		1.61***	1.60***	1.61***		−0.099***	−0.11***	−0.13***
		(28.60)	(28.56)	(18.19)		(−4.19)	(−5.02)	(−4.28)
$cret_{t-10}^{t-6}$		0.22***	0.23***	0.15***		−0.079***	−0.10***	−0.063
		(9.56)	(9.94)	(3.91)		(−3.21)	(−4.63)	(−1.46)
$cret_{t-30}^{t-11}$		0.069***	0.065***	0.056***		−0.046***	−0.093***	−0.027
		(6.18)	(6.38)	(3.71)		(−2.69)	(−6.61)	(−1.11)
$cret_{t-125}^{t-31}$		0.099***	0.10***	0.12***		−0.015	−0.034***	0.0092
		(15.49)	(16.42)	(13.12)		(−1.40)	(−3.89)	(0.51)
$cret_{t-250}^{t-126}$		0.042***	0.050***	0.040***		0.0076	−0.012*	−0.0061
		(7.41)	(9.00)	(4.85)		(0.98)	(−1.89)	(−0.49)
SIZE			−0.0033**	−0.0025			−0.0039*	−0.018***
			(−2.21)	(−0.74)			(−1.83)	(−4.93)
BM			−0.000012	−0.0000048			−0.00012***	−0.000072***
			(−1.46)	(−0.41)			(−13.23)	(−7.13)
TO			0.00088***	0.00070**			0.0076***	0.0093***
			(4.52)	(2.03)			(20.92)	(21.34)
OCAM			−0.0091*	−0.032*			−0.15***	−0.34***
			(−1.79)	(−1.75)			(−21.11)	(−10.39)
Volatility			0.61***	0.51***			2.81***	3.34***
			(6.79)	(3.26)			(23.01)	(15.85)
MISP				0.0015***				0.00033***
				(11.16)				(2.64)
R-squared	0.215	0.235	0.252	0.240	0.250	0.260	0.275	0.252
Observations	6,054,524	6,054,524	6,054,524	1,938,596	6,054,524	6,054,524	6,054,524	1938596

Table 8. Three-Factor Alphas of Portfolios Based on Past Intraday Signals Conditional on the Signs of Past Intraday Returns and *dLend*: NYSE Breakpoints This table reports three-factor alphas of trading strategies that buy past winners and sell past losers according to the past compound intraday return (IDR). Following Barardehi et al. (2025), in each month m, a stock's signals are constructed using intraday returns from months $m - 12$ through $m - 2$. The trading days underlying the past return signals are decomposed into those where IDR and $dLend$ have the same sign and those where IDR and $dLend$ have opposite signs. The time-series equally-weighted month m returns of each of the ten portfolios (deciles with NYSE breakpoints), net of the 1-month T-Bill trade, as well as the high-minus-low (10−1) portfolio returns are regressed on market, size, and value factor returns to estimate the corresponding three-factor alpha, i.e., the intercept. Standard errors are Newey-West adjusted with 3 lags, and the numbers in parentheses are t-statistics, with ***, **, and * identifying statistical significance at the 1%, 5%, and 10% type one errors, respectively. For either portfolio sort, the average number of trading days used to form portfolios; the average past intraday return; the average overnight return following each relevant intraday signal periods ($FONR$); average $dLend/Lratio$ on signal days; and average $dLend/Lratio$ on non-signal days, from months $m - 12$ through $m - 2$ are reported. The sample includes all NMS-listed common shares covered by Markit in 2007-Q4 through 2021-Q4.

	Portfolios of months $m - 12$ to $m - 2$ intraday returns										
Signal	1	2	3	4	5	6	7	8	9	10	10−1
sign(IDR) = sign($dLend$)											
month-m alpha	−0.087	0.29*	0.38***	0.18	0.14	0.17*	0.050	0.15*	0.20*	0.19	0.28
	(−0.29)	(1.79)	(3.00)	(1.59)	(1.22)	(1.97)	(0.60)	(1.89)	(1.96)	(1.47)	(0.84)
Signal-day count	112.65	109.94	107.73	105.60	104.85	105.75	107.84	110.34	112.93	114.64	1.98
Signal-day compound IDR	−58.50	−18.48	−9.37	−3.59	1.09	5.37	9.85	15.07	22.35	45.34	103.84
Signal-day compound $FONR$	22.80	7.49	5.09	4.12	3.54	3.00	2.64	2.49	1.93	0.42	−22.38
Aggregate $dLend/Lratio$	0.00	0.02	0.03	0.03	0.03	0.04	0.05	0.06	0.08	0.14	0.14
sign(IDR) $\neq$ sign($dLend$)											
month-m alpha	−0.42	0.27*	0.15	0.22*	0.29***	0.21**	0.27***	0.28***	0.20**	0.36***	0.78**
	(−1.49)	(1.73)	(1.38)	(1.94)	(2.77)	(2.42)	(2.93)	(3.15)	(1.98)	(3.36)	(2.52)
Signal-day count	119.24	114.88	112.06	109.52	107.72	106.77	107.21	108.94	112.33	116.94	−2.30
Signal-day compound IDR	−61.82	−24.37	−14.58	−8.37	−3.49	0.77	4.85	9.44	15.58	35.03	96.85
Signal-day compound $FONR$	26.63	9.37	6.66	4.96	3.75	2.64	1.73	1.06	0.11	−5.78	−32.41
Aggregate $dLend/Lratio$	0.08	0.07	0.06	0.05	0.04	0.04	0.03	0.03	0.03	0.03	−0.06

Table 9. Three-Factor Alphas of Portfolios Based on Past Intraday Signals Conditional on the Signs of Past Intraday Returns and Existing Measures of Institutional Trading. This table reports three-factor alphas of trading strategies that buy past winners and sell past losers according to the past compound intraday return (IDR). Following Barardehi et al. (2025), in each month m, a stock's signals are constructed using intraday returns from months $m-12$ through $m-2$. The trading days underlying the past return signals are decomposed into those where IDR and a measure of institutional trading have the same sign and those where IDR and the institutional trading measure have opposite signs. *Non-retail_Trade*, *Trade>50K*, and *Institution_Trade* (*ANcerno*) proxy institutional trading. The time-series equally-weighted month m returns of each of the ten portfolios (deciles with NYSE breakpoints), net of the 1-month T-Bill trade, as well as the high-minus-low (10−1) portfolio returns are regressed on market, size, and value factor returns to estimate the corresponding three-factor alpha, i.e., the intercept. Standard errors are Newey-West adjusted with 3 lags, and the numbers in parentheses are t-statistics, with ***, **, and * identifying statistical significance at the 1%, 5%, and 10% type one errors, respectively. The sample includes all NMS-listed common shares covered by Markit in 2007-Q1 through 2021-Q4 for *Trade>50K*, 2010-Q1 through 2021-Q4 for *Non-retail_Trade*, and 2007-Q1 through 2021-Q4 for *Institution_Trade* (*ANcerno*).

	Portfolios of past 12-month intraday returns										
Signal	1	2	3	4	5	6	7	8	9	10	10−1
sign(IDR) = sign(**Institution_Trade**)	0.50	0.45*	0.27	0.17	0.30	0.45**	0.22*	0.11	−0.014	−0.13	−0.63
	[0.89]	[1.90]	[1.31]	[1.19]	[1.23]	[2.15]	[1.75]	[0.90]	[−0.10]	[−0.94]	[−1.07]
Signal-day count	77.65	75.76	70.31	64.12	61.89	65.61	72.49	80.21	84.33	84.09	6.44
sign(IDR) ≠ sign(**Institution_Trade**)	−0.32	0.38	0.29	0.37***	0.29***	0.24***	0.39***	0.25**	0.43***	0.66***	0.98**
	[−0.59]	[1.46]	[1.63]	[3.18]	[3.39]	[2.95]	[4.47]	[2.58]	[5.51]	[3.32]	[2.26]
Signal-day count	189.82	165.18	159.95	157.35	155.83	155.61	156.64	158.35	162.81	182.99	−6.83
sign(IDR) = sign(***Non-retail_Trade***)	−0.92**	−0.22	0.033	0.10	0.017	0.19**	0.099	0.22***	0.11	0.10	1.02***
	[−2.19]	[−1.39]	[0.36]	[1.17]	[0.22]	[2.19]	[1.52]	[2.75]	[1.22]	[0.75]	[2.75]
Signal-day count	120.19	117.67	115.54	114.19	114.16	114.88	116.47	117.65	118.43	119.20	−0.99
sign(IDR) ≠ sign(***Non-retail_Trade***)	−0.70*	0.014	0.086	0.035	0.14	0.17**	0.032	0.17	0.13	−0.089	0.61**
	[−1.97]	[0.08]	[1.12]	[0.49]	[1.63]	[2.11]	[0.44]	[1.58]	[1.33]	[−0.44]	[2.30]
Signal-day count	118.18	115.36	115.42	115.04	114.83	114.30	114.13	114.40	114.35	113.51	−4.68
sign(IDR) = sign(***Trade>50K***)	−1.02***	−0.18	0.0074	0.16	0.26***	0.21***	0.18***	0.20***	0.089	0.076	1.09***
	[−3.49]	[−1.11]	[0.07]	[1.37]	[3.28]	[2.87]	[2.66]	[2.61]	[1.11]	[0.59]	[3.48]
Signal-day count	106.50	104.41	103.92	103.62	103.18	102.93	102.63	102.48	101.24	102.35	−4.15
sign(IDR) ≠ sign(***Trade>50K***)	−0.63**	−0.057	0.13	0.23**	0.19***	0.098	0.099	0.087	−0.068	−0.32**	0.32
	[−2.31]	[−0.42]	[1.17]	[2.34]	[3.02]	[1.10]	[1.38]	[1.13]	[−0.89]	[−2.38]	[1.09]
Signal-day count	91.11	89.20	85.26	82.16	81.31	84.20	86.64	89.53	91.64	91.31	0.20