Lendable Inventory Concentration, Recall Risk, and Equity Pricing Anomalies

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Abstract

I find that the returns of equity pricing anomalies remain large and significant net of fees in stocks whose lendable shares are concentrated among a few lenders. I argue that recall risk explains this pattern. Lenders can recall shares at any time, and when lendable inventory concentration (IC) is high, one withdrawal can recall more shares than borrowers can replace in time. Within firms, a one-standard-deviation higher IC predicts a 2.1 percentage point higher next-month recall event probability (mean 10.9%), controlling for the fee and lendable supply. This recall risk deters short selling even when unlent shares are available. At the highest IC, the same overpricing signal attracts about one quarter as much short interest as at the lowest IC. Less of the overpricing is therefore corrected. Average anomaly returns are 0.43% per month higher in the top IC quintile than in the bottom quintile, mainly through the short leg, and the gap is still 0.33% per month net of fees. Russell 3000 inclusion, which broadens the lender base, lowers recall risk and raises short interest most in overpriced stocks with high pre-inclusion IC.

Keywords: lendable inventory concentration; recall risk; securities lending; short-sale constraints; limits to arbitrage; equity anomalies.
JEL: G12, G14, G23.

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1 Introduction

Muravyev et al. (2025) find that much of the return to equity pricing anomalies disappears once fees are taken into account. Yet in stocks whose lendable shares are held by a few large lenders, anomaly returns remain large net of fees. I argue that the explanation is recall risk, the risk of losing borrowed shares too early. A short seller needs to borrow the shares she sells and keep the loan until the mispricing corrects, but securities loans are open-ended, so a lender can recall its shares at any time. If she cannot find replacement shares before the recall settles, the position must be closed before she can earn the full gain from the correction. Recall risk is higher where lendable inventory is concentrated: when a few lenders hold most of a stock's lendable shares, one lender's withdrawal removes a large part of the available supply, and short sellers may not be able to replace the recalled shares in time. Facing this recall risk, short sellers take smaller positions than fully eliminating the overpricing would require, so part of the overpricing remains and anomaly returns stay large net of fees. Beyond the fee, inventory concentration makes access to lendable shares less durable, which deters short selling and sustains anomaly-related overpricing.

A stock's lendable supply is distributed across lending programs, custodian banks, and investors that lend directly (Figure 1). Lenders withdraw shares when their clients sell or rebalance, or when lending restrictions change. A borrower facing a recall must locate replacement shares before the recall settles, and search frictions limit how much of the other lenders' inventory the borrower can reach in time (Duffie et al., 2002). Two stocks with the same lendable supply can therefore face different recall risk, depending on how that supply is distributed across lenders.

I test this mechanism using daily securities lending data for US stocks from 2006 to 2023. Inventory concentration (IC) is IHS Markit's Herfindahl index of a stock's lendable shares across reporting lenders. Recalls are not reported, so I infer them from joint changes in supply and loans: when borrowers replace withdrawn shares, supply falls but loans do not; when replacement fails, both fall. I measure how often such joint declines occur (recall events) and the share of loans lost to them (the unreplaced recall rate, URR). Joint declines can also arise when borrowers close positions voluntarily on the day a lender withdraws. Fails to deliver from the SEC help separate the two: they build up before recall events and clear on the day loans fall, whereas voluntary covering shows no such pattern. [1]

Inventory concentration and recall risk. A one-standard-deviation increase in IC predicts a 2.1 percentage point increase in next-month recall event probability, relative to a

[1] Fails to deliver are from the SEC. Three trading days before a recall event, fails are higher by 1.27 basis points of shares outstanding ($t = 31.5$), about twice their average of 1.2 basis points, or 6.9% of the shares on loan against 3.3% on other days. The excess disappears on the day loans fall. Days on which loans fall without a decline in supply, the pattern of voluntary covering, show no comparable build-up (Appendix C.1).

mean of 10.9%. The regression controls for the fee, lendable supply, short interest, and ownership and includes firm and month fixed effects. IC also predicts recalls among low-fee general-collateral stocks and in a propensity-score matched sample. Within the same firm, the share class with more concentrated inventory experiences more recalls despite exposure to the same firm fundamentals.

Withdrawals by mutual fund lending programs provide evidence on the mechanism. Following Gabaix and Koijen (2024), I compare holdings growth across programs lending the same stock, removing the component of growth common to all programs. A withdrawal of 1% of shares outstanding by a single lender raises the quarterly recall probability by 1.84 percentage points, even though most inventory remains unlent. When the largest lending program withdraws a large share of its inventory, recall risk rises more in stocks with high IC.

Inventory concentration and overpricing. Only short sellers face recall risk, because investors who buy underpriced stocks do not borrow shares. Higher IC should therefore widen anomaly spreads mainly through lower returns on stocks in the short leg. Across 70 anomalies from Jensen et al. (2023), the average long-short return is 0.43 percentage points per month higher in the top IC quintile than in the bottom. Almost all of the difference comes from the short leg. After fees, the spread remains 0.33 percentage points larger at high IC.

Combining the anomaly signals yields a similar result. For each stock, I count the anomalies that place it in their long portfolio minus those that place it in their short portfolio. The score measures how consistently the anomalies point to underpricing or overpricing: a high score means that many anomalies identify the stock as underpriced, and a low score that many identify it as overpriced. The return spread between the highest and lowest quintiles of this score is 122 basis points per month at high IC versus 31 at low IC. After fees, the spread remains 100 basis points per month at high IC, against 27 at low IC. The spread also remains larger at high IC when IC is ranked within size terciles and when returns are measured relative to DGTW benchmarks.

Inventory concentration and short selling. The borrowing data connect these return patterns to short sellers' positions. A recall can force a short seller to close the position before the overpricing corrects, which lowers the expected gain from shorting. Where IC is high, this risk is larger, so short sellers take smaller positions while more of the overpricing remains. Consistent with this, for the same overpricing signal implied by anomalies, the short interest associated with it is about one quarter as large at the highest IC as at the lowest (0.9 versus 3.6 percentage points of shares outstanding), controlling for the fee, lendable supply and size and including firm and month fixed effects. If short sellers were

instead limited by the number of shares available, they would borrow a large fraction of the remaining inventory. Yet the same overpricing signal also raises utilization less at high IC: short sellers borrow a smaller share of the shares available to them.

When a stock moves into the most overpriced quintile of anomaly signals, its loans rise over the next two months by about 0.9% of shares outstanding at the lowest IC rank and 0.1% at the highest, relative to comparison stocks, and its utilization rises by 3.8 percentage points among low-IC stocks but only 0.8 among high-IC stocks. Before entry, high-IC stocks have unlent inventory equal to 11.6% of shares outstanding, and the fee barely changes after entry. Stocks that move into the most underpriced quintile exhibit no comparable borrowing gap. Russell 3000 inclusion provides a further test, because lower recall risk should raise short selling most where the risk deterred it. Inclusion broadens the lender base and lowers recall probability by about one quarter, with little change in the fee. Among entrants whose inventory was concentrated before inclusion, short interest rises most in stocks with the strongest overpricing signals.

High-IC stocks tend to be smaller, less widely held by institutions, and pay higher fees. The panel regressions control for these differences, the matched sample compares similar stocks, and the share-class comparison absorbs the firm's size, fundamentals and news. Two tests do not isolate the role of IC: the larger effect of large withdrawals at high IC cannot be separated from size and ownership, and Russell inclusion changes lendable supply and lender composition as well as concentration.

Contributions. This paper makes two contributions to the literature on short-sale constraints and mispricing. First, it shows that recall risk depends on the distribution of lendable inventory across lenders. This makes the durability of stock loans a dimension of short-sale constraints distinct from the quantity of lendable shares and the fee. Prior work measures these constraints through lendable supply (Nagel, 2005; Asquith et al., 2005; Kaplan et al., 2013; Porras Prado et al., 2016), fees (Drechsler and Drechsler, 2014; Muravyev et al., 2025), and fee variability (Engelberg et al., 2018), and shows that exits by the lenders a stock depends on disrupt borrowing conditions (Dong and Zhu, 2026). Using daily lending data and withdrawals by mutual fund lending programs, I show that when a few lenders hold most of the inventory, a single withdrawal can remove more shares than borrowers can replace in time. Stocks with similar lendable supply and fees can therefore face different recall risk. Second, the paper links this recall risk to limits on short-sale arbitrage. Muravyev et al. (2025) find that fees account for much of the return to anomaly strategies. In contrast, I find that when lendable inventory is highly concentrated, the same overpricing signal attracts less short interest, and anomaly returns remain large and statistically significant net of fees. These findings are consistent with recall risk deterring short sellers from fully exploiting anomalies, beyond what the fee reflects.

Section 1.1 reviews the related literature. Section 2 describes the securities lending market, and Section 2.2 develops a model linking inventory concentration to recall risk. Section 3 describes the data and defines the recall measures. The empirical analysis proceeds in three steps. Section 4 shows that inventory concentration predicts recall risk and examines withdrawals by mutual fund lending programs. Section 5 examines how anomaly returns vary with inventory concentration. Section 6 tests whether short sellers respond less to overpricing when lendable inventory is concentrated. Section 7 concludes.

1.1 Related Literature

This paper connects three literatures: the structure of the securities lending market, short-sale costs and risks, and limits to arbitrage and equity pricing anomalies. Existing research shows that borrowed shares can be costly, scarce, and recalled (D'Avolio, 2002; Engelberg et al., 2018). I show that the risk of a recall that borrowers cannot replace depends on the concentration of lendable inventory across lenders, and that this recall risk deters short selling and sustains overpricing beyond the fee.

Lender structure, ownership, and lendable supply. Securities lending involves search, bargaining, and lender market power (Duffie et al., 2002; Kolasinski et al., 2013; Chen et al., 2022), and lending conditions and stock prices are jointly determined (Atmaz et al., 2024). Institutional ownership shapes lendable supply and short-sale constraints (D'Avolio, 2002; Nagel, 2005), and passive investors tend to provide more stable supply (von Beschwitz et al., 2025; Palia and Sokolinski, 2024). The closest studies are Porras Prado et al. (2016) and Dong and Zhu (2026). Porras Prado et al. (2016) show that concentrated and short-horizon ownership reduces lendable supply, raises fees, and delays the correction of mispricing. I instead study the concentration of lendable inventory and its effect on recall risk, controlling for ownership concentration, supply, and the fee. Ownership concentration and inventory concentration are distinct: many institutions do not lend (Dong and Zhu, 2026), and lending programs pool shares across owners. Ownership HHI and IC are related, with a rank correlation of 0.66, but they are not interchangeable. Dong and Zhu (2026) show that short sellers depend on a small set of persistent lenders whose exits disrupt borrowing, and that concentrated outstanding loans predict lower returns. I instead measure the concentration of lendable inventory, which includes the lenders that could replace a recalled loan, and link it directly to recall risk and short selling. Sorting on Markit's lender concentration, which measures the concentration of loans rather than of lendable inventory, does not produce larger anomaly spreads, whereas sorting on IC does (Appendix Table E.8). Withdrawals by mutual fund lending programs show the mechanism directly: they cause loans to be lost to unreplaced recalls even when most of the inventory is unlent.

Short-sale costs and short-selling risk. Engelberg et al. (2018) show that the variability of the fee creates short-selling risk beyond its level. Fees also predict returns and account for a substantial part of anomaly profitability (Drechsler and Drechsler, 2014; Engelberg et al., 2025; Muravyev et al., 2025), and lenders with market power, who capture part of anomaly profits through higher fees (Da et al., 2026), make anomalies less profitable. I study a distinct constraint: the risk that borrowed shares are recalled and cannot be replaced, forcing short sellers to close positions before the mispricing corrects. The fee determines the cost of maintaining a position; recall risk threatens its continuation. Inventory concentration predicts recall events after controlling for the fee, and anomaly spreads remain larger net of fees. Lender market power does not readily explain the results either. In mutual fund filings, funds that lend stocks with concentrated inventory withdraw less frequently, not more, but each withdrawal removes a larger share of outstanding loans (Appendix Table A.1). This evidence points to limited substitution between lenders, rather than higher fees or strategic recalls, as the link between concentration and short selling.

Limits to arbitrage and equity pricing anomalies. The anomaly literature debates the robustness of return predictability to data mining, publication, and trading costs (Harvey et al., 2016; Green et al., 2017; Linnainmaa and Roberts, 2018; Hou et al., 2020; McLean and Pontiff, 2016; Frazzini et al., 2012; Novy-Marx and Velikov, 2016), while other studies document anomalies that replicate across samples and markets (Jacobs and Müller, 2020; Chen and Zimmermann, 2022; Jensen et al., 2023). Limits to arbitrage can sustain mispricing (Shleifer and Vishny, 1997; Gromb and Vayanos, 2010), particularly overpricing, whose correction requires short selling (Miller, 1977; Diamond and Verrecchia, 1987). Consistent with this asymmetry, anomaly profits are concentrated in the short leg and are sensitive to short-sale constraints and arbitrage capital (Jones and Lamont, 2002; Hong and Stein, 2003; Cohen et al., 2007; Stambaugh et al., 2012; Hanson and Sunderam, 2014; Lewellen, 2011; Edelen et al., 2016; Chu et al., 2020). Muravyev et al. (2025) show that much of anomaly profitability disappears after fees. I identify a constraint beyond the fee: the risk that shares recalled by a large lender cannot be replaced in time, which forces short positions to close. Fees therefore do not exhaust anomaly profits, because recall risk deters short sellers from taking positions large enough to eliminate them.

2 Institutional Background and Model

This section describes how the securities lending market is organized and when a recall forces a short seller to close a position: when the borrower cannot replace the recalled shares in time. A simple model then shows that this risk rises with the concentration of lendable inventory across lenders.

2.1 Securities lending and recalls

Lendable shares originate from beneficial owners, including mutual funds, pension funds, insurers, ETFs and sovereign wealth funds. Most lend through custodian banks or lending agents that pool inventory across clients, arrange loans and manage collateral; some large asset managers operate their own lending programs. Short sellers access this inventory through prime brokers (Figure 1). Lending is organized by fund family. In N-CEN filings, 81% of fund families with more than one lending fund use a single lending agent, and 90% of their lending funds use only the family's main agent. The share of a fund's holding that is on loan moves most closely with that of other funds of the same family at the same agent (a correlation of 0.46 after removing the stock-quarter mean), compared with 0.09 for funds of other families at the same agent and 0.14 for funds of the same family at a different agent. A lending program's decisions therefore move the inventory of many funds at once.

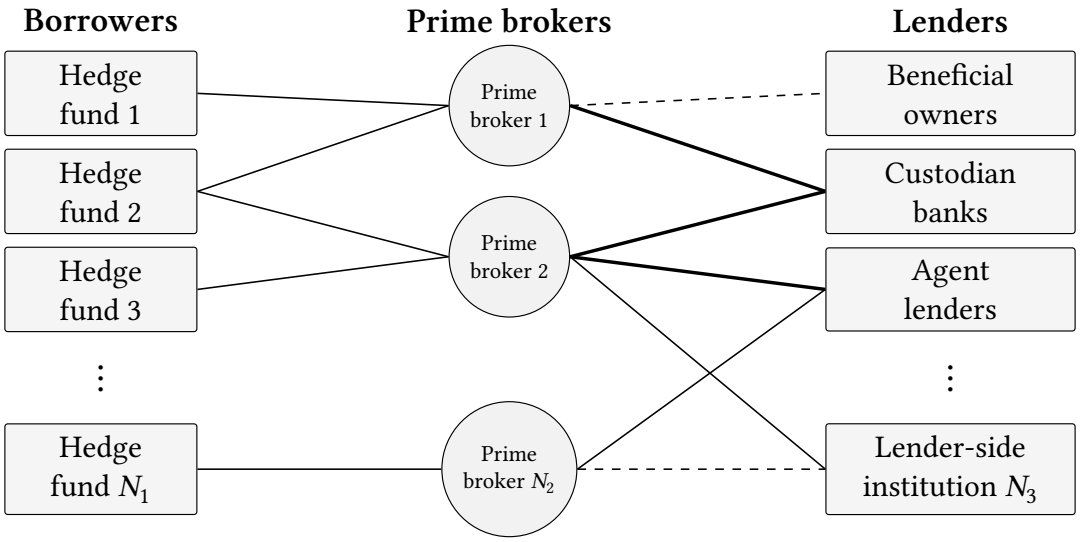


Figure 1: Securities Lending Market Structure

Notes. Lendable inventory comes from beneficial owners such as mutual funds, pension funds, insurers, ETFs and other asset managers. Most of them lend through a custodian bank or an agent lender that runs a lending program on their behalf and pools their shares with those of other clients; a few large owners lend directly. Borrowers reach this inventory through prime brokers. Relationships between prime brokers and lender-side institutions can be regular, occasional or infrequent (thick solid, thin solid and dashed lines). Inventory concentration (IC) is measured on the lender side: it is the Herfindahl index of a stock's lendable inventory across the institutions on the right that report it to Markit, the lending programs and the owners that lend directly, and it does not count the prime brokers that re-lend that inventory.

Not all shares held by beneficial owners are available for lending. Owners restrict lending for voting, liquidity, tax or risk-management reasons, and custodians and agents impose program restrictions and inventory buffers to accommodate client transactions. The distribution of lendable inventory therefore depends on lending arrangements as well as on ownership, and these arrangements are persistent: Dong and Zhu (2026) show that some funds repeatedly lend particular stocks while other funds holding the same stocks do

not. A stock may consequently have many beneficial owners but few institutions supplying its lendable inventory.

Securities loans are generally open-ended, and lenders may recall shares at any time (Baklanova et al., 2015). Following a recall, the borrower must return the shares within the settlement period, two or three trading days during the sample period.[2] The prime broker may obtain replacement shares from another lender, allowing the short position to remain open. If replacement borrowing fails, the position is closed through a market purchase. Recalls do not ordinarily carry a contractual penalty, and open-ended loans provide no guarantee of continued access to the shares. The fee is the current price of obtaining shares, not a guarantee that they will remain available.

Recalls need not disrupt short positions. An agent lender can replace shares withdrawn by one client with inventory from another client in the same program. Disruption arises when the withdrawal exceeds the inventory that can be substituted within the program or obtained from other lenders in time. Finding replacement shares requires search, as in Duffie et al. (2002), and access is limited by existing lending relationships and program restrictions. A large lender's withdrawal can therefore be difficult to replace even when the stock has spare lendable inventory.

2.2 A model of inventory concentration and recall risk

A lender's withdrawal interrupts a short position only if the other lenders cannot supply replacement shares in time. How many shares the other lenders hold depends on how inventory is distributed across lenders: when one lender holds most of it, its withdrawal leaves few shares with the others. The distribution of inventory across lenders therefore matters for the durability of borrowing beyond supply and utilization. The model borrows the search friction of the securities lending model in Duffie et al. (2002): borrowers locate lendable shares through search. It departs from that model in two ways: lenders can be large, so one decision can remove a large part of a stock's inventory, and a loan can be recalled before the position is closed. Appendix A sets out the full model, the proofs and the evidence on the assumptions.

Withdrawals. A stock has lendable inventory L and loans $B = uL$, where u is utilization. A lender is a unit whose inventory leaves the stock's lending pool on one decision: an

[2] The settlement window is set by the loan agreement and the settlement cycle. Under the SIFMA Master Securities Loan Agreement (2017 version, Section 6), the lender may terminate a loan at any time and the borrower must return the loaned securities no later than the end of the standard settlement period for a sale of those securities; if it does not, the lender may purchase replacement securities at the borrower's expense (Section 13). The standard settlement period is set by SEC Rule 15c6-1 (17 CFR 240.15c6-1): three business days until 5 September 2017, two thereafter (Securities Exchange Act Release No. 34-80295, 22 March 2017), and one since 28 May 2024 (Release No. 34-96930, 15 February 2023), after the end of the sample.

owner that lends directly, or a lending program that pools many owners. Over the horizon of a short position, lender i withdraws a fraction $\delta_i \in [0,1]$ of its inventory for reasons unrelated to the borrower's position, such as client sales, outflows or index rebalancing. Withdrawals are independent across lenders, with mean θ and variance v. With lender shares $s_1, \ldots, s_N$, inventory concentration and the aggregate withdrawn share are

$$IC = \sum_{i=1}^{N} s_i^2, \qquad W = \sum_{i=1}^{N} s_i \delta_i. \tag{1}$$

IC is the lender-side Herfindahl index I measure in Section 3.

Proposition 1 (Concentration and withdrawals). $\mathbb{E}[W] = \theta$ *and* $\mathrm{Var}(W) = v\,IC$. *If withdrawals have a component common to all lenders with variance* v_c *and a lender-specific component with variance* v_e, *then* $\mathrm{Var}(W) = v_c + v_e\,IC$.

With one large lender and many small ones, the large lender holds a share $\sqrt{IC}$ of the inventory, and the withdrawn share is

$$W_{IC} = \theta + \sqrt{IC}(\delta - \theta), \tag{2}$$

where δ is the large lender's withdrawal. Concentration does not change how often lenders withdraw; it changes how much of the inventory one withdrawal removes.

Replacement and recall events. Each lender lends out the same fraction u of its inventory, so a withdrawal recalls loans in proportion. A recalled loan must be returned within the settlement window, and within it borrowers can reach only a fraction $\phi \leq 1$ of the spare inventory, because search takes time and a prime broker deals only with the lenders with which it has agreements. A shortage, in which some recalled loans cannot be replaced and must close, occurs when

$$W_{IC} > a(u,\phi) \equiv \frac{\phi(1-u)}{u + \phi(1-u)}. \tag{3}$$

Recall risk therefore has three ingredients: spare inventory, $1-u$, and the share of it borrowers can reach in time, ϕ, which together set the threshold a; and the size of one lender's withdrawal, which rises with IC. Below the threshold, supply falls and loans do not, because borrowers move to other lenders. Above it, supply and loans fall together, which is the recall event I measure in Section 3.3. A squeeze, in which supply falls below the loans outstanding (Schultz, 2024), is the extreme case $W_{IC} > 1-u$.

Proposition 2 (Concentration and recall risk). *Suppose the expected withdrawal can be absorbed,* $a(u,\phi) > \theta$. *The probability of a shortage,* $\pi(IC,u)$, *and the expected fraction of loans*

that must close, $\rho(IC, u)$, are weakly increasing in IC and in utilization and weakly decreasing in ϕ, and $\rho \leq \pi$. A shortage is impossible when IC is below a critical level $IC^*(u)$.

The friction $\phi < 1$ is what makes recall risk relevant at low utilization: with $\phi = 1$, a shortage at the median utilization requires a concentration that almost no stock reaches (Appendix A.2).

Fees, short selling and prices. The fee depends only on utilization,

$$f = F(u), \tag{4}$$

where F is weakly increasing with a common floor f_0 at low utilization, so the fee does not depend on IC.

Corollary 1 (Recall risk beyond the fee). *Conditional on utilization, and hence on the fee, the shortage probability and the expected forced closure increase with IC. The fee therefore reflects the part of recall risk that comes from utilization but not the part that comes from IC.* [3]

A forced closure costs the short seller $C > 0$ per share closed, so the expected cost of a short position is $F(u) + C\rho(IC, u)$. When investors disagree, the price falls as short interest builds (Miller, 1977), and short sellers enter until the marginal position earns its expected cost (Appendix A.1).

Proposition 3 (Short selling and residual overpricing). *A higher IC weakly reduces equilibrium short positions and weakly increases the residual overpricing.*

Empirical predictions.

Corollary 2 (Empirical predictions). *Conditional on utilization, and hence on the fee, greater concentration of lendable inventory implies:*

(a) greater volatility of lendable supply, and more frequent recall events and squeezes;

(b) smaller short positions for the same overpricing, even when most lendable shares are unlent and the fee is low;

(c) larger anomaly returns net of fees (Proposition 3).

[3] The first statement follows from Proposition 2, and the second from equation (4). Because recall risk and the fee both rise with utilization, the model predicts that the fee is positively related to recall risk across stocks, as in the regressions of Section 4. In the data, the fee is slightly higher where IC is high (Appendix A.5). The empirical tests control for the fee rather than impose this restriction, so they require only that the fee does not reflect the whole difference in recall risk across IC.

The predictions require neither that lenders of concentrated stocks withdraw more often nor that borrowers find replacement harder there: θ and ϕ are the same for all stocks. Section 4 tests prediction (a), Section 6 prediction (b), and Section 5 prediction (c).

3 Data and Measures

I combine daily securities lending data from IHS Markit Securities Finance, returns and market equity from CRSP, accounting data from Compustat, quarterly 13F holdings, and monthly anomaly signals from Jensen et al. (2023). The lending data cover July 2006 to December 2023. Unless stated otherwise, observations are stock-months.

3.1 Sample construction

Lending data. I match daily Markit data for US equities to CRSP by CUSIP.[4] Monthly variables average the month's trading days.

Stocks and filters. The sample includes CRSP common stocks (share codes 10 and 11) with formation-month prices of at least \$1, market capitalization of at least \$50 million, at least seven daily fee observations in month t, and monthly fees no higher than 1% (12% annualized). The fee cap excludes stocks whose fees may themselves constrain arbitrage. All filters use information available in month t. I exclude IC values of zero or one, which indicate missing or single-record lending pools. The sample contains 659,915 stock-months for 8,116 stocks over 209 months. All tests use these filters except the dual-class comparison (Appendix C.6). The fee cap removes 10% of stock-months in the top IC quintile and 0.6% in the bottom, excluding stocks where recall risk may be greatest.

Anomalies. I merge the signed anomaly signals of Jensen et al. (2023) with CRSP and Markit, sort each characteristic monthly into equal-weighted quintiles, and retain those with positive full-sample CAPM long-short alphas significant at 10%. Selection does not condition on IC. Of 152 eligible characteristics, 70 qualify, spanning ten of thirteen anomaly clusters (Table G.1). Appendix E.2 reports results for all characteristics.

[4] On a few days, incomplete Markit coverage causes lendable quantity to fall and recover across most stocks. I treat days when more than a fifth of stocks with valid changes lose at least 10% of supply as reporting errors and set all daily changes to missing. This removes four days, in December 2006, January 2007, March 2011 and March 2013.

Anomaly exposure. Each month, the K selected anomalies assign stocks in the top and bottom signal quintiles to their long and short legs. For stock i, the assignment counts are

$$L_{it} = \sum_{k=1}^{K} \mathbf{1}\{i \in \text{Long}_{kt}\}, \qquad S_{it} = \sum_{k=1}^{K} \mathbf{1}\{i \in \text{Short}_{kt}\}. \tag{5}$$

With $R_t(\cdot)$ denoting the within-month percentile rank,

$$NetShort_{it} = R_t(S_{it}), \qquad NetLong_{it} = R_t(L_{it}), \qquad NetLeg_{it} = R_t(L_{it} - S_{it}). \tag{6}$$

Higher NetShort (NetLong) indicates stronger overpricing (underpricing) signals; lower NetLeg indicates greater net overpricing.

Returns and fees. Portfolios formed at month-end t are held through $t + 1$. I use excess returns and characteristic-adjusted returns following Daniel et al. (1997). Benchmark portfolios exclude stocks with formation-month fees above 1% a year, following Muravyev et al. (2025). Net returns charge shorts the holding-month fee, using the formation-month fee when missing, and credit longs with 0.7 times the fee, the lenders' share of lending revenue (D'Avolio, 2002). Appendix E.1 instead credits 0.7× utilization × fee, following Muravyev et al. (2025).

Mutual fund lending data. Public Form N-PORT reports cover the final month of each fund's fiscal quarter and provide security-level holdings and the value of shares on loan. I use quarter-end reports from September 2019 through September 2023 and match securities to CRSP by CUSIP. I identify lending funds from their annual Form N-CEN filings. Of the 7,025 funds in the sample, 3,526 report at least one lending agent. These funds use 50 agents, with the ten largest accounting for 91% of all fund–agent pairs.

Ownership and other data. I calculate institutional ownership (IOR) and the HHI of institutional holdings from 13F filings and carry them forward for three months. Passive ownership, covering index funds and passive ETFs, comes from Sammon (2025) through 2019. Short interest comes from Compustat's semi-monthly exchange reports, scaled by split-adjusted CRSP shares outstanding. Firm characteristics from Jensen et al. (2023) include size, book-to-market, six-month momentum excluding the current month, idiosyncratic volatility from 21-day Fama–French three-factor residuals, and turnover and Amihud illiquidity over 126 trading days.

3.2 Lending variables

Inventory concentration (IC). Markit computes IC as the Herfindahl index of lendable inventory across lenders,

$$IC_{id} = \sum_{\ell} w_{i\ell d}^2, \tag{7}$$

where $w_{i\ell d}$ is lender ℓ's share of stock i's lendable inventory on day d. Lenders are the Markit contributors on the supply side of Figure 1: beneficial owners that lend directly, custodians and agent lenders. IC includes lenders with nothing on loan and excludes prime brokers, which re-lend shares rather than supply them. Some contributors report individual owners and others report pooled lending programs, so IC measures concentration at both levels. Monthly IC is the average of daily IC over the trading days of the month.

High-IC stocks are small and have lower institutional ownership, higher ownership HHI and lower passive ownership. Together, these four characteristics explain 57% of the within-month variation in IC, and 38% of the variance of IC occurs within stocks over time (Appendix B.3). These characteristics shape the lender base, and IC measures the feature of it that the model links to recall risk: how much of the lendable inventory one lender's decision can remove.

Fee, utilization, and supply. The fee is Markit's indicative annualized fee for a representative hedge fund. Utilization is shares on loan divided by lendable shares. Lendable supply (LQ) is the number of lendable shares divided by shares outstanding.

3.3 Measures of recall risk

Recall risk is the probability that an existing loan is recalled and not replaced before the recall settles, forcing the short position to close. Recalls and forced closures are not directly observed. I measure three stages of the mechanism in Section 2.2: supply withdrawals, accompanying loan declines, and squeezes in which the remaining supply cannot cover the loans. For stock i on day d, let L_{id}^a denote active lendable quantity, defined by Markit as inventory free of lending restrictions and buffers; L_{id} total lendable quantity; B_{id} total quantity on loan; and B_{id}^ℓ loans from lenders that report lendable inventory. Daily changes are $g_{id}^L = L_{id}^a / L_{i,d-1}^a - 1$ and $g_{id}^B = B_{id}/B_{i,d-1} - 1$.

Supply drops and recall events. A *supply drop* is a fall in active lendable quantity of at least 5%, $\mathbf{1}\{g_{id}^L \leq -0.05\}$. A *recall event* requires both supply and loans to fall by at least 5%:

$$RE_{id} = \mathbf{1}\{g_{id}^L \leq -0.05 \text{ and } g_{id}^B \leq -0.05\}. \tag{8}$$

Replacing withdrawn shares with another lender leaves total loans unchanged, so a joint decline indicates recalls borrowers could not replace.[5] A *current-lender squeeze*, following Schultz (2024), requires supply and loans to fall by the same number of shares, within 1%; I use this measure in the dual-class tests. Monthly event indicators equal one if an event occurs on any day. *Supply volatility* is the within-month standard deviation of daily active lendable quantity divided by its mean. In the model it rises with $\mathrm{Var}(W) = v\,IC$ (Proposition 1).

Unreplaced recall rate. URR measures the share of loans lost during supply withdrawals. On days when active supply falls by at least 1%, I count the loan decline up to the amount withdrawn, scaled by the previous day's loans:

$$r_{id} = \mathbf{1}\{g^L_{id} \le -0.01\} \cdot \frac{\min\{(L^a_{i,d-1} - L^a_{id})^+,\ (B_{i,d-1} - B_{id})^+\}}{B_{i,d-1}}, \qquad URR_{it} = \min\Big\{\sum_{d \in t} r_{id},\ 1\Big\}. \tag{9}$$

Voluntary covering makes URR an upper bound on the share of loans lost to recalls. It is the empirical counterpart of expected forced closure ρ in Proposition 2.

Squeezes. An *all-lender squeeze*, following Schultz (2024), occurs when remaining lendable quantity falls below the same lenders' previous-day loans and supply remains depressed the next day:[6]

$$SQ_{id} = \mathbf{1}\{L_{id} < B^{\ell}_{i,d-1}\} \cdot \mathbf{1}\{L_{i,d+1} < 0.95\, L_{i,d-1}\}. \tag{10}$$

Validation. A joint decline in supply and loans could also reflect voluntary covering at the time a lender withdraws shares, not a recall. SEC fails-to-deliver data distinguish the two. A lender that sells shares it has lent must recall them to settle the sale. If the borrower returns the shares late, the sale fails to deliver until the shares arrive, and Markit records the decline in loans on that day. A recall that borrowers cannot meet in time should therefore be preceded by fails that clear on the day of the recall event, whereas voluntary covering returns shares that no sale is waiting for. The data show this pattern. Relative to other days of the same stock, fails are about twice their usual level in the days before a recall event

[5] Markit records positions at end-of-day settlement and recalls when shares are returned. Replacement through another lender, including within a lending program, leaves total loans unchanged (correspondence with S&P Global Market Intelligence, Securities Finance, October 2026). Schultz (2024) identifies recalls from equal declines in supply and loans; I require both to fall by at least 5%. Loan declines are substantially more frequent on supply-drop days (Table A.2).

[6] I make two changes to Schultz (2024). First, I compare supply with loans from the same reporting lenders, B^{ℓ}, because about one quarter of loans come from institutions that do not report lendable quantity. Second, I require supply to remain at least 5% below its previous level the next day to exclude temporary reporting gaps.

and return to normal on the day loans decline. Days on which loans fall without a decline in supply show no such build-up. Subsequent returns also differ. Over trading days +11 to +60, cumulative returns are 0.71% lower after recall events ($t = -7.0$) and 0.53% higher after days on which loans fall without a decline in supply ($t = 7.9$). The first is consistent with positions closed in stocks that remain overpriced, the second with informed short sellers covering. Part of the decline after recall events reflects the lenders' own sales: returns also fall by 1.11% after supply withdrawals without a decline in loans. Finally, the loans that URR counts as lost coincide with fails that clear on the same day, and IC predicts the recall events that the fails data confirm (Appendix C.1).

3.4 Summary statistics

Appendix Table B.1 reports summary statistics. IC averages 0.222, with a median of 0.185, equivalent to about five equal-sized lenders. Its autocorrelation is 0.97 at one month and 0.73 at twelve months, yet 38% of its variance is within stocks (Appendix B.2). Lendable supply averages 23% of shares outstanding, utilization averages 15.7%, and the median annual fee of 0.375% is the general-collateral level. Recall events occur in 10.9% of stock-months, supply drops in 22.1% and squeezes in 0.38%; URR averages 7.7% of loans. IC has a rank correlation of −0.66 with size, 0.66 with ownership HHI, −0.50 with institutional ownership and 0.41 with the fee, but 0.02 with utilization (Table B.3).

4 Inventory Concentration and Recall Risk

Prediction (a) of Corollary 2 states that, conditional on the fee, stocks with higher IC experience more frequent recall events and squeezes. Table 1 provides a first test by sorting stocks into IC quintiles each month within three fee groups. The general-collateral group offers a particularly close fee comparison. Fees average 0.44% a year in the top IC quintile and 0.36% in the bottom quintile, and utilization is slightly lower in the top quintile. Yet recall events occur in 10.4% of months in the top quintile, compared with 2.6% in the bottom quintile. Squeezes occur in 0.28% and 0.026% of months, respectively, and URR averages 8.3% and 4.1% of loans. The gaps in squeeze frequency are larger among warm and special stocks: the top IC quintile exceeds the bottom by 4.4 percentage points in the warm group and 8.4 percentage points in the special group, although average fees within each group differ by less than one percentage point. As Corollary 1 predicts, stocks in the same fee group can face very different recall risk.

Without conditioning on the fee, the monthly probability of a recall event rises from 3.3% in the bottom IC quintile to 30.5% in the top quintile, and URR rises from 4.3% to 17.9% of loans (Appendix Table C.2). High-IC stocks are smaller, pay higher fees and have less

Table 1: Inventory concentration and recall events within fee groups

	Fee (% p.a.)	Util.	Squeeze$_{t+1}$ (%)	Supply vol.$_{t+1}$	Supply drop$_{t+1}$ (%)	Recall event$_{t+1}$ (%)	URR$_{t+1}$ (%)
General collateral (fee ≤ 1%) (210 months)							
Q1 (low IC)	0.363	0.115	0.026	0.017	8.252	2.594	4.117
Q5 (high IC)	0.443	0.099	0.284	0.070	22.847	10.394	8.256
Q5–Q1	0.079	-0.017	0.259	0.053	14.594	7.800	4.139
	(25.25)	(-3.22)	(8.27)	(24.16)	(16.34)	(17.32)	(12.66)
Warm (1% to 5%) (210 months)							
Q1 (low IC)	2.250	0.521	0.510	0.131	60.528	25.543	10.894
Q5 (high IC)	2.557	0.146	4.876	0.715	80.750	57.461	33.262
Q5–Q1	0.307	-0.374	4.366	0.583	20.222	31.918	22.368
	(8.03)	(-27.65)	(10.17)	(30.35)	(13.99)	(14.96)	(15.01)
Special (fee > 5%) (210 months)							
Q1 (low IC)	7.873	0.663	1.425	0.115	69.603	37.502	15.153
Q5 (high IC)	7.995	0.292	9.782	0.645	83.453	66.348	33.287
Q5–Q1	0.122	-0.371	8.357	0.530	13.850	28.846	18.134
	(2.01)	(-25.87)	(10.15)	(25.54)	(8.95)	(11.63)	(11.84)

Notes. Each month, stocks are sorted into IC quintiles within three fee groups: general collateral (fee at most 1% a year), warm (above 1% and at most 5%) and special (above 5%). The table reports time-series averages for the bottom and top quintiles and their difference, with Newey-West t-statistics in parentheses. Outcomes are as in Appendix Table C.2.

lendable supply, but their utilization is similar: 16% in the top quintile against 13% in the bottom. More than four fifths of the lendable inventory of high-IC stocks is unlent, so their recall risk is unlikely to come mainly from exhausted inventory. These comparisons are descriptive: high-IC stocks also differ in size, liquidity and ownership. No single design makes inventory concentration random, so I combine four designs that address different concerns. Panel regressions with firm and month fixed effects compare a stock with itself over time. A propensity-score matched sample compares high-IC stocks with stocks of similar observable characteristics, and firms with two listed share classes compare two securities of the same firm on the same day (Appendix C). Withdrawals by individual lending programs, constructed following Gabaix and Koijen (2024), provide shocks to lendable supply that are unrelated to news common to all lenders of a stock, and show how a single lender's decision turns into recall events (Section 4.2).

4.1 Panel regressions

To test whether IC predicts recall risk beyond the fee, I estimate

$$y_{i,t+1} = \beta\, IC_{it} + \gamma' X_{it} + \alpha_i + \delta_t + \varepsilon_{i,t+1}, \tag{11}$$

where $y_{i,t+1}$ is a recall or lending outcome for stock i in month $t+1$, IC_{it} is standardized across stocks within month t, and X_{it} contains month-t controls. Firm and month fixed

effects (α_i and δ_t) absorb persistent firm differences and common monthly shocks. Thus β measures how a stock's next-month outcome varies as its IC changes relative to other stocks, conditional on the controls. Standard errors are clustered by firm and month.

The controls cover firm characteristics, ownership and lending conditions (Table 2). Including ownership HHI distinguishes inventory concentration from the ownership concentration studied by Porras Prado et al. (2016). Including the fee tests the model's prediction that IC predicts recall risk beyond the fee. I also control for lendable supply and short interest. Both may respond to inventory concentration if concentrated lenders supply fewer shares or short sellers borrow less when recall risk is high. I do not control for utilization. It is the ratio of loans to lendable supply, so with short interest and lendable supply already among the controls.

Table 2 shows that a one-standard-deviation increase in IC predicts a 2.09 percentage point increase in next-month recall probability ($t = 8.7$), relative to a sample mean of 10.9%. Squeeze probability increases by 0.36 percentage points ($t = 6.0$), against a mean squeeze frequency of 0.38%. URR, the share of loans lost to unreplaced recalls, increases by 1.16 percentage points ($t = 6.4$) from a sample mean of 7.7%. The fee also predicts recall events, consistent with Corollary 1, under which the fee and recall risk both rise with utilization. With only firm characteristics, institutional ownership and the fee as controls, the IC coefficients are similar: 2.17 percentage points for recall events ($t = 9.3$), 0.35 for squeezes ($t = 6.2$) and 1.23 for URR ($t = 7.1$).

Higher IC also predicts less stable supply. A one-standard-deviation increase in IC predicts a 2.05 percentage point increase in the probability of a supply drop ($t = 6.7$), relative to a mean of 22.1%, and a 0.044 increase in supply volatility ($t = 12.5$). The latter estimate is consistent with Proposition 1, under which individual lenders' decisions account for more of the variation in aggregate supply when inventory is concentrated.

Firm size. High-IC stocks are small, and recall events are more common among small stocks, so the relation could reflect size rather than concentration. Supply data are also noisier for small, thinly lent stocks. In separate regressions by size quintile, IC predicts recall events, URR and supply volatility in every quintile (Appendix Table C.3). The URR t-statistics range from 2.3 to 4.1. Relative to the mean recall frequency, the recall coefficient is largest among the largest stocks at 2.70 percentage points ($t = 4.4$), against a mean of 2.9%.

Ownership. Passive funds are large lenders that rarely recall, raising the possibility that IC proxies for low passive ownership. In the subsample with passive ownership data, which ends in 2019, a ten percentage point increase in passive ownership predicts a 5.4 percentage point decline in recall probability ($t = -9.0$). Conditional on passive ownership, a

Table 2: Inventory concentration and next-month recall risk

	Recall event$_{t+1}$ (1)	URR$_{t+1}$ (2)	Supply drop$_{t+1}$ (3)	Squeeze$_{t+1}$ (4)	Supply vol.$_{t+1}$ (5)
IC (standardized)	2.09***	1.16***	2.05***	0.357***	0.044***
	(0.240)	(0.182)	(0.306)	(0.059)	(0.004)
log ME	-1.58***	-1.18***	-2.97***	0.013	0.003
	(0.297)	(0.229)	(0.359)	(0.041)	(0.003)
BM	0.336*	0.080	0.559**	-0.066***	-8×10^{-6}
	(0.180)	(0.138)	(0.250)	(0.025)	(0.002)
Ret(-6,-1)	1.23***	1.03***	0.255	-0.008	0.003
	(0.326)	(0.252)	(0.314)	(0.040)	(0.002)
IVOL	42.4***	25.5***	43.2***	2.88**	-0.141***
	(4.64)	(3.37)	(5.52)	(1.24)	(0.043)
log Amihud	0.918***	0.368**	1.34***	-0.035	0.018***
	(0.197)	(0.149)	(0.234)	(0.035)	(0.002)
Turnover	1.19***	0.691***	1.56***	0.070**	0.004***
	(0.164)	(0.120)	(0.196)	(0.029)	(0.001)
IOR	-1.59*	-0.373	-6.76***	0.190*	0.005
	(0.934)	(0.627)	(1.36)	(0.098)	(0.008)
Ownership HHI	2.61*	-0.563	3.94**	0.392*	-0.007
	(1.35)	(0.925)	(1.70)	(0.203)	(0.014)
Fee	5.50***	2.46***	6.58***	0.127***	0.036***
	(0.202)	(0.122)	(0.246)	(0.028)	(0.002)
Lendable supply (LQ)	-10.1**	-6.32*	-12.8*	-0.353*	-0.069**
	(4.48)	(3.21)	(6.51)	(0.183)	(0.035)
Short interest	-30.6***	-35.8***	20.7***	1.04**	-0.313***
	(3.62)	(2.37)	(4.29)	(0.473)	(0.027)
Observations	556,131	556,135	556,556	555,479	556,458
R^2	0.30	0.26	0.35	0.12	0.33
Firm fixed effects	✓	✓	✓	✓	✓
Month fixed effects	✓	✓	✓	✓	✓

Notes. Each regression relates a month-$t+1$ outcome to IC standardized within month t. Month-t controls are log market capitalization, book-to-market, return over months $t-6$ to $t-1$, idiosyncratic volatility, log Amihud illiquidity, turnover, institutional ownership, ownership HHI, the fee, lendable supply relative to shares outstanding, and short interest. Recall events and supply drops use a 5% daily threshold. Recall, supply-drop and squeeze probabilities are in percent. URR is the percentage of loans lost to unreplaced recalls. Supply volatility is the standard deviation of daily active lendable quantity divided by its mean. All regressions include firm and month fixed effects. Parentheses report standard errors clustered by firm and month.

one-standard-deviation increase in IC still predicts increases of 1.83 percentage points in recall probability ($t = 7.2$) and 1.04 percentage points in URR ($t = 5.7$) (Appendix Table C.4). Ownership concentration has a smaller association with recall probability than IC: in the main specification, a one-standard-deviation increase in ownership HHI predicts a 0.3 percentage point increase in recall probability ($t = 1.9$), compared with 2.09 percentage points for IC ($t = 8.7$).

Matched sample and dual-class shares. Two additional designs examine whether the panel results reflect differences in observable characteristics or exposure to firm news (Appendix C). The first matches each top-IC-quintile stock to a stock in the bottom three quintiles within the same fee group. Matching uses a propensity score based on size, book-to-market, idiosyncratic volatility, Amihud illiquidity, turnover, institutional ownership, ownership HHI and passive ownership. The matched groups are similar on these characteristics, but mean IC is 0.35 for high-IC stocks and 0.18 for controls. In the following month, recall probability is 3.4 percentage points higher for high-IC stocks ($t = 5.3$), relative to a control mean of 14.1%. URR is 2.2 percentage points higher ($t = 5.5$), and squeeze probability is about twice as high, despite lower utilization (Appendix Table C.5).

The second design follows Porras Prado et al. (2016) and compares listed share classes of the same firm on the same day. Firm × day fixed effects absorb news common to both classes. Controlling for class size, the fee, lendable supply, institutional ownership and ownership HHI, a one-standard-deviation difference in IC predicts a 1.6 percentage point difference in recall probability over the next five trading days ($t = 3.8$), nearly half the sample mean of 3.4% (Appendix Table C.6). The estimated differences in the fee and utilization across classes are statistically insignificant. The within-firm comparison thus shows that IC predicts recall risk even among share classes exposed to the same firm news.

4.2 Withdrawals by lending programs

The panel regressions show that IC predicts recall risk. The model links the two through lender withdrawals. A withdrawal leads to unreplaced recalls when borrowers cannot find enough replacement shares. Concentration increases this exposure because a single lender can withdraw a larger share of supply. I examine two implications using mutual fund lending programs. First, recall risk should rise with the size of a withdrawal. Second, a withdrawal by the largest program should be associated with a larger increase in recall risk at higher IC.

Lending programs. Markit does not identify individual lenders. I therefore combine fund holdings from Form N-PORT with lending-agent identities from Form N-CEN. I define a lending program as the funds in one family that lend through the same agent. These funds

tend to adjust their lending together. Among pairs of funds lending the same stock, both funds reduce their loans without selling the stock in 20.3% of quarters when they share a family and an agent. The frequency is 16.4% for funds in different families using the same agent and 11.8% for funds using different agents. I restrict the sample to non-index funds because changes in index membership can trigger trades related to news about the stock. The sample comprises 58,170 stock-quarters from September 2019 through June 2023, each with at least three lending programs.

Measuring withdrawals. Following Gabaix and Koijen (2024), I compare holdings-weighted and equal-weighted growth across programs holding the same stock. For stock-quarter s, let H_{as} denote program a's holdings at the end of month t. The N_s programs holding the stock own $H_s = \sum_a H_{as}$ shares in total, and program a holds a share $S_{as} = H_{as}/H_s$. Let H'_{as} denote its holdings three months later, with $H'_{as} = 0$ after a complete sale. Holdings growth is

$$g_{as} = \min\left\{\frac{H'_{as} - H_{as}}{H_{as}},\ 1\right\}. \tag{12}$$

A complete sale gives $g_{as} = -1$. The upper bound limits the influence of large purchases. The shock is the difference between the two growth rates,

$$z_s = \sum_a \left(S_{as} - \frac{1}{N_s}\right) g_{as}. \tag{13}$$

The weights sum to zero, so any growth component common to all programs cancels. A negative z_s indicates that programs with larger initial positions had lower holdings growth on average.

I scale the shock by initial program holdings as a fraction of shares outstanding, SO_s, and reverse its sign,

$$W_s = -100\, z_s\, \frac{H_s}{SO_s}. \tag{14}$$

A positive W_s measures a withdrawal relative to the benchmark in which every position grows at the equal-weighted rate, as a percentage of shares outstanding. For example, $z_s = -0.10$ corresponds to a withdrawal of 0.1% of shares outstanding when programs initially hold 1% of the stock and 2% when they hold 20%. Constructing the measure from fund holdings keeps it distinct from changes in loans, which can fall when borrowers cover or lenders recall shares.

Specification. I regress recall outcomes over months $t+1$ through $t+3$ on W_s with quarter fixed effects. The controls are equal-weighted holdings growth; log market capitalization, utilization, the fee and loans relative to shares outstanding at the end of month t; and the stock return, changes in lendable supply and loans, loans lost and URR over months $t-2$

through t.

Withdrawals and recall risk. A measured withdrawal of 1% of shares outstanding raises quarterly recall probability by 1.84 percentage points ($t = 9.55$), relative to a mean of 19.6%. The share of loans lost to unreplaced recalls (URR) increases by 1.17 percentage points ($t = 17.33$), relative to a mean of 9.4%. Wild cluster bootstrap p-values are below 0.001. Lendable supply, loans, and short interest decline by 0.60, 0.27, and 0.06 percentage points of shares outstanding, respectively ($t = -25.2$, $t = -16.8$, and $t = -4.2$). Panel A of Table 3 reports the estimates.

Borrowers can replace withdrawn shares by borrowing from another lender. The estimates imply that 0.11 shares on loan are lost per share of supply withdrawn. Median utilization is only 18.2% even in the top IC quintile. These findings are consistent with some borrowers failing to replace recalled shares despite substantial unlent inventory.

Identification and timing. News about the stock could affect both program sales and borrowing conditions. Small programs respond to news about twice as strongly as large programs, so differencing the two growth rates removes only part of their response, which is why all regressions control for equal-weighted growth. This control reduces the coefficient relating z_s to prior-quarter returns from 0.64 ($t = 4.1$) to 0.03 ($t = 0.18$), and most associations with earnings news become insignificant, apart from a small association with the absolute earnings surprise (0.022, $t = 3.0$). In the same test, the association with prior returns is small for lending programs (-0.08, $t = -0.49$) but significant when the shock is built from index funds (1.66, $t = 8.73$) or lending agents (0.68, $t = 4.38$; Appendix Table D.4). Withdrawals coincide with lower same-quarter returns (-0.67 percentage points, $t = -3.0$), but controlling for these returns leaves the recall estimates essentially unchanged, and the association with next-quarter returns is insignificant (-0.16, $t = -0.89$). Withdrawals and recall outcomes are measured over the same quarter, so their order within it is unknown, but withdrawals are unrelated to recall events in the previous quarter (-0.08, $t = -0.45$). Selection on unobservables would have to be 5.0 times as strong as selection on observables to remove the recall estimate (Oster, 2019).

Concentration and withdrawal size. Recall risk rises with the size of a withdrawal relative to lendable supply. Compared with stock-quarters without a withdrawal, the probability of a recall event over the next three months is 1.14 percentage points higher when programs withdraw up to 2% of supply and 10.37 percentage points higher when they withdraw 10% to 25% (Table D.2). Withdrawals exceeding 10% of supply occur in 2.6% of stock-quarters in the top IC tercile and 0.6% in the bottom tercile. The distribution of holdings across programs explains this difference. Although total program holdings fall from

19.7% to 14.8% of lendable supply from the bottom to the top IC quintile, they are concentrated in fewer programs: the median number of programs falls from 55 to 5, and the largest program's share of program holdings rises from 23% to 62%. The largest program thus holds roughly twice the fraction of lendable supply in the top quintile that it holds in the bottom quintile (Appendix Table D.3).

Withdrawals by the largest program. I test whether a withdrawal by the largest program is associated with a greater increase in recall risk at higher IC. Let $\ell(s) = \arg\max_a H_{as}$ denote the largest program at the end of month t, and let $\bar{g}_{-a,s}$ denote mean holdings growth among the other programs. The indicator $Largest_s$ equals one if the largest program's holdings growth is at least 25 percentage points below the mean for its peers, $g_{\ell(s),s} - \bar{g}_{-\ell(s),s} \leq -0.25$. The indicator $Other_s$ equals one if any other program with $S_{as} \geq 0.10$ meets the same criterion relative to its peers. I estimate

$$\begin{aligned} y_s = {} & \beta_1 Largest_s + \beta_2\, Largest_s \times IC_s + \gamma_1 Other_s + \gamma_2\, Other_s \times IC_s \\ & + \delta\, IC_s + \theta' X_s + \alpha_t + \varepsilon_s, \end{aligned} \tag{15}$$

where y_s is a recall outcome over months $t+1$ through $t+3$, IC_s is the within-quarter percentile rank of IC at the end of month t, X_s contains the controls described above, and α_t denotes quarter fixed effects.

At the lowest IC rank, a withdrawal by the largest program is associated with a 1.11 percentage point increase in recall probability ($t = 1.44$). At the highest rank, the estimate is 5.83 percentage points ($t = 6.76$). The difference is 4.72 percentage points ($t = 3.36$). For URR, the corresponding estimates rise from 0.51 to 2.58 percentage points of loans, with an interaction coefficient of 2.06 ($t = 3.22$). For withdrawals by another large program, the estimated interactions are small for both recall probability (0.30, $t = 0.23$) and URR (0.04, $t = 0.07$). Panel B of Table 3 reports the estimates.

The interaction between IC and a large withdrawal by the largest program remains significant with further controls, industry-by-quarter fixed effects and most alternative withdrawal definitions (Appendix Table D.5). It loses significance with stock fixed effects, because IC varies little within a stock over 16 quarters, and with interactions with size, institutional ownership and ownership HHI, which explain 56% of the variation in IC. Large program exits therefore cause recalls, but the withdrawals cannot clearly separate IC from the ownership characteristics that shape it.

Withdrawals are associated with more loans lost to unreplaced recalls even when most inventory is unlent: for withdrawals of up to 25% of supply, median utilization ranges from 4.6% to 18.0% (Table D.2). Full replacement would prevent this loss. The evidence that concentration itself matters comes from the panel regressions, in which IC predicts

recalls conditional on size and ownership HHI, and from dual-class firms, in which the class with higher IC faces greater recall risk within the same firm on the same day (Section 4.1 and Appendix C.6).

Table 3: Withdrawals by lending programs and recall risk

	Recall event (pp)	URR (pp of loans)
Panel A. Withdrawal of 1% of shares outstanding		
Programs (non-index funds)	1.84	1.17
	(9.55)	(17.33)
Index funds	2.71	0.76
	(12.89)	(11.22)
Panel B. Large withdrawals by the largest program		
Large withdrawal by the largest program, lowest IC	1.11	0.51
	(1.44)	(1.75)
Large withdrawal by the largest program, highest IC	5.83	2.58
	(6.76)	(6.28)
Large withdrawal by the largest program × IC rank	4.72	2.06
	(3.36)	(3.22)
Large withdrawal by another large program × IC rank	0.30	0.04
	(0.23)	(0.07)
Panel C. Timing and inference		
Outcome in the previous quarter on the raw withdrawal	-0.08	0.16
	(-0.45)	(2.18)
Next quarter's withdrawal	-0.48	-0.21
	(-2.85)	(-3.72)
Wild bootstrap p, clustered by largest program	<0.001	<0.001
Oster δ for a zero effect ($R_{\max} = 1.3R^2$)	5.0	8.3
Mean of the outcome (%)	19.6	9.4
Stock-quarters	58,170	

Notes. N-PORT holdings of mutual funds grouped into lending programs (a fund family at its lending agent, from N-CEN), quarter ends from September 2019 to June 2023, stocks with at least three programs. Panel A: effect of the withdrawal W_s of equation (14), in percent of shares outstanding; the index-fund row builds the same withdrawal from index funds. Panel B: equation (15), with indicators of a large withdrawal: the largest program, or another program with at least 10% of the holdings, cuts its holdings by at least 25 percentage points more than the other programs; rows report the effect at the lowest and highest IC rank and the interaction. The largest program cuts its holdings in this way in 10.4%, 12.2% and 16.1% of stock-quarters in the bottom, middle and top IC terciles. Panel C: the outcome over the previous quarter regressed on the unpurged withdrawal; next quarter's withdrawal added to the regression of Panel A; wild cluster bootstrap with Rademacher weights, null imposed, 9,999 draws; δ from Oster (2019). Outcomes over the three months after the quarter end, defined in Section 3.3. Controls: the stock's return, the changes in lendable supply and loans, loans lost and URR over the previous quarter, log market capitalization, utilization, the fee, loans relative to shares outstanding and the equal-weighted growth of all programs; quarter fixed effects. Standard errors clustered by stock; t-statistics in parentheses.

5 Inventory Concentration and Equity Anomalies

5.1 Anomaly portfolios

Prediction (c) of Corollary 2 concerns anomaly returns net of fees. Where IC is high, recall risk deters short sellers from trading against overpricing, while investors who buy underpriced stocks face no corresponding risk. The model therefore predicts larger anomaly spreads at high IC. The spreads should remain larger after fees. I test this prediction with the 70 anomalies described in Section 3.

Portfolio construction. At the end of each month t, I assign stocks to three IC groups. Low contains the bottom quintile, Mid the middle three quintiles, and High the top quintile. Within each group, I sort stocks into quintiles of each anomaly signal and measure returns in month $t+1$. Let r_g^L and r_g^S denote the returns on stocks in the long and short quintiles of IC group g. The difference in anomaly spreads between the High and Low groups is

$$\left(r_H^L - r_H^S\right) - \left(r_L^L - r_L^S\right) = \underbrace{\left(r_H^L - r_L^L\right)}_{\text{long-quintile difference}} - \underbrace{\left(r_H^S - r_L^S\right)}_{\text{short-quintile difference}}. \tag{16}$$

Because the anomaly spread is the long-quintile return minus the short-quintile return, a lower short-quintile return at high IC widens the spread. I report averages across the 70 anomalies with sufficient stocks in each IC group and within each anomaly cluster.

Returns by leg. Across the 70 anomalies, the equal-weighted long-short spread is 0.43 percentage points per month larger in the High IC group than in the Low IC group ($t = 3.6$). The value-weighted difference is 0.32 percentage points ($t = 1.9$). The equal-weighted difference comes almost entirely from the short leg. Stocks in the short quintile earn 0.36% per month at high IC and 0.77% at low IC, a High-minus-Low difference of −0.40 percentage points ($t = -2.1$). Long-quintile returns are nearly identical at 0.92% and 0.90%, respectively ($t = 0.2$ for the difference). Panel A of Table 6 reports the portfolio returns. DGTW-adjusted returns show a similar pattern (Appendix E.1).

Short-quintile returns are lower at high IC in all ten anomaly clusters (Table 4). The monthly differences, in percentage points, are significant for short-term reversal (−0.59, $t = -2.8$), profit growth (−0.51, $t = -2.6$), value (−0.53, $t = -2.3$), momentum (−0.50, $t = -2.1$), and investment (−0.50, $t = -2.9$). The difference is marginally significant for low risk (−0.39, $t = -1.8$). No cluster has a statistically significant long-quintile difference.

Returns after fees. High-IC stocks carry higher fees. After charging the short leg the holding-month fee and crediting the long leg with 70% of the fee, the average High-minus-

Table 4: Excess returns by anomaly cluster and inventory concentration

Cluster	High LS Ret.	Low LS Ret.	High–Low LS Ret.	Long Contri.	Short Contri.
Short-Term Reversal	0.86***	0.18	0.68***	0.09	−0.59***
	(3.62)	(0.90)	(2.99)	(0.46)	(-2.81)
Profit Growth	0.74***	0.06	0.68***	0.18	−0.51**
	(3.87)	(0.50)	(3.58)	(0.91)	(-2.57)
Value	0.74**	0.20	0.54**	0.01	−0.53**
	(2.24)	(0.93)	(2.27)	(0.03)	(-2.28)
Momentum	0.69**	0.02	0.67***	0.17	−0.50**
	(2.34)	(0.07)	(2.70)	(0.90)	(-2.06)
Investment	0.65***	0.12	0.53***	0.03	−0.50***
	(4.78)	(0.81)	(3.39)	(0.15)	(-2.90)
Profitability	0.58*	0.20	0.38	0.02	−0.36
	(1.66)	(0.88)	(1.46)	(0.16)	(-1.34)
Quality	0.56**	0.31*	0.25	−0.04	−0.29
	(2.48)	(1.68)	(1.16)	(-0.25)	(-1.23)
Seasonality	0.48***	0.13	0.35**	0.26	−0.09
	(3.33)	(1.26)	(2.08)	(1.62)	(-0.45)
Low Risk	0.38	−0.01	0.39*	0.00	−0.39*
	(1.07)	(-0.02)	(1.89)	(0.00)	(-1.77)
Debt Issuance	0.16	0.08	0.08	−0.13	−0.22
	(1.40)	(0.81)	(0.62)	(-0.73)	(-1.33)

Notes. Each month, stocks are assigned to the Low (bottom IC quintile), Mid, or High (top IC quintile) group and sorted into quintiles of each anomaly signal within that group. High and Low report the cluster's average equal-weighted long-short return in each group, in percent per month. Long and Short report the High-minus-Low differences in returns on stocks in the respective legs. A negative Short entry increases the High-minus-Low spread in equation (16). Parentheses report t-statistics for the monthly time series. *, **, and *** denote significance at the 10%, 5%, and 1% levels. The sample runs from 2006 to 2023.

Low spread is 0.33 percentage points per month ($t = 2.7$). Crediting lending income only on shares actually lent, following Muravyev et al. (2025), gives a difference of 0.27 percentage points ($t = 2.2$). Table 6 reports the baseline adjustment described in Section 3, and Appendix Table E.1 reports the adjustment for shares lent.

The net-of-fee spread is larger at high IC in all ten clusters (Table 5). The monthly High-minus-Low difference, in percentage points, is significant for short-term reversal (0.61, $t = 2.7$), profit growth (0.65, $t = 3.4$), momentum (0.60, $t = 2.5$), and investment (0.46, $t = 3.0$). Within the High IC group, the net-of-fee CAPM alpha is significant at the 5% level in every cluster except debt issuance. Differences in fees therefore do not account for the larger anomaly spreads at high IC, as prediction (c) states.

Table 5: Net-of-fee anomaly returns by cluster and inventory concentration

	Long-short return			CAPM α		
Cluster	High	Low	High–Low	High	Low	High–Low
Short-Term Reversal	0.78***	0.17	0.61***	0.84***	0.17	0.66***
	(3.30)	(0.85)	(2.71)	(3.50)	(0.87)	(2.88)
Profit Growth	0.69***	0.04	0.65***	0.71***	0.09	0.62***
	(3.60)	(0.38)	(3.38)	(3.63)	(0.77)	(3.18)
Momentum	0.60**	−0.01	0.60**	0.93***	0.34	0.59**
	(2.04)	(-0.02)	(2.45)	(3.45)	(1.25)	(2.35)
Investment	0.57***	0.10	0.46***	0.60***	0.14	0.46***
	(4.15)	(0.69)	(2.96)	(4.36)	(0.93)	(2.90)
Value	0.56*	0.18	0.38	0.90***	0.27	0.63***
	(1.70)	(0.82)	(1.62)	(2.91)	(1.24)	(2.84)
Seasonality	0.42***	0.12	0.30*	0.45***	0.12	0.33*
	(2.92)	(1.16)	(1.78)	(3.07)	(1.10)	(1.94)
Quality	0.41*	0.29	0.12	0.54**	0.44**	0.10
	(1.82)	(1.58)	(0.56)	(2.44)	(2.53)	(0.46)
Profitability	0.39	0.17	0.22	0.71**	0.39*	0.32
	(1.12)	(0.77)	(0.83)	(2.13)	(1.84)	(1.22)
Low Risk	0.25	−0.04	0.29	0.88***	0.44**	0.44**
	(0.71)	(-0.14)	(1.44)	(3.36)	(2.00)	(2.20)
Debt Issuance	0.10	0.06	0.04	0.16	0.10	0.06
	(0.90)	(0.66)	(0.30)	(1.41)	(1.06)	(0.44)

Notes. Portfolios are formed as in Table 4. Short positions pay the holding-month fee, and long positions earn 70% of the fee. CAPM α is the intercept from a regression of the cluster's monthly net-of-fee long-short return on the market excess return.

Size. High-IC stocks tend to be small, so the spread could reflect size rather than IC. Two adjustments address this. When IC groups are formed within size terciles, the equal-weighted High-minus-Low spread is 0.25 percentage points per month ($t = 2.6$), about 60% of the original estimate, and remains concentrated in the short quintile (−0.35, $t = -2.2$; Appendix Table E.7). When each stock's return is measured relative to a DGTW benchmark portfolio of stocks with similar size, book-to-market and momentum, the spread is 0.40 percentage points per month ($t = 3.6$; Appendix Table E.1).

Table 6: Average anomaly portfolio returns by IC group before and after fees

	Long (5)	4	3	2	Short (1)	Long − Short
Panel A. Excess returns (% a month)						
High IC	0.92	0.94	0.82	0.62	0.36	0.56
	(2.49)	(2.57)	(2.16)	(1.49)	(0.71)	(2.99)
Low IC	0.90	0.88	0.86	0.83	0.77	0.13
	(2.42)	(2.38)	(2.26)	(2.04)	(1.62)	(0.92)
High − Low	0.02	0.06	-0.04	-0.20	-0.40	0.43
	(0.16)	(0.36)	(-0.25)	(-1.20)	(-2.10)	(3.55)
Panel B. Net of fees (% a month)						
High IC	1.03	0.94	0.82	0.62	0.59	0.44
	(2.79)	(2.57)	(2.16)	(1.49)	(1.16)	(2.35)
Low IC	0.93	0.88	0.86	0.83	0.82	0.11
	(2.50)	(2.38)	(2.26)	(2.04)	(1.73)	(0.76)
High − Low	0.11	0.06	-0.04	-0.20	-0.23	0.33
	(0.69)	(0.36)	(-0.25)	(-1.20)	(-1.17)	(2.74)
Panel C. Fee (% a year)						
High IC	1.88	1.68	1.76	1.97	2.76	
Low IC	0.47	0.42	0.43	0.45	0.61	

Notes. Each of the 70 selected anomalies has sufficient stocks in every IC group. Entries are monthly equal-weighted portfolio returns averaged across anomalies, in percent. Quintile 5 is the long leg and quintile 1 the short leg. High − Low compares the top and bottom IC quintiles. In Panel B, the short-quintile entry is the stock return plus the holding-month fee. This entry is subtracted when computing the long-short return. The long quintile earns 70% of the fee, and quintiles 2 through 4 receive no fee adjustment. Panel C reports average annualized fees in percent. Parentheses report t-statistics for the monthly time series. The sample runs from 2006 to 2023.

5.2 NetLeg portfolios within IC groups

A stock that appears in the short legs of several anomalies carries a stronger aggregate signal of overpricing. I use NetLeg, defined in equation (6), to test whether such stocks earn especially low returns when their lendable inventory is concentrated.

Portfolio construction. Each month, I form anomaly quintiles within the Low, Mid, and High IC groups as in Section 5.1 and compute each stock's NetLeg, defined in equation (6), from the long and short quintiles of its group. Within each IC group, I sort stocks into NetLeg quintiles at the end of month t and hold equal-weighted portfolios in month $t+1$. Q1 contains the stocks with the greatest net exposure to anomaly short legs, the most overpriced stocks of the group, and Q5 those with the greatest net exposure to long legs. Both the anomaly signals and the NetLeg quintiles therefore rank stocks relative to their IC peers. Section 6 instead forms anomaly quintiles over all stocks, so that a stock in the short leg has the same signal cutoff at every level of IC.

Returns by leg. The Q5-minus-Q1 spread earns 122 basis points per month at high IC ($t = 2.7$) and 31 at low IC ($t = 0.8$). The High-minus-Low difference is 91 basis points ($t = 3.3$). Most of this difference comes from Q1. Its stocks earn just 1 basis point per month above the risk-free rate at high IC, compared with 63 basis points at low IC. Their monthly CAPM alphas are −122 basis points ($t = -3.1$) and −61 basis points ($t = -2.3$),

respectively (Table 7).

For the Q5-minus-Q1 spread, the monthly CAPM alpha is 183 basis points at high IC ($t = 4.7$) and 81 at low IC ($t = 2.9$). The corresponding annualized Sharpe ratios are 0.66 and 0.21.

Table 7: NetLeg portfolio returns by inventory concentration

Metric	Group	1	2	3	4	5	H–L
r	Low-IC	63.14	88.42	88.03	90.35	93.85	30.71
		(1.10)	(1.94)	(2.28)	(2.61)	(3.20)	(0.83)
	High-IC	1.17	37.19	74.03	108.82	122.71	121.54
		(0.02)	(0.63)	(1.70)	(2.66)	(3.30)	(2.66)
Avg. Fee	Low-IC	6.01	3.96	3.60	3.39	3.33	–
	High-IC	29.72	21.05	14.82	14.00	11.67	–
SR	Low-IC	0.272	0.471	0.543	0.598	0.734	0.211
	High-IC	0.004	0.174	0.471	0.786	1.005	0.663
r^{feeadj}	Low-IC	69.15	91.19	90.54	92.73	96.18	27.03
		(1.20)	(2.01)	(2.34)	(2.67)	(3.28)	(0.73)
	High-IC	30.89	51.92	84.40	118.63	130.88	99.99
		(0.45)	(0.89)	(1.94)	(2.90)	(3.53)	(2.20)
SR^{feeadj}	Low-IC	0.298	0.486	0.559	0.614	0.753	0.186
	High-IC	0.118	0.244	0.537	0.857	1.073	0.546
α_{CAPM}	Low-IC	-61.39	-19.49	-6.45	2.00	19.11	80.50
		(-2.33)	(-1.29)	(-0.56)	(0.19)	(2.23)	(2.86)
	High-IC	-122.12	-69.36	-4.17	39.58	60.57	182.69
		(-3.12)	(-2.43)	(-0.19)	(1.68)	(2.90)	(4.72)
α_{CAPM}^{feeadj}	Low-IC	-55.35	-16.71	-3.93	4.39	21.44	76.79
		(-2.10)	(-1.11)	(-0.34)	(0.42)	(2.51)	(2.73)
	High-IC	-92.48	-54.54	6.30	49.40	68.76	161.24
		(-2.38)	(-1.93)	(0.29)	(2.10)	(3.30)	(4.18)
Num. Months	Low-IC	209	209	209	209	209	–
	High-IC	209	209	209	209	209	–
Avg. Num. Stocks	Low-IC	127	127	126	126	126	–
	High-IC	126	125	125	126	126	–

Notes. Each month, anomaly quintiles are formed within each IC group, and stocks are sorted into quintiles of their long-leg minus short-leg count within the group. Low and High contain the bottom and top IC quintiles. Quintile 1 has the greatest net exposure to anomaly short legs and quintile 5 the greatest net exposure to long legs; H–L denotes quintile 5 minus quintile 1. r is the equal-weighted next-month excess return, and Avg. Fee is the average monthly fee, both in basis points. SR is the annualized Sharpe ratio. The fee-adjusted return r^{feeadj} charges the holding-month fee on quintile 1 and credits 70% of the fee to quintile 5. α_{CAPM} denotes CAPM alpha. Parentheses report Newey–West t-statistics with three lags. The sample runs from 2006 to 2023.

Returns after fees. Q1 stocks have a fee of 30 basis points per month at high IC and 6 at low IC. After fees, the Q5-minus-Q1 spread earns 100 basis points per month at high IC ($t = 2.2$) and 27 at low IC ($t = 0.7$). The High IC spread has a net-of-fee CAPM alpha of 161 basis points per month ($t = 4.2$). When lending income is credited only on shares actually

lent, the High IC spread earns 93 basis points per month ($t = 2.0$; Appendix Table E.5). Figure 2 shows how these returns accumulate over the sample. Net of fees, the anomaly spread therefore remains larger at high IC, as prediction (c) states.

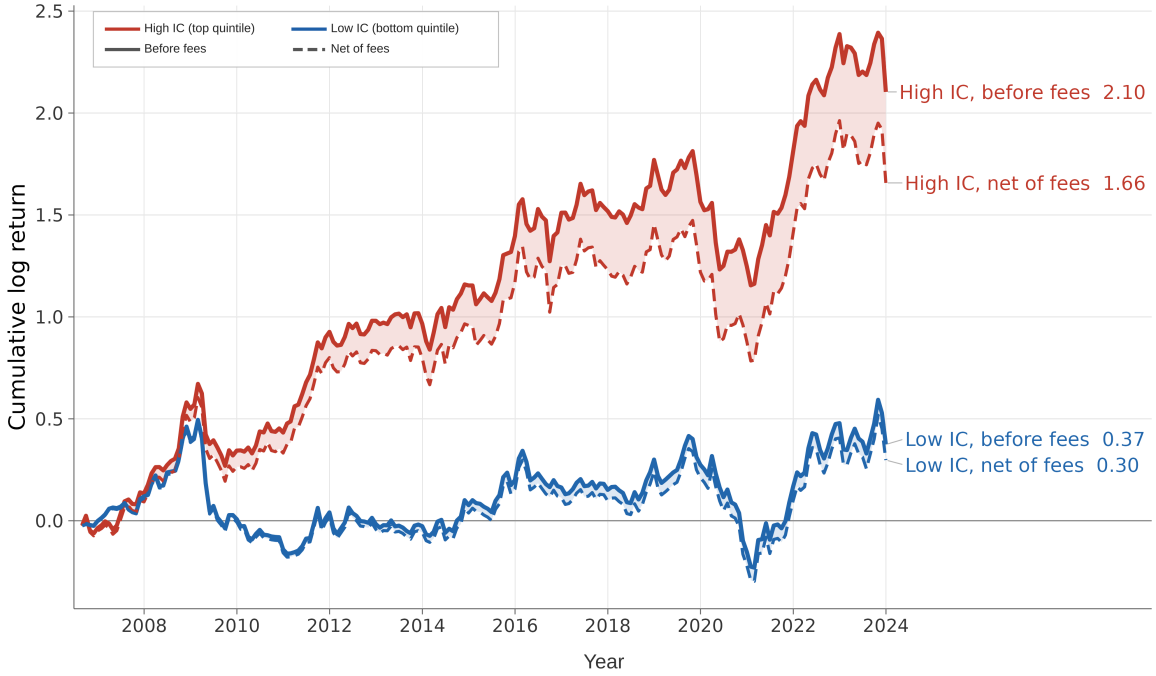


Figure 2: Cumulative NetLeg spread by IC group. Lines show cumulative log returns on NetLeg quintile 5 minus quintile 1 in the High and Low IC groups from 2006 to 2023. Solid lines show returns before fees. Dashed lines charge the holding-month fee on quintile 1 and credit 70% of the fee to quintile 5. Shading shows the cumulative net fee adjustment. End labels give cumulative log returns through the end of the sample.

Size. When IC is ranked within size terciles, the High-minus-Low difference in the Q5-minus-Q1 spread falls from 91 to 58 basis points per month and remains significant ($t = 2.4$; Appendix Table E.7). When returns are measured relative to DGTW benchmark portfolios of stocks with similar size, book-to-market and momentum, the Q5-minus-Q1 spread is 124 basis points per month at high IC ($t = 3.5$) and 32 at low IC ($t = 1.3$; Appendix Table E.4).

Summary. Anomaly spreads are larger where lendable inventory is concentrated, mainly through the short leg. Net of fees, anomaly profits remain large and significant at high IC, for both the average anomaly and the NetLeg portfolio, but not at low IC. The difference also remains within size terciles and after DGTW adjustment. Section 6 tests whether short sellers, facing higher recall risk, respond less to overpricing where IC is high.

6 Inventory Concentration and Short Selling

Section 5 shows that anomaly spreads are larger where inventory is concentrated and remain larger net of fees. Prediction (b) of Corollary 2 gives the mechanism: when a short position is more exposed to recall, short sellers commit less capital to an overpriced stock. I test this prediction by examining how short interest responds to anomaly signals. I then track borrowing as stocks enter the anomaly short leg, and examine how short selling changes when Russell 3000 inclusion adds passive lenders and broadens the lender base.

6.1 Short positions and anomaly exposure

I regress next-month short interest and utilization on NetShort, NetLong, and their interactions with IC (Table 8). NetShort and NetLong measure how often a stock appears in anomaly short and long legs, respectively. NetShort, NetLong, IC and the controls enter as within-month ranks (equation (6)), centered at 0.5, so the NetShort coefficient is the response of the median stock. I form anomaly legs across all stocks rather than within IC groups, so the same NetShort rank represents the same overpricing signal at every level of IC. All specifications control for IC, the fee, firm size, Amihud illiquidity orthogonalized to size, idiosyncratic volatility, and lendable supply.

Short interest is higher in stocks with greater exposure to anomaly short legs, but the relation is weaker where inventory is concentrated. In the firm fixed effects specification (Table 8, column 2), stocks at the top of the NetShort distribution have 2.24 percentage points of shares outstanding more short interest than stocks at the bottom, for the median stock ($t = 19.3$). The NetShort × IC coefficient is -2.68 ($t = -8.6$), so this gap is 3.6 percentage points at the lowest IC rank and 0.9 at the highest. For the same exposure to anomaly short legs, overpricing thus attracts about one quarter as much short interest where inventory is most concentrated as where it is most dispersed.

Utilization helps distinguish a weaker borrowing response from a smaller pool of lendable shares. If short sellers were limited by the number of shares available, they would borrow a large fraction of the available inventory, so utilization, loans divided by lendable supply, would be higher in overpriced stocks with concentrated inventory. Yet utilization is less related to NetShort at high IC. Across the NetShort distribution, it is higher by 8.6 percentage points at the lowest IC rank and by 5.4 at the highest (interaction coefficient -3.26, $t = -3.6$, column 5). Short sellers thus borrow less at high IC even relative to the inventory available to them.

The result remains when NetShort and NetLong are interacted with every control, including the fee, lendable supply, institutional ownership and ownership HHI. The NetShort × IC coefficient is -0.86 for short interest ($t = -2.7$, column 3) and -7.08 for utilization ($t = -6.6$, column 6). From the lowest to the highest IC rank, the response falls from 2.6

to 1.7 percentage points for short interest and from 11.4 to 4.4 for utilization. For utilization, the interaction with ownership HHI has the opposite sign (5.69, $t = 4.6$). Adding passive ownership, available through 2019, yields IC interactions of −1.05 for short interest ($t = -2.9$) and −6.55 for utilization ($t = -5.3$) in columns 4 and 7. Measuring both outcomes at the end of month t gives similar results (Appendix F.1).

6.2 Borrowing around entry into the anomaly short leg

I estimate how borrowing changes around entry into the anomaly short leg and how that response varies with pre-entry inventory concentration.

Event definition. Each month, I sort all stocks into NetLeg quintiles. A stock enters the short leg if it moves from quintiles 3–5 at the end of month $t-1$ to quintile 1 (Q1) at the end of month t, having been outside Q1 at the ends of months $t-2$ and $t-3$. Q1 contains the stocks with the strongest overpricing signals. The sample includes 1,448 entries. Comparison stocks satisfy the same pre-event restrictions and remain above the NetLeg median at the ends of both $t-1$ and t.

Because the signals can change during months $t-1$ and t, I use the last trading day of $t-2$ as the baseline. I measure changes in daily Markit loans as a percentage of shares outstanding on that day. IC and the controls enter as within-month ranks measured at the same baseline and centered at 0.5.

Borrowing response. The borrowing gap opens during formation and widens afterward (Figure 3). Among low-IC entrants, loans rise by 0.33% of shares outstanding by the end of month t, 0.78% one month later, and 1.34% three months later. The corresponding increases among high-IC entrants are 0.13%, 0.18%, and 0.42%. Among comparison stocks, loans rise by less than 0.1% of shares outstanding.

To estimate how the borrowing response varies with pre-event IC, I pool entrants and comparison stocks and estimate

$$\begin{aligned}\Delta L_{i,k} = \alpha_{m(i),q(i)} + \alpha_{f(i)} + \beta J_i + \gamma\,\mathrm{IC}_i + \delta' X_i \\ + \theta\, J_i \times \mathrm{IC}_i + J_i \times \left(\lambda' X_i + \kappa_{q(i)}\right) + \varepsilon_{i,k},\end{aligned} \tag{17}$$

where $\Delta L_{i,k}$ is the change in loans from baseline to trading day k, and J_i indicates entry into Q1. The coefficient of interest, θ, measures how the borrowing gap between entrants and comparison stocks varies with pre-event IC. The controls X_i are the fee, lendable supply, Amihud illiquidity, idiosyncratic volatility, institutional ownership, and ownership HHI. The specification includes formation-month by size-quintile fixed effects, $\alpha_{m(i),q(i)}$, and allows the entry response to vary by size quintile $q(i)$. The firm fixed effects specification

Table 8: Short positions and inventory concentration

	Short interest$_{t+1}$ (% of shares)				Utilization$_{t+1}$ (%)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
NetShort	3.37	2.24	2.14	2.00	6.98	7.90	7.80
	(26.55)	(19.33)	(19.70)	(17.70)	(21.29)	(24.70)	(21.10)
NetShort × IC	-5.83	-2.68	-0.86	-1.05	-3.26	-7.08	-6.55
	(-17.52)	(-8.64)	(-2.67)	(-2.86)	(-3.61)	(-6.58)	(-5.34)
NetLong	0.89	0.65	0.57	0.45	-1.85	-1.63	-1.92
	(8.22)	(6.94)	(6.73)	(4.84)	(-7.19)	(-6.48)	(-6.57)
NetLong × IC	-0.77	0.34	0.65	0.68	-1.83	0.74	2.21
	(-2.77)	(1.28)	(2.23)	(2.05)	(-2.39)	(0.76)	(2.04)
NetShort × Inst. ownership			-0.01	0.05		-4.57	-3.40
			(-0.02)	(0.08)		(-3.43)	(-2.13)
NetShort × Ownership HHI			-0.03	0.31		5.69	4.84
			(-0.08)	(0.66)		(4.59)	(3.30)
NetShort × Passive ownership				1.50			1.01
				(2.72)			(0.65)
NetShort × Fee			7.32	7.57		28.53	27.88
			(20.34)	(18.79)		(26.24)	(22.99)
NetShort × Lendable supply			4.62	4.21		0.13	0.90
			(8.97)	(7.04)		(0.10)	(0.57)
NetShort × Size			3.14	2.56		13.82	12.46
			(7.09)	(5.29)		(9.65)	(7.83)
IC, fee, size, Amihud, IVOL, lendable supply	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Inst. ownership, ownership HHI	No	No	Yes	Yes	No	Yes	Yes
Passive ownership	No	No	No	Yes	No	No	Yes
NetShort × Amihud, IVOL	No	No	Yes	Yes	No	Yes	Yes
NetLong × each control	No	No	Yes	Yes	No	Yes	Yes
Firm FE	No	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	637,084	637,084	581,107	448,440	651,816	594,818	456,384

Notes. Panel regressions of short interest (exchange short interest in percent of shares outstanding) and lender utilization in month $t+1$ on the anomaly exposure of the stock in month t. NetShort and NetLong are within-month percentile ranks of the number of anomaly short and long legs the stock belongs to. IC is the within-month rank of Markit inventory concentration. All specifications control for IC, fee, size, Amihud illiquidity orthogonal to size, idiosyncratic volatility and lendable supply relative to market capitalization (ranks). All ranks are centered at 0.5, so NetShort and NetLong are the effects at the median stock; centering leaves the interactions unchanged. Columns 3, 4, 6 and 7 also include 13F institutional ownership and ownership HHI (ranks), and interact NetShort and NetLong with every control; they use the stock-months with 13F data. Columns 4 and 7 add the passive ownership share (index funds and ETFs, rank) and its interactions with NetShort and NetLong to columns 3 and 6, on the months for which it is available. Standard errors are clustered by firm and month; t-statistics in parentheses. Sample: 2006 to 2023 in columns 1 to 3, 5 and 6, and 2006 to 2019 in columns 4 and 7, the period for which passive ownership is available.

also includes $\alpha_{f(i)}$.

One and two months after formation, the pooled estimates of θ are -0.61 and -0.77, respectively, or -0.56 and -0.68 with firm fixed effects (Table 9). At the median of the other characteristics, the estimated two-month increase in loans is about 0.9% of shares outstanding at the lowest IC rank and 0.1% at the highest. None of the six interactions between entry and the other controls is statistically significant, including the interaction with ownership HHI (Appendix F.2).

Available inventory and fees. High-IC entrants have substantial unused inventory before the event. Lendable shares account for 13.5% of shares outstanding, and shares available but not on loan account for 11.6% of shares outstanding. Additional borrowing uses about 2% of that unused inventory. Over two months, utilization rises by 3.8 percentage points among low-IC entrants and 0.8 among high-IC entrants. The pooled entry × IC coefficient for utilization is -3.0 after one month ($t = -2.6$) and -3.1 after two ($t = -2.1$). The annualized fee changes little, falling by 0.01 percentage points among high-IC entrants and rising by 0.02 among low-IC entrants.

Timing, placebo, and size. One month before formation ends, the estimated entry × IC coefficient for loans is small (-0.15, $t = -1.0$). Entry into Q5, the quintile with the strongest underpricing signals, also produces little difference by IC. The corresponding interactions are 0.03 for loans ($t = 0.1$) and -0.25 for utilization ($t = -0.3$).

Firm size accounts for part of the borrowing gap. High-IC entrants have a mean size rank of 0.25, compared with 0.64 for low-IC entrants. Among entrants alone, the IC coefficients are -0.88 one month after formation ($t = -3.0$) and -1.17 after two months ($t = -3.2$). Within size quintiles, the estimates are -0.71 and -0.84, respectively. Size and IC have a rank correlation of -0.66 (Table B.3), which limits the precision with which their contributions can be distinguished.

Search frictions at entry. Difficulty locating shares when opening a position could also dampen borrowing at high IC. In the model, the same search friction makes a recalled loan harder to replace. The event study captures the weaker response when positions are opened, while Section 4 provides separate evidence that high IC predicts recalls and unreplaced loans on existing positions.

6.3 Russell 3000 inclusion

Russell 3000 inclusion brings index funds into stocks near the membership cutoff, broadening the lender base among firms of similar size. If concentration raises recall risk, inclusion should reduce recalls most where inventory was initially concentrated. If recall risk

Table 9: Loans and utilization after entry into the anomaly short leg, by inventory concentration

	Short leg (1,448 entries)				Long leg, placebo (3,081 entries)			
Trading day	-22	21	42	63	-22	21	42	63
Panel A. Loans, percent of shares outstanding								
High-IC minus low-IC tercile	-0.04	-0.76	-1.09	-1.20	0.11	0.33	0.31	0.21
	(-0.34)	(-4.20)	(-4.73)	(-3.94)	(1.50)	(2.53)	(2.18)	(1.54)
IC rank, entrants only	-0.28	-0.88	-1.17	-1.16	0.12	0.38	0.39	0.39
	(-1.53)	(-2.99)	(-3.24)	(-2.64)	(1.12)	(2.41)	(2.02)	(1.97)
IC rank, entrants only, size FE	-0.19	-0.71	-0.84	-0.74	0.14	0.36	0.40	0.46
	(-1.04)	(-2.49)	(-2.30)	(-1.59)	(1.19)	(2.15)	(2.02)	(2.25)
Entry × IC (DiD)	-0.15	-0.61	-0.77	-0.48	0.05	0.09	0.03	0.06
	(-1.01)	(-2.50)	(-2.61)	(-1.30)	(0.49)	(0.58)	(0.13)	(0.27)
Entry × IC (DiD), firm FE	-0.15	-0.56	-0.68	-0.52	0.05	-0.04	-0.15	-0.15
	(-0.96)	(-2.17)	(-2.09)	(-1.32)	(0.45)	(-0.21)	(-0.67)	(-0.68)
Mean change, entrants	0.16	0.45	0.54	0.57	-0.07	-0.15	-0.09	-0.02
Panel B. Utilization, percentage points								
High-IC minus low-IC tercile	0.46	-1.87	-2.71	-2.91	-0.03	0.71	0.54	0.15
	(0.78)	(-1.81)	(-2.24)	(-2.14)	(-0.08)	(1.40)	(1.02)	(0.28)
Entry × IC (DiD)	-0.98	-2.98	-3.07	-1.46	-0.08	0.07	-0.25	-0.46
	(-1.33)	(-2.55)	(-2.13)	(-0.88)	(-0.15)	(0.09)	(-0.29)	(-0.52)
Entry × IC (DiD), firm FE	-0.97	-2.69	-2.41	-1.32	-0.03	-0.45	-0.82	-1.07
	(-1.32)	(-2.19)	(-1.58)	(-0.73)	(-0.05)	(-0.57)	(-0.86)	(-1.11)
Mean change, entrants	0.63	1.52	1.88	1.79	-0.41	-0.88	-0.72	-0.74
IC rank rows (loans): entrants only; controls at $t-2$; month FE, second row month × size FE								
Entry × IC rows: entrants and comparison stocks; controls at $t-2$, alone and × entry; entry × size quintile; month × size-quintile FE; firm FE in the second row only								
Stock-months, loans	239,723	237,140	241,982	234,803	218,312	216,403	221,191	214,954

Notes. Entry into the short leg: stocks that move from NetLeg quintile 3, 4 or 5 at the end of month $t-1$ into the most net-short quintile at the end of month t, having been outside it at the end of $t-2$ and $t-3$. Entry into the long leg: the same move from quintiles 1 to 3 into the most net-long quintile. 2006 to 2023. The outcome is the change relative to the base day, the last trading day of month $t-2$, at the given trading day relative to the end of the formation month t (day -22 is about one month before its end, days 21, 42 and 63 one, two and three months after) in Markit loans in percent of shares outstanding on the base day (Panel A) or in utilization, loans in percent of lendable inventory (Panel B). High-IC minus low-IC tercile: the average change of entrants in the top IC tercile minus the bottom tercile, IC measured at the end of month $t-2$, averaged within formation-month cohorts and then across cohorts, with t-statistics from the time series of cohort differences. IC rank, entrants only: the coefficient on the within-month IC rank at the end of month $t-2$ in a regression of the change in loans among the entrants on IC and the controls (fee, lendable supply, Amihud illiquidity, idiosyncratic volatility, institutional ownership, ownership HHI, ranks at the end of month $t-2$) with formation-month fixed effects, in the second row formation month × size-quintile fixed effects; for utilization, whose denominator moves with the entrants' small lendable inventory, this entrants-only estimate is noisy and only the difference-in-differences is reported. Entry × IC: the coefficient on the entry indicator interacted with the IC rank in a regression that pools the entrants with the comparison stocks, those that satisfied the same conditions and stayed on the other side of the NetLeg median at the end of $t-1$ and t. The regression includes the entry indicator, IC and the controls, their interactions with the entry indicator, the interaction of the entry indicator with the size quintile, and formation month × size-quintile fixed effects; the second row adds firm fixed effects. Appendix F.2 reports every coefficient of this regression. Mean change, entrants: the average change relative to the base day across entrants. Changes winsorized at 0.5% and 99.5% by day; standard errors clustered by firm and month; t-statistics in parentheses.

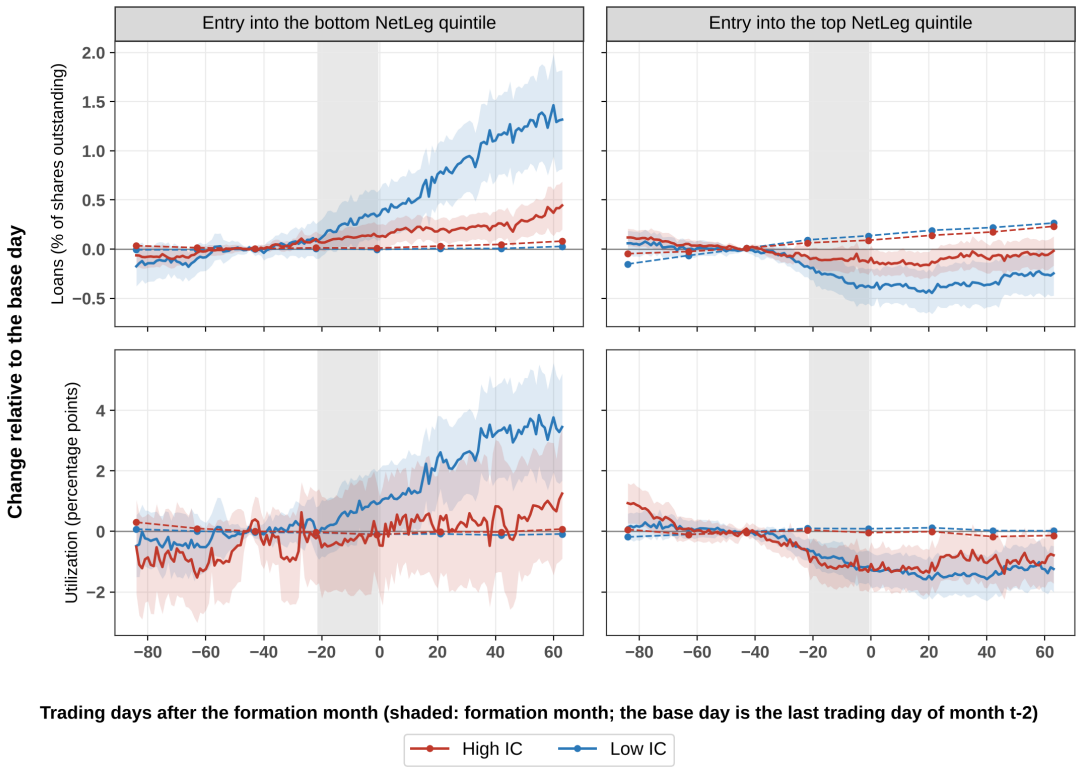


Figure 3: Borrowing around entry into anomaly short and long legs. Lines show average changes in daily Markit loans from the last trading day of month $t-2$, as a percentage of shares outstanding on that day. The left panel shows entries from NetLeg quintiles 3–5 at the end of $t-1$ into Q1 at the end of t. The right panel shows placebo entries from quintiles 1–3 into Q5. IC terciles are measured at the end of $t-2$. Solid lines show entrants. Dashed lines show comparison stocks that remain on the opposite side of the NetLeg median from the destination quintile at both month ends. Bands are 95% confidence intervals based on variation across formation-month cohort averages. Shading marks month t. The sample runs from 2006 to 2023.

constrains short selling, inclusion should also increase short selling in those stocks when anomaly signals indicate overpricing.

Design. I reconstruct the rank-day ordering from company-level CRSP market capitalization and calibrate each year's cutoff using discontinuities in passive ownership and index additions. The calibration uses neither lendable supply nor recall outcomes. The sample covers prior non-members within 250 ranks of the cutoff from 2007 to 2021 and comprises 3,248 stock-years, including 1,202 additions. I estimate

$$y_{it} = \beta\,(\mathrm{Out}_i \times \mathrm{Post}_t) + f(r_i) \times \mathrm{Post}_t + \alpha_{i,y} + \gamma_t + \varepsilon_{it}, \tag{18}$$

where Out_i indicates that a stock ranks beyond the membership cutoff and Post_t indicates months after reconstitution. $f(r_i)$ is a linear trend in the distance to the cutoff, with separate slopes on each side, so that β measures the change in outcomes at the cutoff. Stock-year and month fixed effects are denoted by $\alpha_{i,y}$ and γ_t. The window extends from six months before July to eleven months after July, excluding June and July. I cluster standard errors by stock and report $-\beta$, so positive estimates indicate an increase associated with inclusion.

Recall risk and short selling. Inclusion lowers IC by 0.063 from a pre-entry mean of 0.40 ($t = -6.0$). The probability of a recall event falls by 9.6 percentage points ($t = -4.1$), about one-quarter of its pre-entry level, and URR falls by 6.9 percentage points ($t = -4.4$). Lendable supply rises by 2.37 percentage points of shares outstanding, with no statistically significant change in the fee. Short interest and loans rise by 1.73 and 1.01 percentage points of shares outstanding, respectively ($t = 5.6$ and $t = 5.8$), and utilization rises by 4.24 percentage points from a pre-entry mean of 19.1% ($t = 3.2$). Loans therefore grow faster than supply, so the higher borrowing reflects greater demand from short sellers, not only additional shares. Table 10 reports the estimates.

Table 11 splits entrants at the median IC before reconstitution and interacts entry with NetShort. Among entrants with dispersed inventory (Panel B), short interest rises by 1.68 percentage points at the bottom of the NetShort distribution ($t = 3.0$), with no significant additional increase at the top (0.21, $t = 0.3$). Among entrants with concentrated inventory (Panel C), short interest barely rises at the bottom of the NetShort distribution (0.23, $t = 0.4$) but rises by 1.93 percentage points more at the top ($t = 2.0$). Loans show the same pattern (0.92, $t = 2.1$), while the fee of these entrants does not change significantly at either the bottom or the top of the NetShort distribution, and exposure to anomaly long legs does not raise the response in either group. The probability of a recall event also falls more where inventory was concentrated, by 13.1 percentage points ($t = -3.7$) against 6.4 ($t = -2.1$) (Appendix Table F.5).

Table 10: Russell 3000 entry: recall risk and short selling

Outcome	Effect of entry	t	Pre-entry mean (entrants)	N
Recall event (monthly prob.)	−0.096	-4.1	0.371	46,666
URR (% of loans)	−6.89	-4.4	22.14	46,665
Inventory concentration	−0.063	-6.0	0.397	46,971
Lendable supply (% of shares)	+2.37	9.5	7.06	48,469
Utilization (%)	+4.24	3.2	19.11	48,515
Fee (bp, annual)	−68.0	-1.0	445.1	48,814
Markit loans (% of shares)	+1.01	5.8	1.38	49,020
Exchange short interest (% of shares)	+1.73	5.6	2.22	42,758

Notes. Diff-in-RD at the entry cutoff, 2007 to 2021, 3,248 stock-years of which 1,202 enter: equation (18) on prior non-members within 250 ranks of the rebuilt Russell 3000 cutoff, event months −6 to +11 around June, June and July dropped, stock-year and month fixed effects, standard errors clustered by stock; the table reports $-\beta$. Passive ownership, recall events by size and the lender base in fund filings are in Table F.4.

Table 11: Russell 3000 entry, anomaly exposure and the pre-entry lender base

	Short interest (% of shares)		Markit loans (% of shares)	
	Effect	(t)	Effect	(t)
Panel A. All entrants				
Entry	+1.14	(2.9)	+0.52	(1.9)
Entry × NetShort	+0.83	(1.3)	+0.80	(2.1)
Entry × NetLong (separate regression)	+0.37	(0.6)	+0.07	(0.2)
Stock-years	2372		2435	
Panel B. Entrants with dispersed inventory before entry (IC below the median)				
Entry	+1.68	(3.0)	+0.96	(2.2)
Entry × NetShort	+0.21	(0.3)	+0.66	(1.1)
Entry × NetLong (separate regression)	+0.83	(1.0)	+0.29	(0.5)
Stock-years	1327		1343	
Panel C. Entrants with concentrated inventory before entry (IC above the median)				
Entry	+0.23	(0.4)	+0.01	(0.0)
Entry × NetShort	+1.93	(2.0)	+0.92	(2.1)
Entry × NetLong (separate regression)	−0.51	(-0.6)	−0.50	(-1.0)
Stock-years	1045		1092	

Notes. Prior non-members within 250 ranks of the rebuilt cutoff, 2007 to 2021, with anomaly exposure in April before reconstitution. Equation (18) with the interaction of entry with NetShort, the within-month rank of the number of anomaly short legs the stock belongs to (0 to 1), and with post × NetShort. Entry is the effect at NetShort of zero and Entry × NetShort the additional effect at the top of the NetShort distribution. The NetLong row replaces NetShort with the rank of anomaly long legs in a separate regression. Panels B and C split the entrants at the median IC in April before reconstitution. June and July dropped, stock-year and month fixed effects, standard errors clustered by stock. In the sample of Panel C, Entry × NetShort is +53 basis points (t 0.4) with the fee and +1.25 percentage points (t 1.8) with lendable supply as the outcome. Before entry, in the top NetShort quintile of these entrants, lendable supply was 4.7% and loans 1.6% of shares outstanding, median utilization was 15%, 76% of stock-months had utilization of at most 50%, and the median fee was 269 basis points a year.

Interpretation and limits. The decline in recalls and the increase in short selling among overpriced, high-IC stocks are consistent with recall risk constraining short positions. Inclusion, however, changes more than the concentration of inventory: it adds index funds, which may lend more consistently, and expands lendable supply, somewhat more in the short legs of high-IC entrants (1.25% of shares outstanding, $t = 1.8$). Additional supply alone is unlikely to explain the pattern. Before inclusion, supply did not bind in these stocks: median utilization was 15%, and 76% of stock-months had utilization of at most 50%. The fee did not fall (53 basis points, $t = 0.4$), and lendable supply rose more among entrants with dispersed inventory (2.92 against 1.94 percentage points of shares outstanding; Appendix Table F.5), whose short interest rose without concentrating in the short legs. The comparison across IC groups splits entrants by IC before inclusion and rests on 1,327 and 1,045 stock-years. Russell inclusion therefore shows the consequences of broadening the lender base rather than isolating the effect of IC. Appendix F.3 reports evidence from fund filings and results for alternative bandwidths, placebo cutoffs, and sample years.

Summary. Short sellers respond less to overpricing where lendable inventory is concentrated, although unused inventory is available and the fee is stable. When Russell inclusion broadens the lender base and lowers recall risk, short sellers increase their positions most in overpriced stocks whose inventory was concentrated.

7 Conclusion

To profit from overpricing, a short seller needs to borrow shares at a fee and keep them until the mispricing corrects. A recall can force the position to close early if the seller cannot find replacement shares in time. This paper shows that recall risk depends not only on how scarce shares are, which the fee reflects, but also on how lendable inventory is distributed across lenders. When one lender holds much of the inventory, a single withdrawal can recall more shares than search frictions allow borrowers to replace from the other lenders in time. Stocks with concentrated inventory accordingly experience more frequent recall events and lose a larger share of their loans to unreplaced recalls, even when most of their inventory is unlent.

This recall risk deters short selling. Where inventory is more concentrated, the same overpricing signal implied by anomalies attracts less short interest, and loans rise less when a stock enters the anomaly short leg, even though unlent shares are available and the fee barely changes. As a result, less of the overpricing is corrected: anomaly returns are higher at high IC, mainly through the short leg, and remain large and statistically significant net of fees. Russell 3000 inclusion supports this interpretation: it broadens the lender base and lowers recall risk, and among entrants with high pre-inclusion IC, short interest rises most

in stocks with the strongest overpricing signals.

The distribution of lendable inventory across lenders is thus a determinant of recall risk, distinct from lendable supply and the fee. Changes in the lender base can therefore facilitate the arbitrage of anomalies by lowering recall risk. One such change is the growth of passive ownership: passive investors hold stable positions and lend a large share of their holdings, so more passive ownership adds stable lenders to the lending market. Lower entry costs for institutional investors in the lending market also add lenders and reduce the share of lendable inventory held by any single lender. Search frictions matter as well: when electronic lending platforms and public reporting of securities loans make replacement shares easier to find, short sellers can trade more fully against overpricing. Policies and market developments that broaden and stabilize the lender base or reduce search frictions can therefore improve price efficiency beyond their effects on lendable supply and borrowing fees.

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Appendix A presents the model, proofs, evidence on the assumptions, and an example. Appendix B describes the distribution and persistence of inventory concentration and its relation to size and ownership. Appendix C validates the recall measures and reports matched-sample and dual-class comparisons, additional panel regressions, and the comparison with fee risk. Appendix D describes the construction of lending-program withdrawals and assesses their exogeneity and robustness. Appendix E presents the earnings-announcement test and additional anomaly-portfolio results. Appendix F reports further evidence on short positions and Russell 3000 inclusion. Appendix G lists the selected anomalies.

A Model

A.1 The full model

Forced closure. Withdrawals displace $uW_{IC}L$ borrowed shares and leave spare inventory of $(1-u)(1-W_{IC})L$, of which borrowers can reach a fraction ϕ in time. Recalled borrowers are rationed symmetrically against this capacity, and the loans that cannot be replaced are

$$K_{IC} = \left[\, uW_{IC}L - \phi(1-u)(1-W_{IC})L \,\right]^{+}, \tag{A.1}$$

which is positive if and only if equation (3) holds. The probability of a shortage is $\pi(IC,u) = \Pr(W_{IC} > a)$, and the expected fraction of borrowed shares that must close is

$$\rho(IC,u) = \frac{\mathbb{E}[K_{IC}]}{B} = \mathbb{E}\left[\left(W_{IC} - \frac{\phi(1-u)}{u}(1-W_{IC})\right)^{+}\right], \tag{A.2}$$

which under symmetric rationing is also the probability that a given borrowed share is closed. When $a(u,\phi) > \theta$ and $IC > 0$, the shortage probability is

$$\pi(IC,u) = 1 - G\left(\theta + \frac{a(u,\phi)-\theta}{\sqrt{IC}}\right), \tag{A.3}$$

where G is the distribution of withdrawals, and $\pi(0,u) = 0$. A shortage is impossible when

$$IC \le IC^{*}(u) \equiv \left(\frac{a(u,\phi)-\theta}{1-\theta}\right)^{2}. \tag{A.4}$$

More generally, for any $x > 0$ such that closing a fraction x of loans requires a withdrawal above θ, the probability $\Pr(K_{IC} \ge xB)$ is increasing in IC. Of the three ingredients of recall risk, the fee of equation (4) prices only spare inventory; borrowers' reach is common to all stocks, so conditional on the fee, recall risk differs across stocks only through IC.

Short selling and prices. A forced closure imposes an incremental expected loss $C > 0$ per share closed, relative to keeping the position, and C is common across stocks. The expected cost of borrowing a share is

$$c(IC, u) = F(u) + C\rho(IC, u). \tag{A.5}$$

As in Miller (1977), investors disagree, so each share sold short must be held by a less optimistic investor, and the price falls as short interest builds. I linearize that relation,

$$m(B) \equiv P(B) - V = m_0 - \kappa B, \qquad m_0 > 0,\ \kappa > 0, \tag{A.6}$$

where V is the expected value at the planned closing date, so that $m(B)$ is both the remaining mispricing and the gross expected payoff of a short position. With competitive, risk-neutral short sellers, an interior equilibrium $B^*(IC) \in (0, L)$ satisfies

$$m_0 - \kappa B^*(IC) = F\left(\frac{B^*(IC)}{L}\right) + C\rho\left(IC, \frac{B^*(IC)}{L}\right), \tag{A.7}$$

and is unique when it exists. Proposition 3 states that $IC' > IC$ implies $B^*(IC') \leq B^*(IC)$ and $P(B^*(IC')) - V \geq P(B^*(IC)) - V$. Short sellers enter until the marginal position, which faces the smallest remaining mispricing, earns its cost, so a higher expected cost of forced closure stops short positions at a larger mispricing.

A.2 Details

Replacement within the settlement window. A recalled loan must be returned within a settlement window of length Δ, short relative to the holding period. Search takes time: each unit of spare inventory is contacted at intensity λ, so over the window a broker locates a fraction $1 - e^{-\lambda\Delta}$ of the inventory it can reach at all, and it can reach only a fraction r of spare inventory, because lending runs through the agent lenders and direct lenders with which a prime broker already has agreements and through persistent relationships between particular lenders and stocks (Duffie et al., 2002; Dong and Zhu, 2026). The share of spare inventory available for replacement in time is therefore

$$\phi = r\left(1 - e^{-\lambda\Delta}\right) \in (0, 1]. \tag{A.8}$$

In Duffie et al. (2002) a located share is lent immediately and no loan is recalled, which is the case $\phi = 1$ with $a = 1 - u$; the shortage is then the squeeze of Schultz (2024).

Inventory concentration and the largest lender. Consider one large lender with share s and a fringe of n equally sized lenders, and let $n \to \infty$. The fringe's withdrawals converge to

θ and IC converges to s^2, which gives equation (2) with $s = \sqrt{IC}$. For arbitrary lender shares, IC bounds the largest share rather than pinning it down, $IC \leq s_1 \leq \sqrt{IC}$. In the data the two are close, with a correlation of 0.96, and with the controls of Table 2 each predicts recall events with a similar coefficient (2.05 and 1.81 percentage points per standard deviation).

The critical level of concentration. With $\phi = 1$, a shortage at low utilization requires an extreme concentration: with $\theta = 5\%$ and utilization of 8%, close to the sample median, the critical level IC^* of equation (A.4) is 0.84, which almost no stock-month reaches. With $\phi = 0.1$, IC^* falls to 0.26, and with $\phi = 0.05$ to 0.11. For comparison, IC averages 0.40 in the top quintile and 0.14 in the bottom quintile (Table C.2). Dong and Zhu (2026) provide direct evidence of such limits: when the mutual funds that lend a stock exit, its short interest falls and its fee rises, so borrowers are not fully moved to other lenders.

The cost of a forced closure. The loss C has three sources. First, a forced closure ends the position before the mispricing has fully corrected (D'Avolio, 2002), and the short seller forgoes the remaining expected correction unless she can re-establish the position, which requires searching for a lender again (Duffie et al., 2002). Second, the closure occurs at a time the short seller does not choose: mispricing can widen before it corrects (Shleifer and Vishny, 1997), recalls can coincide with squeezes (Lamont, 2012; Schultz, 2024), and a recall that arrives after the price has risen turns a paper loss into a realized one. Third, a forced closure requires buying back shares at short notice, which incurs price impact in the less liquid stocks in which inventory tends to be concentrated, and the other borrowers of the same lender may have to buy at the same time. The results do not depend on treating C as a constant. If the only loss from a forced closure is the forgone correction, $C = m$, equation (A.7) becomes $(1 - \rho)\, m = F$, and the remaining mispricing $m^* = F/(1 - \rho)$ still rises with the probability of closure. Risk aversion or limited capital (Shleifer and Vishny, 1997) would in addition lead each short seller to hold a smaller position, but the model does not need them.

A.3 Limitations

The model signs comparative statics and does not match magnitudes. At plausible values of θ and ϕ the expected forced closure it generates is far below the differences in realized recall rates across IC quintiles, and nothing in the paper rests on the level of π or ρ, only on their ordering in IC. The model is restricted in three further respects. Lenders do not optimize: withdrawals are exogenous, no lender chooses how much inventory to make available, and none offers committed availability at a price, so the fee that a borrower and a large lender would negotiate remains an open question. Proportional lending makes a lender's share of the loans equal to its share of the inventory, so the model treats inventory

concentration and loan concentration as one object and cannot account for the difference between them. And ϕ is held common across stocks: were replacement also harder where inventory is concentrated, concentration would operate through two channels rather than one, so this restriction works against the results. Section A.5 reports the evidence on each assumption and the restrictions that are imposed rather than tested.

A.4 Proofs

Proposition 1. $\mathbb{E}[W] = \sum_i s_i \mathbb{E}[\delta_i] = \theta \sum_i s_i = \theta$. By independence, $\mathrm{Var}(W) = \sum_i s_i^2 \mathrm{Var}(\delta_i) = v\,IC$. With $\delta_i = c + e_i$, $W = c + \sum_i s_i e_i$, and c is independent of the e_i, so $\mathrm{Var}(W) = v_c + v_e\,IC$. With a large lender holding s and n fringe lenders holding $(1-s)/n$ each, $IC_n = s^2 + (1-s)^2/n \to s^2$ and $W_n = s\delta_0 + \frac{1-s}{n}\sum_{j=1}^{n} \delta_j \to \theta + s(\delta_0 - \theta)$ almost surely by the law of large numbers, which is equation (2) with $s = \sqrt{IC}$. For general shares, $s_1^2 \le IC = \sum_i s_i^2 \le s_1 \sum_i s_i = s_1$, so that $IC \le s_1 \le \sqrt{IC}$.

The threshold and forced closures. $K_{IC} > 0$ if and only if $uW_{IC} > \phi(1-u)(1-W_{IC})$, or equivalently $W_{IC}[u + \phi(1-u)] > \phi(1-u)$, which gives equation (3). The threshold $a = \phi(1-u)/[u+\phi(1-u)] = 1/[1+u/(\phi(1-u))]$ is decreasing in u and increasing in ϕ. It equals $1-u$ when $\phi = 1$, and $a \le 1-u$ is equivalent to $\phi \le 1$, so every squeeze, $W_{IC} > 1-u$, is also a shortage. Dividing equation (A.1) by $B = uL$ gives the share of loans that must close,

$$\frac{K_{IC}}{B} = \psi(W_{IC}), \qquad \psi(w) = [(1+k)w - k]^+ = [w - k(1-w)]^+, \qquad k = \frac{\phi(1-u)}{u},$$

where ψ is convex and strictly increasing where positive, and k decreases in u and increases in ϕ.

Proposition 2, shortage probability. For $IC > 0$, $W_{IC} > a$ if and only if $\delta > \theta + (a-\theta)/\sqrt{IC}$, which gives equation (A.3). When $a > \theta$ the right-hand side decreases in IC, so π is weakly increasing in IC. Since a decreases in u and increases in ϕ, so does the right-hand side, and π is weakly increasing in u and weakly decreasing in ϕ. Since $\delta \le 1$, the largest possible withdrawal is $\theta + \sqrt{IC}(1-\theta)$, which does not exceed a when $IC \le IC^*(u)$. For $x > 0$, the event $K_{IC} \ge xB$ is $W_{IC} \ge w(x) \equiv (x+k)/(1+k)$ because ψ is strictly increasing where positive, and the same argument applies with $w(x)$ in place of a whenever $w(x) > \theta$.

Proposition 2, forced closure. $\rho(IC, u) = \mathbb{E}[\psi(W_{IC})]$. Fix u and $0 \le IC < IC'$, and let $\omega = \sqrt{IC/IC'} \in [0,1)$. Equation (2) implies $W_{IC} = (1-\omega)\theta + \omega W_{IC'}$. By convexity of ψ, $\mathbb{E}[\psi(W_{IC})] \le (1-\omega)\psi(\theta) + \omega\,\mathbb{E}[\psi(W_{IC'})] \le \mathbb{E}[\psi(W_{IC'})]$, where the second inequality uses Jensen's inequality, $\psi(\theta) = \psi(\mathbb{E}[W_{IC'}]) \le \mathbb{E}[\psi(W_{IC'})]$. Since $1 - w \ge 0$ and k decreases in u

and increases in ϕ, $\psi(w)$ is weakly increasing in u and weakly decreasing in ϕ at every w, and W_{IC} does not depend on u or ϕ. Finally, $\psi(W_{IC})$ is zero outside a shortage and at most $W_{IC} \leq 1$ during one, so $\rho \leq \pi$.

Corollary 1. Under equation (4) the fee depends on u only, while π and ρ increase with IC at every u by Proposition 2.

Proposition 3. Define $h_{IC}(B) = m_0 - \kappa B - F(B/L) - C\rho(IC, B/L)$. It is continuous and strictly decreasing in B: the gross payoff decreases strictly, and the fee and the expected forced-closure cost are weakly increasing in utilization by equation (4) and Proposition 2. It therefore has at most one zero. By Proposition 2, $h_{IC'}(B) \leq h_{IC}(B)$ at every B when $IC' > IC$, so $B^*(IC') \leq B^*(IC)$ whenever both interior equilibria exist. The price result follows from equation (A.6).

Corollary 2. (a) Recall events and squeezes are the events $K_{IC} \geq xB$ and $W_{IC} > 1-u$; both become more likely with IC by the argument of Proposition 2, with $w(x)$ or $1-u$ in place of a, and supply is more volatile by Proposition 1. (b) follows from Proposition 3. (c) By equation (A.7), residual overpricing net of the fee equals $C\rho(IC, B^*/L) = m_0 - \kappa B^* - F(B^*/L)$; the right-hand side decreases in B^*, and B^* decreases in IC. A long position requires no loan.

A.5 Evidence on the assumptions

The model rests on four assumptions, which the data can check to different degrees: one lender can withdraw much of a high-IC stock's inventory at once; loans are spread across lenders in proportion to inventory; borrowers cannot replace all recalled loans in time; and the fee does not reflect the part of recall risk that comes from IC. I examine each in turn.

***IC* and large withdrawals.** In the model IC enters through the share of the largest lender, $\sqrt{IC}$; in the data the two have a correlation of 0.96 (Section A.2). Table A.1 shows the same in mutual fund filings. A single fund withdraws more than 10% of a stock's loans in 5.8, 8.5 and 11.7% of stock-quarters across IC terciles, and with stock and quarter fixed effects such an exit raises the probability of a recall event by 5.4, 9.8 and 8.6 percentage points. What rises with IC is the size of an exit and not its frequency, which makes the assumption of a common withdrawal distribution conservative: a fund that lends a stock withdraws in 28.0% of quarters in the top tercile against 36.9% in the bottom, and less often in high-IC stocks within the same fund and quarter, while its loan is 4.0% against 1.3% of the stock's loans. Panel B of Table A.2 shows the same in daily data: when a stock with utilization below 50% runs out of shares, it loses a median of 90% of its supply in one day, and its IC

lies at the 92nd percentile of the month. At low utilization a squeeze requires a withdrawal of nearly the whole inventory, which only a lender that holds most of it can make.

Loans in proportion to inventory. Section 2.2 gives each lender the same share of the loans as of the inventory, which is what allows the model to work with *IC* alone. In the filings the largest fund's loan is 6.6, 9.6 and 16.0% of the stock's loans across *IC* terciles, so its share of the loans rises with concentration as its share of the inventory does (Table A.1). The assumption holds in the cross-section and not lender by lender, and it is what prevents the model from distinguishing inventory concentration from loan concentration.

The replacement friction. With frictionless replacement, loans fall after a withdrawal only if supply drops below the loans outstanding. Panel A of Table A.2 shows that they fall more often. When supply falls by at least 5% while the remaining supply is still at least twice the loans outstanding, so that the other lenders hold more than enough shares to cover every recalled loan, loans fall on 26.8% of days, 11.7 percentage points above the same stock's normal rate, and the excess is 15.6 points when the remaining supply is below twice the loans, as the threshold a implies. Because a recall that another lender replaces leaves aggregate loans unchanged, this excess is consistent with recalls that were not replaced within the settlement window, which is the friction $\phi < 1$. Where this happens is what matters for the mechanism: these are not stocks that have run out of shares or become expensive to borrow. Utilization is 16% in the top *IC* quintile against 13% in the bottom, so more than four fifths of the inventory sits unlent, and the gradient in recall events is present among general-collateral stocks, where the fee sits at its floor and carries no information (Table 1). Loans are lost while shares are available at an ordinary fee, which is what a replacement friction predicts and a shortage of supply does not.

The fee and recall risk. A loan can be recalled at any time without penalty, so no lender can promise to keep its shares available, and the fee, the price of a new loan today, does not include such a promise. In Duffie et al. (2002) the fee is bargained when a borrower meets a lender, so the direction of the omission is known: a loan that is more likely to be recalled is worth less to the borrower, and a bargained fee reflecting recall risk would be lower where inventory is concentrated. In the data it is slightly higher, and the difference is small where recall risk differs most. Among general-collateral stocks, the top *IC* quintile pays 0.44% a year against 0.36% in the bottom quintile, yet has a recall event in 10.4% of months against 2.6% (Table 1). The fee difference of 8 basis points a year, set against about 0.9 additional recall events a year, amounts to 8.5 basis points of the position per additional event. For this difference to compensate for recall risk, a forced closure would have to cost no more than that, before the expected return of the abandoned position is counted. Consistent

with the fee not reflecting the whole difference in recall risk across *IC*, the anomaly spread between high-*IC* and low-*IC* stocks remains 0.33% a month net of fees.

Restrictions that are imposed. Four further restrictions cannot be checked. That ϕ is common across stocks is imposed, and it is the conservative choice, since replacement being harder where inventory is concentrated would add a second channel. That C is positive and common across stocks is likewise imposed; equation (A.7) identifies only the product $C\rho$, so I do not estimate C. Symmetric rationing among recalled borrowers is a simplification with no counterpart in the data. And equation (A.6) linearizes the relation between short interest and the marginal investor's valuation rather than deriving it.

Table A.1: Mutual fund withdrawals and recall events by inventory concentration

	IC tercile		
	Low	Middle	High
Panel A. Lending funds			
Fund withdraws (% of quarters)	36.9	33.5	28.0
Fund's loan (% of the stock's loans)	1.3	1.8	4.0
Fund-stock-quarters	184,864	188,368	122,891
IC rank, within fund and quarter		−3.05 (−5.3)	
Panel B. Stocks			
Mean IC	0.155	0.197	0.343
Largest fund's loan (% of the stock's loans)	6.6	9.6	16.0
Single-fund exit above 10% of loans (% of quarters)	5.8	8.5	11.7
Recall event in the quarter (% of quarters)	6.5	15.7	54.8
Effect of a single-fund exit on recall events (pp)	5.4 (5.1)	9.8 (9.2)	8.6 (8.4)

Notes. Mutual fund holdings and securities lending from Form N-PORT and lending agents from Form N-CEN, 2019 to 2023, funds with a single lending agent. Stocks are sorted each quarter into terciles of IC at the previous quarter end. A fund withdraws when its holding of a stock falls; the withdrawal is the fall in its loan of the stock, $\max(\text{loan}_{q-1} - \text{loan}_q, 0)$. Panel A: fund-stock-quarters with a loan at the start of the quarter. The last row is the coefficient on the within-quarter rank of IC (0 to 1) in a regression of the withdrawal indicator (in percent) on that rank, log market capitalization and utilization, with fund × quarter fixed effects; t-statistic in parentheses, standard errors clustered by stock. Panel B: stock-quarters. Loans are relative to the stock's Markit quantity on loan at the previous quarter end, winsorized at 1% and 99%. A single-fund exit is a quarter in which one fund withdraws more than 10% of the stock's loans; a recall event in the quarter is a recall event in any of its three months. The last row is the coefficient on the exit indicator, by tercile, in a regression of the recall-event indicator (in percent) on the exit indicator interacted with the tercile, the tercile, mutual funds' loans relative to the stock's loans, utilization, log market capitalization and the previous quarter's recall-event indicator, with stock and quarter fixed effects; t-statistics in parentheses, standard errors clustered by stock.

A.6 An example

The deletion of Surmodics from the S&P SmallCap 600 illustrates a recall that borrowers cannot meet although lendable shares remain available. S&P Dow Jones Indices announced on March 3, 2023 that the stock would leave the index before the open on March 20. Funds

Table A.2: Unreplaced recalls in daily data

Panel A. How often loans fall, by the change in supply that day

Change in supply	Stock-days (thousands)	Loans fall by ≥5% (% of days)	Excess over the stock's normal rate (pp)
Unchanged (baseline)	10,101	14.2	–
Rises by ≥5%	385	14.1	1.1
Falls by ≥5%,			
remaining supply ≥ 2× loans	83	26.8	11.7
remaining supply < 2× loans	54	26.9	15.6
Falls below loans (squeeze)	177	55.0	43.0

Panel B. Recall events at utilization below 50%

	Events	Median change in supply (%)	Median IC rank
Squeeze: supply falls below loans	918	−90	0.92
Supply stays above loans	3,072	−9	0.61

Notes. Daily Markit data for the stock-months of the main sample, 2006 to 2023, stock-days with utilization of at least 1% the day before. Supply is active lendable quantity; loans are quantity on loan. Panel A classifies stock-days by the change in supply (unchanged: a change of less than 1%; remaining supply is supply after the fall, compared with loans the day before) and reports the share of days on which loans fall by at least 5%. A recall that another lender replaces leaves loans unchanged, so a fall in loans while ample supply remains marks recalls that were not replaced in time. The excess compares each stock-day with the same stock's rate on days with unchanged supply, averaged across stock-days; it differs from the difference in pooled rates because stocks contribute to the rows in different proportions. Panel B splits recall events (supply and loans both fall by at least 5%) at utilization below 50% by whether supply falls below the loans outstanding the day before, and reports the median change in supply on the event day and the median within-month IC rank.

that track the index had to sell their shares, and shares they had lent had to be recalled: a withdrawal unrelated to the short sellers' positions, on a known date. Table A.3 and Figure A.1 report Markit's lendable supply and loans and the SEC fails to deliver.

Before the announcement, lendable supply was about 5.4 million shares, 2.6% of it on loan, and the fee was 0.31% a year, the level of general-collateral stocks. Between March 16 and March 21, supply fell from 5.27 to 3.73 million shares, by 29%. Loans fell by 64% on March 21, from 132 to 47 thousand shares, although the remaining supply was 79 times the remaining loans. On March 20, 10.4 thousand shares failed to deliver; on March 21, the day loans fell, the fails cleared. This is the pattern of Section C.1: recalled loans that borrowers did not return within the settlement period and did not replace from the spare inventory. Loans averaged 53 thousand shares over the following four weeks, about a third of their level before the announcement, so the positions were closed rather than moved to other lenders.

Two qualifications apply. First, loans rose to 242 thousand shares on March 9, after the announcement, consistent with short sellers positioning for the deletion, and part of their unwinding may be voluntary. By March 20, however, loans were back at 132 thousand shares, and the decline on March 21 took them well below their level before the announcement. Second, the funds that track the index withdrew together, a withdrawal common to a group of lenders, and the IC of Surmodics was 0.23. The example therefore illustrates a withdrawal that borrowers cannot replace in time at an unchanged fee, the friction $\phi < 1$ of Section 2.2, and not the role of concentration, which Section 4 estimates.

Table A.3: An example: Surmodics, March 2023

	Lendable supply (thousands)	Loans (thousands)	Utilization (%)	Fails to deliver (thousands)
February 27 to March 2, average	5,410	143	2.6	0.0
March 9 (highest loans)	5,319	242	4.6	0.0
March 16	5,269	135	2.6	0.0
March 17 (recall event)	4,986	120	2.4	0.0
March 20 (effective date)	4,764	132	2.8	10.4
March 21 (recall event)	3,726	47	1.3	0.0
March 22 to April 14, average	3,417	53	1.6	0.2

Notes. Surmodics (SRDX). S&P Dow Jones Indices announced on March 3, 2023 that Surmodics would be deleted from the S&P SmallCap 600 before the open on March 20, 2023. Lendable supply is Markit's active lendable quantity and loans are Markit's quantity on loan; utilization is loans relative to lendable supply. Fails to deliver are from the SEC fails-to-deliver files, by settlement date. Recall events: lendable supply and loans both fall by at least 5% on the day. Supply, loans and fails are in thousands of shares; shares outstanding are 14.1 million. The fee averages 0.31% a year in March 2023, the level of general-collateral stocks, and IC is 0.23 on March 16.

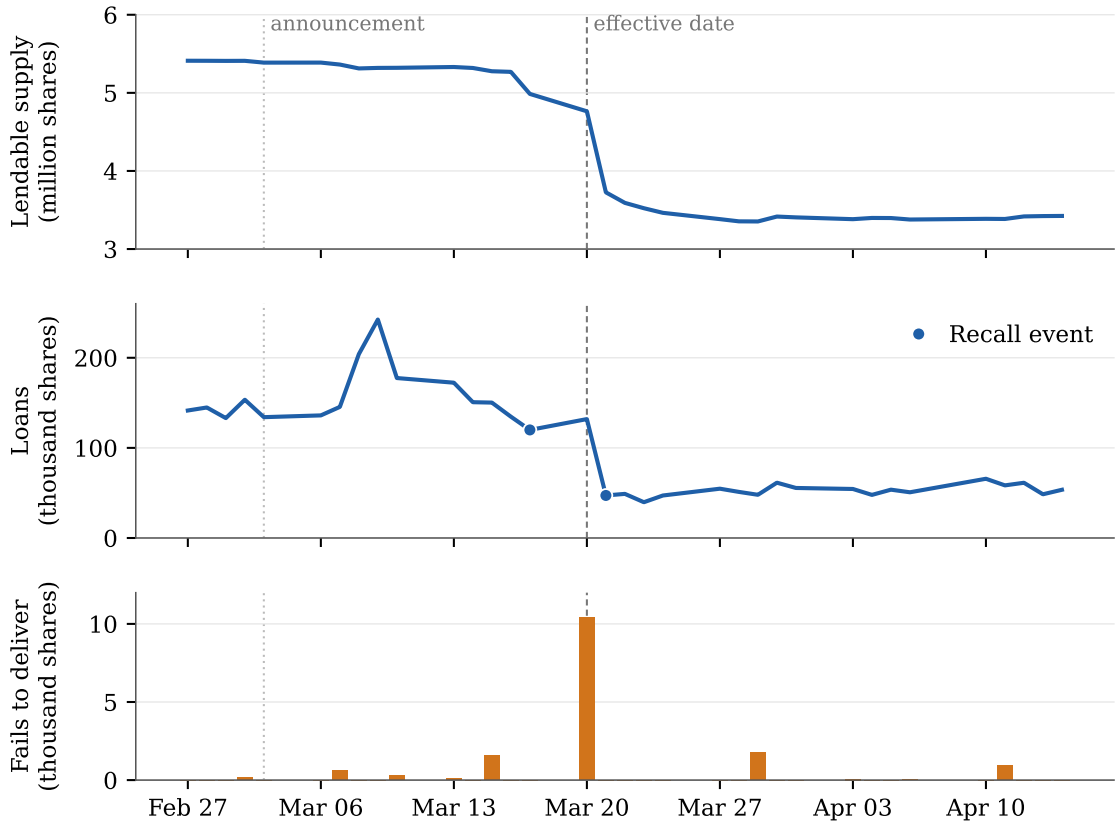


Figure A.1: An example: Surmodics, March 2023. Daily lendable supply (Markit's active lendable quantity), loans (Markit's quantity on loan) and fails to deliver (SEC, by settlement date) from February 27 to April 14, 2023. Dotted line: announcement of the deletion from the S&P SmallCap 600 (March 3); dashed line: effective date (March 20). Dots mark recall events, days on which lendable supply and loans both fall by at least 5%.

B Inventory concentration

B.1 Summary statistics

Table B.1 reports summary statistics for the main sample; Section 3 discusses them.

B.2 Distribution and persistence

Figure B.1 describes IC in the main sample. Its distribution is right-skewed (Panel a): the median stock-month has IC of 0.19, the equivalent of about five equal lenders, and a long tail of stocks rests on one or two lenders. Panel (b) shows the cross-section month by month. The median falls from about 0.30 in 2006 to 0.18 by 2008, as Markit's coverage of lenders expands, and stays between 0.15 and 0.21 afterwards. The upper tail moves more than the median: the 90th percentile is highest in 2010 and 2011 and again in 2021 and 2022, at about 0.40.

Table B.2 reports persistence and the sources of variation. IC is persistent, with an autocorrelation of 0.97 at one month and 0.73 at twelve months, more persistent than the fee (0.92 and 0.52) and utilization (0.96 and 0.68). The lender base of a stock changes slowly, but it does change: 62% of the variance of IC is between stocks and 38% within stocks, and month fixed effects explain only 2.6%. The panel regressions of Section 4, which absorb stock and month fixed effects, therefore use more than a third of the variation in IC. Table B.3 reports the average cross-sectional rank correlations of IC with size, the lending market, the fee, fee risk and ownership discussed in Section 3.

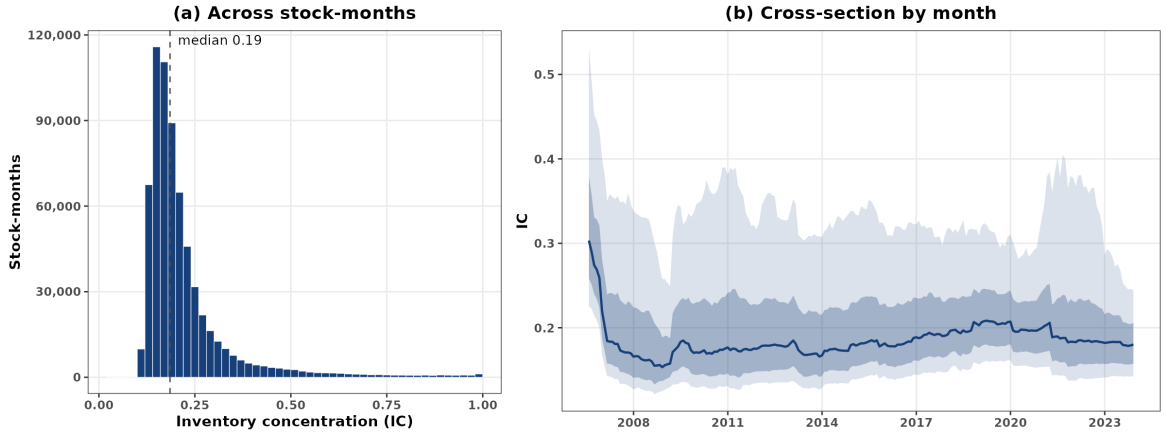


Figure B.1: Inventory concentration in the main sample. (a) Distribution of IC across stock-months, with the median. (b) Cross-sectional distribution of IC by month: the median (line), the 25th to 75th percentiles (dark band) and the 10th to 90th percentiles (light band). 2006 to 2023.

Table B.1: Summary statistics

Variable	N	Mean	SD	P25	Median	P75
Panel A: Firm characteristics and ownership						
ME ($ millions)	659,915	7,477	41,516	253.126	861.559	3,314
BM	627,955	0.640	0.677	0.263	0.501	0.826
Short interest	646,167	0.050	0.058	0.014	0.031	0.066
Amihud illiquidity	653,189	0.558	7.856	0.001	0.003	0.025
Turnover (%)	653,348	0.933	1.148	0.379	0.680	1.136
Institutional ownership (IOR)	598,528	0.631	0.276	0.436	0.704	0.861
Ownership HHI	598,528	0.104	0.127	0.044	0.062	0.104
Passive ownership	504,751	0.087	0.062	0.042	0.078	0.121
Panel B: Securities lending and short-selling risk						
IC	659,915	0.222	0.124	0.155	0.185	0.235
LQS	587,585	0.603	0.178	0.498	0.624	0.727
Lendable supply (LQ)	659,915	0.231	0.144	0.124	0.233	0.322
Average tenure (days)	659,914	77.981	71.729	35.279	61.089	98.598
Utilization (%)	659,915	15.663	18.802	2.415	8.050	21.764
Fee (annualized, %)	659,914	0.921	1.727	0.324	0.375	0.488
Supply volatility, month $t+1$	659,245	0.083	0.280	0.006	0.013	0.033
URR (% of loans), month $t+1$	658,682	7.670	18.157	0.000	0.000	6.077
Panel C: Lending-supply events in month $t+1$ (% of stock-months)						
			Size quintile		IC quintile	
	N	All	Smallest	Largest	Lowest	Highest
Recall event ≥5%	658,675	10.9	30.0	2.9	3.5	30.4
Supply drop ≥5%	659,431	22.1	49.0	7.7	10.2	50.0
Squeeze	657,696	0.38	1.1	0.07	0.06	1.5

Notes. Stock-months in the main sample, 2006 to 2023: CRSP common stocks with price of at least $1, market capitalization of at least $50 million, at least 7 days with a Markit fee and a fee of at most 1% a month in the formation month, and IC strictly between 0 and 1. IC is the Herfindahl index of lendable inventory across lenders. LQS is Markit's lendable-quantity stability. LQ is lendable quantity relative to shares outstanding. Short interest is relative to shares outstanding. Turnover is the average daily share turnover over six months. IOR is the 13F institutional ownership ratio and ownership HHI the Herfindahl index of 13F holdings. Passive ownership is the fraction of shares held by passive funds (index funds and ETFs), available to 2019. Supply volatility is the standard deviation of daily active supply in month $t+1$ divided by its mean. URR, the unreplaced recall rate, is the share of loans lost in month $t+1$ on days on which active supply falls by at least 1%, counting on each such day the smaller of the loans lost and the supply withdrawn. Panel C reports the percentage of stock-months with at least one day in month $t+1$ on which active lendable supply and loans both fall by at least 5% (recall event), on which active lendable supply falls by at least 5% (supply drop), or on which supply falls below the previous day's loans (squeeze), for all stock-months and within the smallest and largest quintiles of market capitalization and of IC, formed each month.

Table B.2: Inventory concentration: persistence and variance decomposition

Panel A. Autocorrelation at a lag of				
	1 month	3 months	6 months	12 months
Inventory concentration	0.97	0.91	0.83	0.73
Fee	0.92	0.80	0.68	0.52
Utilization	0.96	0.88	0.80	0.68
Lendable supply	0.97	0.96	0.85	0.79

Panel B. Share of the variance (%)					
	Between stocks	Within stocks	R^2 month FE	R^2 stock FE	R^2 both
Inventory concentration	62.1	37.9	2.6	62.0	64.9
Fee	47.0	53.0	1.0	46.8	48.0
Utilization	47.0	53.0	5.5	47.0	53.3
Lendable supply	57.5	42.5	5.7	57.4	68.2

Notes. Main sample, monthly averages of daily Markit data. Panel A: correlation, within stock, between the value in month t and the value k calendar months earlier, pooled over stocks and months. Panel B: the variance of the stock means (between) and of the deviations from them (within) as shares of the total variance, and the R^2 of regressions on month, stock, and stock and month fixed effects. Lendable supply is lendable quantity relative to shares outstanding.

Table B.3: Correlations of inventory concentration with size, the lending market, the fee and ownership

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(1) IC	1	-0.66	-0.57	0.02	0.41	0.35	-0.50	0.66	-0.38
(2) log ME	-0.49	1	0.52	-0.07	-0.44	-0.36	0.49	-0.67	0.37
(3) Lendable supply	-0.53	0.46	1	-0.06	-0.50	-0.45	0.71	-0.61	0.77
(4) Utilization	-0.00	-0.14	-0.12	1	0.29	0.17	-0.05	0.17	0.02
(5) Fee (% p.a.)	0.35	-0.28	-0.36	0.46	1	0.71	-0.40	0.44	-0.39
(6) log FeeVar	0.42	-0.38	-0.48	0.34	0.65	1	-0.36	0.36	-0.37
(7) IOR	-0.47	0.44	0.69	-0.15	-0.34	-0.42	1	-0.59	0.63
(8) Ownership HHI	0.43	-0.38	-0.47	0.13	0.30	0.34	-0.48	1	-0.56
(9) Passive ownership	-0.43	0.29	0.75	-0.06	-0.28	-0.39	0.64	-0.51	1

Notes. Main sample of Table B.1. Time-series averages of monthly cross-sectional correlations, Pearson below the diagonal and Spearman rank correlations above it, using pairwise complete observations. IC is inventory concentration; log ME is log market capitalization; lendable supply is relative to shares outstanding; utilization is in percent; the fee is in percent a year; log FeeVar is the log variance of the daily fee within the month; IOR is the 13F institutional ownership ratio and ownership HHI the Herfindahl index of 13F holdings; passive ownership is the share held by index funds and ETFs, available to 2019, so its correlations average the months to 2019.

B.3 Inventory concentration, size and ownership

High-IC stocks are small and have lower institutional ownership, higher ownership HHI and lower passive ownership. The average within-month rank correlation of IC is −0.66 with log market capitalization, −0.50 with institutional ownership, 0.66 with ownership HHI and −0.38 with passive ownership (Table B.3).

Table B.4 reports how much of the within-month variation in IC these characteristics explain. On its own, size explains 46%, ownership HHI 44%, institutional ownership 26% and passive ownership 16%. Size, institutional ownership and ownership HHI together explain 56%, and 57% with passive ownership added. Almost half of the cross-sectional variation in IC is therefore not explained by these characteristics.

Table B.4: Inventory concentration, size and ownership

	Size	Institutional ownership	Ownership HHI	Passive ownership	All three	All three and passive ownership
Full sample, 2006–2023	0.46	0.26	0.44		0.56	
Passive ownership sample, 2006–2019	0.47	0.27	0.45	0.16	0.56	0.57

Notes. Average R^2 of monthly cross-sectional regressions of the within-month percentile rank of IC on the within-month percentile ranks of the characteristics in each column. "All three" is size, institutional ownership and ownership HHI. The sample is the stock-month panel of Table 2; the second row uses the months with passive ownership data.

C Additional evidence on recall risk

This appendix collects the evidence on recall risk that supports Section 4. Section C.1 validates the recall measures with SEC fails-to-deliver data. Sections C.2 to C.4 report recall outcomes by IC quintile and further specifications of the panel regressions. Sections C.5 and C.6 report two designs that address the concern that high-IC stocks differ from other stocks in ways the panel regressions do not capture. Section C.7 compares recall risk with fee risk.

C.1 Validation of the recall measures

Data. The SEC publishes, twice a month, the balance of shares that failed to deliver for each security and settlement date, aggregated over all clearing members of the National Securities Clearing Corporation. A record shows the total number of shares that sellers had not delivered as of that date; securities without fails do not appear, and I set their fails to zero. The data do not identify the seller or the reason for the fail. I use the files from July 2009, when the current close-out requirements of Regulation SHO were in place and

coverage is complete, to December 2023, and match them to Markit and CRSP by CUSIP and date.

How a recall produces a fail. Consider a fund that sells 100,000 shares on a Monday, 30,000 of which are on loan to a short seller. The fund recalls the 30,000 shares. Under two-day settlement, it must deliver 100,000 shares to the buyer on Wednesday. If the borrower has not returned the shares by then, the fund delivers only 70,000, and 30,000 shares appear in the SEC data as a fail to deliver. Markit continues to report the 30,000 shares as on loan, because they have not been returned. When the borrower returns them, for example by buying them in the market on the following Monday, the fund completes the delivery and the fail disappears; on the same day, Markit records a decline in loans of 30,000 shares, because it records a recall when the shares are returned. A recall that the borrower cannot meet within the settlement period therefore produces fails that rise in the days before the decline in loans and clear on the day loans decline. Voluntary covering produces no such pattern, because the returned shares do not settle any pending sale. Before September 2017, settlement took three days, which lengthens the interval but does not change the pattern.

Fails around recall events. I compare three types of days: recall events, on which active lendable quantity and quantity on loan both fall by at least 5%; days on which loans fall by at least 5% and days on which supply falls by at least 5% and loans do not, which include withdrawals of unlent shares and withdrawals that borrowers replace. I regress fails on each trading day from five days before to ten days after on indicators for the three types, with stock and date fixed effects, so that each coefficient compares a day with other days of the same stock and with other stocks on the same date. Panel A of Table C.1 measures fails in basis points of shares outstanding, which recalls cannot change. Fails are higher by 1.09 basis points five days before a recall event and by 1.27 basis points three days before ($t = 31.5$), about twice their average of 1.2 basis points, and the difference falls to 0.27 basis points on the day loans decline. Panel B measures fails relative to the shares on loan six days before the event, which gives the size of the effect for borrowers: three days before a recall event, the excess fails equal 6.9% of those shares ($t = 26.2$), against an average of 3.3% on other days, and the excess disappears on the day loans decline. Days on which loans fall without a decline in supply show no comparable build-up, and fails are lower afterward. Fails are also elevated around supply withdrawals without a decline in loans, because any sale by a lender can fail; what distinguishes recall events is that the fails clear on the day loans decline.

Returns. Panel C reports cumulative returns around the same days, with date fixed effects. Over trading days +11 to +60, returns are 0.71 percentage points lower after recall

events ($t = -7.0$) and 0.53 percentage points higher after days on which loans fall without a decline in supply ($t = 7.9$). Voluntary covering is followed by rising prices, consistent with informed short sellers, whereas recalls are followed by falling prices, consistent with positions closed in stocks that remain overpriced. Part of the decline after recall events reflects the lenders' own sales: returns also fall after supply withdrawals without a decline in loans.

URR and fails. If the loans that URR counts as lost are recalls that borrowers could not meet in time, fails should clear on the same days. Regressing the fails that clear on a day on the loans lost as counted in URR and on declines in loans on days on which supply does not fall, both in basis points of shares outstanding and with stock and date fixed effects, each share of loans counted in URR coincides with 0.065 shares of fails clearing ($t = 28.5$), against 0.009 for declines in loans without a decline in supply ($t = 22.6$).

Fails-confirmed measures. The fails data also give stricter versions of the recall measures. A recall failure is a month with a recall event on a day on which the stock's outstanding fails clear; it occurs in 4.9% of stock-months. Fails-confirmed URR counts only the loans lost on such days, up to the number of failed shares that clear, and averages 0.45% of loans a month, about 6% of URR, in line with the share-by-share estimate above. URR and fails-confirmed URR therefore bound the loans lost to recalls that borrowers could not meet in time. Panel D shows that a one-standard-deviation increase in IC raises the probability of a recall failure in the following month by 1.38 percentage points ($t = 7.3$) and fails-confirmed URR by 0.31 percentage points ($t = 8.4$), about 28% and 70% of their means. IC lowers the probability of a month in which fails clear on a day of voluntary covering (−1.28 percentage points, $t = -5.5$).

Limitations. Fails are aggregated across all sellers and are not tagged by cause, so they confirm recall events but cannot replace them as a measure. Most recalled shares are returned within the settlement period and leave no fail, so the fails-confirmed measures capture the recalls that borrowers met late and understate the recalls that forced positions to close.

C.2 Recall risk by inventory concentration quintile

Table C.2 compares IC quintiles. From the bottom to the top quintile, the monthly probability of a recall event rises from 3.3% to 30.5%, that of a supply drop from 10.0% to 49.8%, and that of a squeeze from 0.052% to 1.55%. URR rises from 4.3% to 17.9% of loans. High-IC stocks are also smaller (median market capitalization of $150 million against $5.2 billion), pay higher fees (2.04% against 0.47% a year) and have less lendable supply (9% against 30%

Table C.1: Recall events and fails to deliver

	Recall event	Covering only	Replaced supply drop
Panel A. Fails to deliver relative to the day (basis points of shares outstanding)			
Day −5	1.09 (29.04)	0.12 (5.86)	0.69 (22.31)
Day −3	1.27 (31.48)	0.16 (7.90)	0.73 (22.71)
Day −1	0.92 (25.99)	0.05 (2.63)	0.84 (26.52)
Day 0	0.27 (8.93)	−0.18 (−10.90)	0.63 (22.49)
Day +1	0.33 (11.17)	−0.15 (−9.44)	0.62 (21.88)
Day +3	0.30 (10.55)	−0.16 (−9.99)	0.54 (20.35)
Day +5	0.24 (8.94)	−0.17 (−10.36)	0.44 (17.37)
Day +10	0.22 (8.33)	−0.16 (−9.76)	0.39 (14.36)
Panel B. Fails to deliver relative to the day (% of shares on loan six days before)			
Day −5	5.00 (23.39)	0.99 (7.13)	1.35 (8.17)
Day −3	6.95 (26.23)	1.52 (9.33)	1.62 (7.91)
Day −1	4.10 (15.37)	0.56 (3.37)	3.90 (17.77)
Day 0	−0.35 (−1.42)	−1.00 (−7.24)	2.42 (12.25)
Day +1	2.35 (9.49)	−0.08 (−0.55)	2.23 (11.07)
Day +3	3.33 (12.88)	0.02 (0.14)	1.69 (7.90)
Day +10	4.03 (14.95)	0.34 (1.97)	0.94 (4.31)
Panel C. Cumulative return (%)			
Days −5 to −1	−0.28 (−11.87)	−0.03 (−1.43)	0.03 (1.32)
Days 0 to +2	−0.18 (−11.32)	−0.01 (−0.75)	−0.15 (−9.36)
Days +3 to +10	−0.19 (−6.94)	0.06 (2.39)	−0.22 (−8.05)
Days +11 to +60	−0.71 (−7.00)	0.53 (7.87)	−1.11 (−11.96)
Panel D. Next-month outcomes on IC			
	IC	Mean	
Recall event (%)	3.00 (10.04)	10.23	
Recall failure (%)	1.38 (7.33)	4.89	
URR (% of loans)	1.51 (6.49)	7.48	
Fails-confirmed URR (% of loans)	0.305 (8.38)	0.446	
Covering only, fails clear (%)	−1.28 (−5.46)	58.45	
Replaced supply drop, fails clear (%)	0.34 (1.95)	7.59	
Observations (Panels A, B / C / D)	1,649,815, 1,647,534 / 1,660,591 / 457,447		

Notes. July 2009 to December 2023. SEC fails-to-deliver data matched to Markit and CRSP by CUSIP and date. A recall event is a day on which active lendable quantity and quantity on loan both fall by at least 5%; covering only, a day on which quantity on loan falls by at least 5% and active lendable quantity does not; a replaced supply drop, a day on which active lendable quantity falls by at least 5% and quantity on loan does not. Panel A: fails to deliver on the trading day relative to the event day, in basis points of shares outstanding, regressed on the three day types with stock and date fixed effects; the average on other days is about 1.2 basis points. Panel B: the same regression with fails in percent of the shares on loan six trading days before the day, which precedes the window, winsorized at the 99.5th percentile; the average on other days is 3.3%. Panel C: cumulative daily returns over the window, with date fixed effects. Panels A to C use all recall events and replaced supply drops, 6% of covering-only days and 3% of other days, selected by a fixed hash of stock and date; standard errors clustered by stock. Panel D: next-month outcomes regressed on IC, standardized within month, with stock and month fixed effects and the within-month ranks of market capitalization, book-to-market, idiosyncratic volatility, Amihud illiquidity, turnover, institutional ownership and short interest, ownership HHI, the fee and lendable supply; standard errors clustered by stock and month. A recall failure is a month with a recall event on a day on which the stock's outstanding fails fall. Fails-confirmed URR counts the loans lost on such days, up to the fails that clear, relative to the previous day's loans. The last two rows apply the same condition to covering-only days and replaced supply drops. t-statistics in parentheses.

of shares outstanding). Their utilization, however, is similar (16% against 13%), so more than four fifths of their lendable inventory is unlent.

Table C.2: Inventory concentration and next-month recall events

	Q1 (low IC)	Q2	Q3	Q4	Q5 (high IC)	Q5–Q1
IC	0.140	0.163	0.185	0.221	0.404	0.264
						(48.37)
Largest lender share	0.230	0.264	0.296	0.346	0.543	0.312
						(52.09)
Fee (% p.a.)	0.473	0.520	0.638	0.913	2.042	1.569
						(18.36)
Utilization	0.132	0.150	0.164	0.172	0.157	0.025
						(3.97)
Lendable supply / ME	0.301	0.291	0.266	0.209	0.093	-0.208
						(-34.69)
Market cap ($M, median)	5,230.921	2,092.543	1,066.066	491.550	150.287	-5,080.634
						(-13.83)
Squeeze_{t+1} (%)	0.052	0.063	0.105	0.190	1.553	1.501
						(13.71)
$\text{Loans uncovered}_{t+1}$	0.000	0.000	0.000	0.001	0.008	0.007
						(11.06)
$\text{Supply volatility}_{t+1}$	0.020	0.024	0.033	0.060	0.273	0.253
						(15.90)
Supply drop_{t+1} (%)	9.952	11.417	14.922	22.964	49.846	39.894
						(22.35)
$\text{Recall event}_{t+1}$ (%)	3.327	4.110	5.770	10.427	30.460	27.133
						(20.55)
URR_{t+1} (% of loans)	4.317	4.265	4.884	6.862	17.859	13.542
						(15.12)

Notes. Stocks are sorted monthly into IC quintiles. Cells report time-series averages of monthly cross-sectional means (medians for market capitalization). Next-month outcomes are percentages of stock-months, except supply volatility and URR. Recall events and supply drops use a 5% daily threshold. Parentheses report Newey-West t-statistics for Q5–Q1 differences, with three lags.

C.3 Panel regressions by firm size

Recall events are concentrated in small stocks, so the results could come from noisy supply data in thinly lent stocks. Table C.3 re-estimates the specification of Table 2 within quintiles of market capitalization. The coefficients on IC for recall events and URR are significant in every quintile, and relative to the base rate the recall-event coefficient is largest among the largest stocks: 2.70 percentage points ($t = 4.4$) against a base of 2.9%. Supply volatility also rises with IC in every size quintile, as Proposition 1 predicts.

Table C.3: Inventory concentration and recall risk by size, and a threshold-free measure

	Recall event$_{t+1}$ (%) (1)	URR$_{t+1}$ (%) (2)	log supply CV$_{t+1}$ (3)	Mean of (1) in sample
All stocks	2.09	1.16	0.110	10.9
	(8.68)	(6.38)	(10.35)	
Size quintile 1 (smallest)	1.27	0.826	0.097	30.0
	(4.45)	(3.73)	(7.80)	
Size quintile 2	1.49	0.891	0.142	11.7
	(3.55)	(3.66)	(8.06)	
Size quintile 3	2.45	1.14	0.104	6.0
	(5.45)	(4.01)	(6.56)	
Size quintile 4	2.15	1.33	0.045	4.1
	(4.33)	(4.10)	(2.31)	
Size quintile 5 (largest)	2.70	0.753	0.041	2.9
	(4.41)	(2.34)	(2.08)	
Mean of outcome, all stocks	10.90	7.67	1.20	

Notes. Coefficient on IC, standardized within month on all stocks, in the specification of Table 2 (all controls, firm and month fixed effects, standard errors clustered by firm and month; t-statistics in parentheses), for all stocks and within quintiles of market capitalization formed each month. Column 1 is the recall-event indicator in percent; the last column is its mean in each sample. Column 2 is URR, the share of loans lost to unreplaced recalls, in percent. Column 3 is the log of one plus the coefficient of variation of daily active lendable supply in month $t + 1$, in percent; it uses no threshold and is defined for every stock-month with valid daily changes. Stock-months: 556,131 in column 1.

C.4 Panel regressions with passive ownership

Passive funds are large and stable lenders, so stocks with more passive ownership may have both a more dispersed lender base and more stable supply. Table C.4 adds the share of shares outstanding held by passive funds to the specification of Table 2, on the months from 2006 to 2019 for which it is available. A one-standard-deviation increase in IC raises the probability of a recall event by 1.83 percentage points ($t = 7.2$) and URR by 1.04 percentage points of loans ($t = 5.7$). Passive ownership itself lowers recall risk: a passive share higher by 10 percentage points lowers the probability of a recall event by 5.4 percentage points ($t = -9.0$). IC therefore predicts recall risk beyond the composition of the lender base that passive ownership captures.

Table C.4: Inventory concentration and recall risk: passive ownership

	Recall event$_{t+1}$ (1)	URR$_{t+1}$ (2)	Supply drop$_{t+1}$ (3)	Squeeze$_{t+1}$ (4)	Supply vol.$_{t+1}$ (5)	log FeeVar$_{t+1}$ (6)
IC (standardized)	1.83***	1.04***	1.87***	0.263***	0.043***	0.175***
	(0.253)	(0.183)	(0.340)	(0.067)	(0.004)	(0.019)
log ME	-1.70***	-0.645***	-3.26***	0.026	0.003	-0.104***
	(0.332)	(0.226)	(0.467)	(0.049)	(0.003)	(0.032)
BM	0.302	0.061	0.490*	-0.071**	-9×10^{-5}	-0.035**
	(0.187)	(0.129)	(0.286)	(0.029)	(0.002)	(0.015)
Ret(-6,-1)	1.01***	0.681**	-0.065	-0.051	-0.002	-0.001
	(0.376)	(0.277)	(0.377)	(0.051)	(0.002)	(0.016)
IVOL	43.1***	23.3***	45.2***	2.01*	-0.168***	2.28***
	(5.44)	(3.69)	(7.00)	(1.11)	(0.045)	(0.348)
log Amihud	0.903***	0.581***	1.35***	-0.025	0.018***	0.137***
	(0.210)	(0.153)	(0.271)	(0.040)	(0.002)	(0.019)
Turnover	1.35***	1.17***	2.00***	0.180***	0.008***	0.082***
	(0.235)	(0.160)	(0.359)	(0.062)	(0.002)	(0.017)
IOR	2.62***	2.90***	0.293	0.055	0.038***	-0.329***
	(0.968)	(0.565)	(1.47)	(0.101)	(0.008)	(0.111)
Ownership HHI	0.934	-1.45	1.56	0.506**	-0.011	0.007
	(1.47)	(1.000)	(1.79)	(0.222)	(0.016)	(0.123)
Passive ownership	-53.5***	-45.8***	-75.5***	0.877	-0.471***	-3.51***
	(5.97)	(3.41)	(9.20)	(0.711)	(0.051)	(0.681)
Fee	4.09***	1.77***	4.71***	0.085***	0.025***	0.405***
	(0.172)	(0.087)	(0.193)	(0.023)	(0.001)	(0.016)
Lendable supply (LQ)	-11.8***	-3.63***	-16.1***	-1.01***	-0.030**	-3.00***
	(2.56)	(0.996)	(4.77)	(0.323)	(0.013)	(0.704)
Short interest	-16.8***	-30.2***	39.3***	0.567	-0.230***	5.14***
	(3.29)	(2.20)	(4.73)	(0.499)	(0.023)	(0.391)
Observations	430,914	430,914	431,046	430,725	431,007	272,930
R^2	0.29370	0.26991	0.33771	0.12784	0.35883	0.62054
Firm fixed effects	✓	✓	✓	✓	✓	✓
Month fixed effects	✓	✓	✓	✓	✓	✓

Notes. As in Table 2, adding the share of shares outstanding held by passive funds (index funds and ETFs) at month t, available from 2006 to 2019. The last column is log FeeVar, the log variance of the daily fee. Firm and month fixed effects; standard errors clustered by firm and month in parentheses.

C.5 Matched sample

Design. Each month, I match stocks in the top IC quintile to stocks in the bottom three quintiles, with replacement, using the nearest propensity score within the same fee group (at most 1%, 1% to 5%, or above 5% a year) and a caliper of 0.05 standard deviations of the score. The score is a logit of being in the top IC quintile on log market capitalization, book-to-market, idiosyncratic volatility, log Amihud illiquidity, turnover, institutional ownership, ownership HHI and passive ownership, with month fixed effects. Because passive ownership is available until 2019, the matched sample covers 2006 to 2019.

Results. Table C.5 reports the results for 51,723 matched pairs. Matching removes most of the differences in observable characteristics, including the fee and ownership HHI, while IC remains distinct (0.35 against 0.18). In the following month, high-IC stocks have a 3.4 percentage point higher probability of a recall event ($t = 5.3$), against a control mean of 14.1%, and a 2.2 percentage point higher URR ($t = 5.5$), against 8.6%. Their squeeze probability is 0.30 percentage points higher ($t = 4.1$), about twice the control mean of 0.28%, and their supply is more volatile ($t = 7.5$). These differences arise although high-IC stocks have lower utilization than their matched controls (14.4% against 18.3%). Without passive ownership among the matching variables, the sample extends to 2023 and the recall-event difference is 3.9 percentage points ($t = 6.7$).

C.6 Dual-class shares

Design. Changes in IC within a stock may coincide with firm news that also affects recall risk. The listed share classes of the same firm are claims on the same cash flows and are exposed to the same news on the same day. Porras Prado et al. (2016) use dual-class firms to show that concentrated ownership reduces lendable supply, raises the fee and limits arbitrage. I follow their approach and ask whether the class with more concentrated lendable inventory faces greater recall risk. I identify firms with at least two listed common share classes in CRSP and Markit from 2006 to 2023. To exclude tracking stocks, I require each class's monthly return to have a correlation of at least 0.8 with another class of the same firm. The sample contains 64 firms, 62 of them with ownership data.

Class differences. Panel A of Table C.6 follows Porras Prado et al. (2016). Each month, I compare the highest-IC class with the other listed classes of the same firm, average the differences within firms, and test whether their mean across firms is zero. The higher-IC class has IC greater by 0.22 ($t = 8.1$). In the following month, its probability of a recall event is 6.6 percentage points higher ($t = 3.8$), its URR is 5.5 percentage points higher ($t = 5.8$), and its supply is more volatile ($t = 6.1$). The fee and utilization do not differ significantly

Table C.5: Propensity-score matched sample: high- versus low-IC stocks

Panel A. Covariate balance

	High IC	Matched control	Standardized difference	
	mean	mean	before	after
IC	0.346	0.178	1.98	1.92
log ME	5.450	5.594	-1.85	-0.13
BM	0.743	0.734	0.28	0.01
IVOL	0.025	0.027	0.47	-0.09
log Amihud	-3.202	-3.326	2.14	0.07
Turnover	0.540	0.609	-0.73	-0.08
IOR	0.447	0.421	-1.61	0.10
Ownership HHI	0.154	0.183	0.95	-0.17
Passive ownership	0.056	0.053	-1.15	0.07
Fee (% p.a.)	1.096	1.045	0.66	0.03
Utilization	14.377	18.331	-0.03	-0.20
Lendable supply	0.125	0.149	-1.77	-0.24

Panel B. Next-month outcomes, high IC minus matched control

	Difference	t	Control mean	Pairs
Recall event$_{t+1}$	3.377	(5.34)	14.136	51,723
URR$_{t+1}$	2.215	(5.52)	8.584	51,723
Supply drop$_{t+1}$	3.000	(3.26)	31.684	51,723
Squeeze$_{t+1}$	0.300	(4.14)	0.280	51,723
Supply vol.$_{t+1}$	0.042	(7.48)	0.083	51,723

Notes. Each month, stocks in the top IC quintile are matched with replacement to the stock in the bottom three IC quintiles with the nearest propensity score, within the same month and fee group (fee up to 1%, 1% to 5%, above 5% a year), with a caliper of 0.05 standard deviations of the score. The score is a logit of being in the top quintile on log market capitalization, book-to-market, idiosyncratic volatility, log Amihud illiquidity, turnover, institutional ownership, ownership HHI and passive ownership, with month fixed effects. Passive ownership is available to 2019, so the sample is 2006 to 2019. Without passive ownership, over the full period, the recall-event difference is 3.876 (t = 6.66). Standardized differences are differences in means divided by the pooled standard deviation. Panel B reports the coefficient on the high-IC indicator in a regression on the matched pairs with month fixed effects; standard errors clustered by firm. Recall events and supply drops use a 5% daily threshold and, like squeezes, are in percent.

between the classes (0.36 percentage points a year, $t = 1.2$, and -2.6 percentage points, $t = -0.9$). The higher-IC class is smaller (log market capitalization lower by 0.98, $t = -8.6$), has less lendable supply relative to shares outstanding, lower institutional ownership (-0.29, $t = -6.1$) and higher ownership HHI (0.16, $t = 6.2$), and its short interest is lower by 3.5% of shares outstanding ($t = -4.0$).

Daily regressions. Panel B asks whether the relation between IC and recall risk remains after controlling for these class differences. I estimate

$$D_{j,t+1:t+5} = \beta\, IC_{j,t} + \gamma' X_{j,t} + \alpha_{f(j),t} + \varepsilon_{j,t}, \tag{C.1}$$

where $D_{j,t+1:t+5}$ indicates an event for class j over the next five trading days, $IC_{j,t}$ is the class's IC averaged over the preceding 20 trading days and standardized, and $X_{j,t}$ contains class characteristics measured before the outcome window. Firm × day fixed effects $\alpha_{f(j),t}$ absorb everything common to the classes of firm $f(j)$ on day t, so β is identified from differences between the classes of the same firm. I keep one observation every five trading days, so that outcome windows do not overlap. With controls for class size and indicators of Markit's Daily Cost of Borrow Score (row 1), a one-standard-deviation increase in IC raises the probability of a recall event by 1.7 percentage points ($t = 4.0$), against a mean of 3.4%, and URR by 0.9 percentage points of loans ($t = 3.9$). Adding lendable supply, institutional ownership and ownership HHI (row 2), the effects are 1.6 ($t = 3.8$) and 0.7 percentage points ($t = 3.1$). Ownership HHI among the controls separates concentration of lendable inventory from the concentration of ownership that Porras Prado et al. (2016) study. With 62 firms, inference rests on few clusters; a firm-level bootstrap gives p-values below 0.002 for the recall-event coefficient in both rows.

Further specifications. Table C.7 reports monthly regressions with firm × month fixed effects (Panel A), further daily specifications (Panel B) and the timing of recall events in the two classes (Panel C). With the controls of row (2) of Table C.6, a one-standard-deviation increase in IC raises the probability of a recall event in the following month by 2.7 percentage points ($t = 3.1$), against a mean of 9.7%, and URR by 2.0 percentage points of loans ($t = 2.6$). With utilization, lendable supply and the fee as the only controls, the monthly estimates are smaller (1.7, $t = 1.9$, and 0.5, $t = 0.6$), whereas adding utilization to the daily baseline leaves them significant (1.9, $t = 4.4$, and 0.8, $t = 3.5$). Across the daily specifications, the recall-event estimate lies between 0.8 and 3.3 percentage points, with t-statistics of at least 2.3. Recall events in the two classes are only weakly synchronized: on the same day, the other class has a recall event 1.7 times as often as around an arbitrary day, with a bootstrap interval of [0.7, 3.6] that includes one. Recalls are therefore more consistent with

Table C.6: Within-firm evidence: dual-class shares

Panel A. Higher-IC minus lower-IC class, firm averages

	Difference	t	Share positive	Firms
IC	0.220	(8.09)	1.00	64
Recall event	0.066	(3.78)	0.67	64
URR	0.055	(5.82)	0.77	64
Supply drop	0.124	(4.45)	0.72	64
Supply volatility	0.124	(6.11)	0.84	64
Fee (% a year)	0.359	(1.20)	0.81	64
Utilization (%)	-2.614	(-0.93)	0.55	64
Short interest (% of shares)	-3.493	(-4.04)	0.23	64
Lendable supply	-0.137	(-8.65)	0.11	64
Log class market cap	-0.979	(-8.63)	0.17	64
Institutional ownership	-0.289	(-6.07)	0.24	62
Ownership HHI	0.156	(6.23)	0.85	62

Panel B. Daily: event in the next five trading days, firm × day fixed effects

	Recall event	URR	Current-lender squeeze	5% supply drop	Firms
Mean of outcome	0.034	0.021	0.023	0.080	
(1) Class size and DCBS	0.017	0.009	0.012	0.023	62
	(4.02)	(3.91)	(3.07)	(3.83)	
(2) Plus supply, IOR and ownership HHI	0.016	0.007	0.014	0.018	62
	(3.75)	(3.12)	(3.22)	(2.72)	
Class-days	46,349				

Notes. Firms with two or more listed common share classes in CRSP and Markit, 2006 to 2023, excluding tracking stocks (classes whose monthly returns correlate below 0.8 with every other class). Panel A follows Porras Prado et al. (2016): each month the class with the highest IC is compared with the other classes of the firm; differences are averaged within firm, and the t-statistic tests whether the mean across firms is zero. Outcomes are for the next month; recall event: supply and loans both fall by at least 5% on one day; supply drop: supply alone; supply volatility: standard deviation of daily supply divided by its mean. Short interest: Markit short-loan quantity relative to shares outstanding, averaged over the month; exchange short interest is reported for only one class in most firms. Panel B: coefficient on a one-standard-deviation higher IC of the class, averaged over the previous 20 trading days; outcomes over the next five trading days, one observation every five trading days, class-days with 13F data. URR: share of loans lost to unreplaced recalls, summed over the window. Current-lender squeeze: supply and loans fall by the same amount on one day. Row (1) controls for the class's log market capitalization at the previous month end and indicators for Markit's Daily Cost of Borrow Score (DCBS; 2, 3, 4, 5–6, 7–10, with score 1 or missing the base). Row (2) adds lendable supply relative to shares outstanding and the class's 13F institutional ownership and ownership HHI at the previous month end. Standard errors clustered by firm; t-statistics in parentheses. A firm-level bootstrap of the recall-event coefficient gives p-values of <0.002 (1) and <0.002 (2).

decisions by the lenders of each class than with news about the firm, which both classes share.

C.7 Fee risk and recall risk

Engelberg et al. (2018) find that short-selling risk lowers returns, price efficiency, and short selling. Their main measure, fee variability, captures one cost of maintaining a short position. A fee increase makes an open position more expensive. An unreplaced recall forces the short seller to close the position at the prevailing price. I compare the potential costs of these risks and test whether IC predicts recalls after controlling for fee variability.

I define FeeVar as the log of the within-month variance of the daily fee. With the controls of Table C.4, on the months from 2006 to 2019, a one-standard-deviation increase in IC predicts a 0.18 increase in next-month FeeVar ($t = 9.2$). This result is consistent with the model. When a large lender withdraws, the loss of supply can both raise the fee and make recalled shares harder to replace.

Panel A of Table C.8 compares the cost of a fee increase with the cost of a forced closure. In the bottom and top IC quintiles, the median within-month standard deviations of the annualized fee are 0.045 and 0.17 percentage points, respectively. A fee increase of one standard deviation sustained for a month would therefore cost 0.4 and 1.5 basis points of the position. The fee is constant in about one-fifth of stock-months. Pooled monthly recall frequencies are 3.5% in the bottom IC quintile and 30.5% in the top. Dividing the monthly fee cost by the corresponding recall frequency gives a break-even cost per recall of about 11 basis points in the bottom quintile and 5 in the top. Above these thresholds, the expected monthly cost of recalls exceeds the cost of the assumed fee increase. A forced purchase can incur both the bid–ask spread and price impact, particularly in small stocks, as well as the opportunity cost of closing the position early.

Panel B tests whether IC predicts recalls conditional on FeeVar and the controls of Table 2. Because the log variance is undefined when the fee is constant, I estimate both specifications on stock-months with positive fee variance. On this sample, the baseline recall coefficient is 2.39 percentage points, compared with 2.09 in the full sample. Adding FeeVar reduces the coefficient to 1.96 ($t = 7.7$), about 80% of the same-sample baseline. The squeeze coefficient remains at 0.35 percentage points ($t = 5.2$). Among stocks with annual fees of at most 1%, the recall coefficient falls only from 1.75 to 1.65 percentage points ($t = 7.3$). IC thus predicts the risk of losing borrowed shares even among stocks with low fees and after controlling for fee variability.

Table C.7: Dual-class shares: further specifications

Panel A. Monthly: next-month outcomes, firm × month fixed effects

	Recall event	URR	5% supply drop	Supply volatility	Firms
Mean of outcome	0.097	0.078	0.217	0.104	
No lending controls	0.094	0.055	0.147	0.131	64
	(7.45)	(6.62)	(10.78)	(7.96)	
Baseline	0.017	0.005	0.042	0.066	64
	(1.93)	(0.63)	(3.22)	(6.27)	
Excluding record-date months	0.019	0.006	0.044	0.071	64
	(2.15)	(0.79)	(3.26)	(6.27)	
Both classes fee $\leq$ 1%	0.013	-0.003	0.057	0.061	62
	(1.61)	(-0.39)	(3.96)	(6.98)	
Controlling class market cap	0.019	0.009	0.030	0.062	64
	(2.15)	(1.16)	(2.37)	(5.06)	
Classes within 3× in size	0.059	0.032	0.050	0.068	40
	(2.30)	(1.31)	(1.69)	(2.82)	
Controlling class ownership HHI and IO	0.034	0.023	0.040	0.067	62
	(3.90)	(2.89)	(2.78)	(4.38)	
Supply-side controls (Table C.6, row 2)	0.027	0.020	0.036	0.062	62
	(3.09)	(2.59)	(2.54)	(4.23)	

Panel B. Daily: event in the next five trading days, firm × day fixed effects

	Recall event	URR	Current-lender squeeze	5% supply drop	Firms
Mean of outcome	0.034	0.021	0.023	0.080	
Baseline	0.016	0.007	0.014	0.018	62
	(3.75)	(3.12)	(3.22)	(2.72)	
Class size only	0.033	0.014	0.024	0.034	62
	(5.46)	(5.50)	(4.71)	(3.74)	
Class size, DCBS and supply	0.011	0.004	0.010	0.013	62
	(2.31)	(1.78)	(2.25)	(2.19)	
Plus utilization	0.019	0.008	0.016	0.021	62
	(4.39)	(3.47)	(3.55)	(3.04)	
Plus short interest	0.014	0.005	0.011	0.021	62
	(2.85)	(1.89)	(2.40)	(2.61)	
Fee bins	0.015	0.007	0.013	0.018	62
	(3.72)	(3.00)	(3.08)	(2.78)	
Fee	0.028	0.011	0.022	0.036	62
	(4.70)	(4.03)	(3.99)	(4.07)	
Excluding record-date windows	0.017	0.007	0.014	0.019	62
	(3.86)	(3.17)	(3.08)	(2.83)	
Both classes fee $\leq$ 1%	0.008	0.004	0.006	0.020	59
	(3.43)	(2.52)	(3.50)	(2.81)	

Panel C. Does the other class have a recall event within $\pm k$ trading days?

	$k = 0$	$k = 1$	$k = 5$
After a recall event in the class	0.0170	0.0400	0.0868
Around any day of the class	0.0101	0.0271	0.0729
Ratio	1.68	1.48	1.19
	[0.67, 3.58]	[0.84, 2.42]	[0.80, 1.75]

Notes. Sample as in Table C.6. Coefficients on a one-standard-deviation higher IC of the class. Panel A: baseline controls are utilization, lendable supply and fee-bin indicators (cut-offs at 0.5, 1, 2, 5, 10 and 25% a year), plus class market capitalization in the size row; the second-to-last row adds the class's 13F ownership HHI and institutional ownership; the last row uses the controls of row (2) of Table C.6 with fee bins in place of DCBS (class market capitalization, fee-bin indicators, lendable supply, institutional ownership and ownership HHI, without utilization). Panel B: the baseline is row (2) of Table C.6 (class market capitalization, DCBS indicators, lendable supply, 13F institutional ownership and ownership HHI); other rows change one element. Class size, DCBS and supply omits the two ownership variables. Utilization and short interest (Markit short-loan quantity relative to shares outstanding) are averaged over the previous 20 trading days. Fee bins and the fee replace the DCBS indicators with fee-bin indicators or the indicative fee. URR: share of loans lost to unreplaced recalls. Current-lender squeeze: supply and loans fall by the same amount on one day. Panel C: probability that the other class has a recall event within k trading days of one in the class, around any day of the class, and their ratio with a 95% firm-level bootstrap interval. Standard errors clustered by firm; t-statistics in parentheses.

Table C.8: Fee risk and recall risk

Panel A. Magnitudes by IC quintile

IC quintile	Fee (% a year)	SD of daily fee (% a year)	No fee variance (% of months)	Cost of 1-SD move (bp, one month)	Recall event$_{t+1}$ (%)
1 (dispersed)	0.48	0.045	22	0.37	3.5
2	0.52	0.045	24	0.37	4.2
3	0.64	0.048	23	0.40	5.9
4	0.92	0.060	19	0.50	10.6
5 (concentrated)	2.04	0.174	18	1.45	30.5

Panel B. Coefficient on IC, without and with fee variance as a control

	Recall event$_{t+1}$		Squeeze$_{t+1}$		Recall event, fee $\leq$ 1%	
	(1)		(2)		(3)	
IC (standardized)	2.39	(9.0)	0.36	(5.2)	1.75	(7.6)
IC (standardized), controlling for log FeeVar	1.96	(7.7)	0.35	(5.2)	1.65	(7.3)
Observations	436,236		435,936		370,386	

Notes. Panel A: stocks sorted each month into IC quintiles; pooled means, except medians for the SD of the daily fee and the cost of a fee move. The SD of the daily fee is the square root of FeeVar, the variance of Markit's daily indicative fee over the last 21 trading days of the month; "No fee variance" is the share of stock-months in which it is zero or undefined. The cost of a one-standard-deviation fee move is that SD divided by 12, the extra fee on a position held for one month, in basis points of the position. Panel B: coefficient on IC in linear probability regressions in percent with the controls of Table 2, which include the fee, firm and month fixed effects, on stock-months in which FeeVar is defined; the second row adds log FeeVar, standardized within month, as a control. Column (3) keeps stocks with a fee of at most 1% a year. Standard errors clustered by firm and month; t-statistics in parentheses.

D Withdrawals by lending programs

This appendix complements Section 4.2. Section D.1 gives the details of the data and the lending programs. Section D.2 follows the construction of the withdrawal step by step. Section D.3 reports the full relation between the size of withdrawals, recall risk and IC, and Section D.4 reports alternative units, inference and specifications.

D.1 Data and lending programs

Holdings. I use N-PORT holdings at quarter ends from September 2019 to September 2023, from the SEC data sets for filing quarters 2019Q4 to 2023Q4, which give initial quarter ends from September 2019 to June 2023 and holdings changes over the following three months. I keep the latest filing for each fund and quarter and require a fund to report at both ends of a quarter pair, so that a missing filing is not counted as a sale. N-PORT CUSIPs are linked to CRSP, and a position is kept only when its reported value per share is within a factor of two of the CRSP price.

Lending programs. A fund's lending agents come from its most recent N-CEN filing on or before the quarter end, at most 550 days earlier. The holdings of a fund with several agents are split equally across them. A lending program is a registrant, which approximates a fund family, at one lending agent.

D.2 Construction and exogeneity

Table D.1 follows the construction of the withdrawal in five steps, one per column. Panel A reports the effect on recall outcomes, Panel B the relation with the stock's return before, during and after the withdrawal quarter, and Panel C the relation with earnings news. All measures are signed so that a positive value is a withdrawal and are measured as a percentage of shares outstanding.

Holdings-weighted and equal-weighted growth. Columns (1) and (2) use holdings-weighted and equal-weighted growth on their own. Both follow bad news: a withdrawal of 1% of shares outstanding follows a previous-quarter return that is lower by 0.84 percentage points for holdings-weighted growth and by 1.48 for equal-weighted growth (Panel B), and a lower earnings surprise (-0.029 and -0.067 standard deviations, Panel C). Sales that follow bad news coincide with fewer recall events (-1.42 and -4.08 percentage points, Panel A), so neither measure isolates a shock to lendable supply.

The difference. Column (3) is W_s of equation (14). Because equal-weighted growth responds about twice as strongly to news, the difference reverses the sign of the response rather than removing it: it follows higher previous-quarter returns (0.64, $t = 4.1$) and higher earnings surprises (0.033, $t = 5.0$), and its recall effect is 3.02 percentage points.

Equal-weighted growth as a control. Column (4) adds equal-weighted growth as a control, which lets programs with large and small holdings respond to news differently. The coefficient on the withdrawal is then unrelated to the previous quarter's return (0.03, $t = 0.18$), to earnings surprises in the withdrawal quarter and the previous quarter (0.013, $t = 1.9$, and 0.008, $t = 1.3$) and to announcement returns, apart from the absolute earnings surprise (0.022, $t = 3.0$). The recall effect is 1.56 percentage points ($t = 6.5$). This is the minimal specification of the design.

All controls. Column (5) adds the remaining controls of Table 3 and gives the main-text estimate, 1.84 percentage points ($t = 9.6$). Panel D adds, one at a time, recall events in the previous quarter, the return during the quarter and the earnings news measures. The recall estimate stays between 1.81 and 1.89 on the full sample and is unchanged on the samples with news measures.

Loss per share of supply withdrawn. Panel E instruments the change in Markit's active lendable quantity with the withdrawal. A fall in lendable supply of 1% of shares outstanding raises the probability of a recall event by 3.06 percentage points and lowers loans by 0.113% of shares outstanding (first-stage F of 636).

D.3 Size of withdrawals and inventory concentration

Panel A of Table D.2 groups withdrawals by their size relative to lendable supply, using the 55,432 stock-quarters in which program holdings do not exceed supply. URR rises with the size of the withdrawal in the same way as recall events, from 0.42 percentage points of loans for withdrawals of up to 2% of supply to 6.25 for withdrawals of 10% to 25%. Withdrawals above 25% of supply are rare (132 stock-quarters) and occur in stocks with a median utilization of 53.2%, in which recall events are already frequent, so the estimate for this group is imprecise (5.30, $t = 1.40$).

Panel B reports the distribution of withdrawals by IC tercile. Beyond the frequency of withdrawals above 10% of supply, the 99th percentile of withdrawals rises from 8.5% of supply in the bottom tercile to 9.9% and 19.7% in the middle and top terciles. Table D.3 reports the holdings of the programs by IC quintile. In addition to the figures in the main text, the standard deviation of the withdrawal relative to the programs' holdings rises from

Table D.1: Withdrawals by lending programs: exogeneity

	(1) Holdings-weighted growth	(2) Equal-weighted growth	(3) Withdrawal (1) − (2)	(4) Withdrawal, (2) controlled	(5) All controls
Panel A. Effect of 1% of shares outstanding					
Recall event (pp)	-1.42 (-5.85)	-4.08 (-14.05)	3.02 (14.02)	1.56 (6.49)	1.84 (9.55)
URR (pp of loans)	-0.52 (-4.55)	-1.91 (-12.83)	1.62 (18.12)	0.96 (10.06)	1.17 (17.33)
Loans lost (% of shares)	0.089 (11.46)	0.061 (7.70)	0.050 (7.24)	0.087 (10.59)	0.068 (11.68)
Panel B. Stock return (%)					
Previous quarter (months $t-2$ to t)	-0.84 (-5.81)	-1.48 (-10.24)	0.64 (4.12)	0.03 (0.18)	control
Quarter of the withdrawal (months $t+1$ to $t+3$)	-1.61 (-7.79)	-2.07 (-10.83)	0.28 (1.57)	-0.66 (-2.97)	-0.67 (-3.02)
Next quarter (months $t+4$ to $t+6$)	0.12 (0.74)	0.35 (2.12)	-0.25 (-1.61)	-0.12 (-0.66)	-0.16 (-0.89)
Panel C. Earnings news (standard deviations)					
Earnings surprise (SUE), quarter of the withdrawal	-0.029 (-3.69)	-0.067 (-7.96)	0.033 (4.97)	0.013 (1.86)	0.011 (1.65)
Absolute SUE, quarter of the withdrawal	-0.001 (-0.13)	-0.033 (-3.25)	0.030 (3.90)	0.022 (3.00)	0.018 (2.51)
SUE, previous quarter	-0.016 (-2.28)	-0.039 (-4.82)	0.020 (3.03)	0.008 (1.32)	0.008 (1.27)
Announcement return, quarter of the withdrawal	-0.020 (-3.98)	-0.040 (-7.90)	0.018 (4.35)	0.005 (1.07)	0.004 (0.95)
Announcement return, previous quarter	-0.017 (-3.61)	-0.033 (-7.32)	0.016 (3.60)	0.004 (0.90)	0.003 (0.67)
Panel D. All controls: further checks					
	Recall event (pp)	URR (pp of loans)	Loans lost (% of shares)		
δ for a zero effect (Oster, $R_{\max} = 1.3R^2$)	5.0	8.3	n.a.		
Controls and past recall events	1.89 (9.94)	1.17 (17.40)	0.068 (11.68)		
Controls and the return during the quarter	1.81 (9.43)	1.16 (17.26)	0.067 (11.57)		
SUE sample: controls	1.31 (5.45)	1.04 (12.05)			
and SUE	1.31 (5.42)	1.04 (12.01)			
Announcement-return sample: controls	1.70 (8.51)	1.17 (17.33)			
and announcement returns	1.70 (8.52)	1.17 (17.33)			
Panel E. Loss per 1% of lendable supply withdrawn					
	Recall event (pp)	URR (pp of loans)	Loans lost (% of shares)		
Change in lendable supply instrumented by the withdrawal	3.06 (9.66)	1.93 (16.43)	0.113 (11.53)		
first-stage F		636			
Stock-quarters (Panels A, D and E)			58,170		

Notes. Programs (non-index funds). Columns (1) to (5) follow the construction of the withdrawal, each signed so that a positive value is a withdrawal and expressed in percent of shares outstanding. (1): the holdings-weighted growth of the programs, $-100 \sum_a S_{as} g_{as} H_s / SO_s$. (2): the equal-weighted holdings growth, $-100\, \bar{g}_s H_s / SO_s$. (3): the withdrawal W_s of equation (14), (1) minus (2). (4): W_s with (2) as a control; the coefficient equals that on (1) with (2) as a control. (5): W_s with all controls of Table 3, the specification of the main text. Panels A and B: quarter fixed effects in all columns, and in (4) and (5) the controls stated; the stock return is the log return in percent, and the previous quarter's return is a control in (5). Panel C: the news variable on the measure of each column, both divided by their standard deviations, with quarter fixed effects; in (4) and (5) the measure is the residual of W_s from a pooled regression on (2) or on all controls, with quarter fixed effects. SUE is actual minus mean forecast EPS, scaled by the absolute value of actual EPS; the announcement return is the three-day return around the announcement; both are winsorized at 1% and 99% and taken for the last announcement in the three months of the withdrawal or the three months before. Panel D: the specification of column (5); δ from Oster (2019), not applicable where the effect rises with the controls; the news rows use the stock-quarters with the news variable, without and with it as a control. Panel E: the outcome on the change in lendable supply, instrumented by the withdrawal, with the controls and quarter fixed effects; first-stage F: Wald statistic on the withdrawal. Standard errors clustered by stock; t-statistics in parentheses.

12.2% in the bottom quintile to 22.7% in the top quintile, as Proposition 1 predicts for more concentrated holdings.

Table D.2: Withdrawals by lending programs: size and exposure

Withdrawal (% of lendable supply)	≤ 0	0 to 2	2 to 5	5 to 10	10 to 25	> 25
Panel A. Effect relative to stock-quarters without a withdrawal						
Recall event (pp)	–	1.14 (4.19)	4.02 (7.47)	6.44 (6.52)	10.37 (5.94)	5.30 (1.40)
URR (pp of loans)	–	0.42 (4.44)	1.70 (8.75)	3.21 (8.54)	6.25 (7.90)	4.24 (2.43)
Stock-quarters	31,382	17,604	4,190	1,495	629	132
Utilization (%, median)	6.3	4.6	6.6	11.3	18.0	53.2

Panel B. Distribution of the withdrawal (% of lendable supply)	95th percentile	99th percentile	Above 10% (% of stock-quarters)
Low IC	4.0	8.5	0.6
Middle IC	3.7	9.9	1.0
High IC	5.7	19.7	2.6

Notes. Programs (non-index funds), stock-quarters in which the programs' holdings do not exceed Markit's active lendable quantity at the quarter end (55,432 stock-quarters). The withdrawal of Table 3 is rescaled to percent of active lendable quantity. Panel A: recall events and URR regressed on indicators of the size groups, with the controls and quarter fixed effects of Table 3; the reference group is no withdrawal; the last two rows give the number of stock-quarters and the median utilization at the quarter end in each group. Panel B: percentiles of the withdrawal and the share of stock-quarters with a withdrawal above 10% of lendable supply, by IC tercile. Standard errors clustered by stock; t-statistics in parentheses.

Table D.3: Withdrawals by lending programs: concentration of the programs' holdings

	IC quintile				
	1	2	3	4	5
Largest program's share of the programs' holdings (median)	0.23	0.30	0.34	0.42	0.62
Number of programs (median)	55	38	27	17	5
Standard deviation of the withdrawal relative to the programs' holdings (%)	12.2	13.8	15.1	16.8	22.7
Programs' holdings relative to lendable supply (%, median)	19.7	16.5	12.7	9.3	14.8
Utilization (%, median)	3.3	4.6	5.9	8.4	18.2
Stock-quarters	58,170				

Notes. Programs (non-index funds), all stock-quarters, by IC quintile within quarter. The withdrawal relative to the programs' holdings is $-100\, z_s$ from equation (13). Lendable supply is Markit's active lendable quantity; utilization is measured at the quarter end.

D.4 Units, inference and robustness

Aggregation units. Table D.4 builds the withdrawal from non-index lending programs, lending agents, index funds and all funds. In Panel A, which uses the withdrawal before the

remaining controls, the shock built from all funds is also related to the previous quarter's return (1.24, $t = 11.2$), like those built from agents and index funds. The shock is related to the previous quarter's change in lendable supply for every unit (0.17, $t = 8.2$, for programs), which is why the recall regressions control for it. Panel C shows that the recall-event effect is similar with agents as the unit, with two-way clustering, and without the Russell reconstitution quarters or 2020. Wild cluster bootstrap p-values, clustered by the largest unit, are 0.004 for agents, with only 26 agent clusters.

Loans lost per share sold. Panel B relates the loss of loans to the funds' own sales. Loans lost per share that the funds sold while it was on loan are 3.34, so the funds' reported sales alone do not account for the decline in loans. This is consistent with withdrawals by other clients of the same programs, which the filings do not show, and is why Panel E of Table D.1 scales the loss by the change in Markit supply instead.

Controls and fixed effects. Panel A of Table D.5 varies the controls and fixed effects. The effect of a withdrawal of 1% of shares outstanding on the probability of a recall event lies between 1.73 and 2.00 percentage points.

The largest program. Panel B of Table D.5 reports the alternative specifications and withdrawal definitions summarized in the main text. Panel C uses stock fixed effects. The effect of a withdrawal by the largest program is 1.33, 2.71 and 3.63 percentage points across terciles of the stock's average IC, but the continuous interaction is not significant (2.23, $t = 1.6$). The gradient also does not survive interactions with the ranks of size, institutional ownership and ownership HHI, or IC residualized on these ranks (Nagel, 2005), consistent with these characteristics shaping the lender base (Appendix B.3).

Table D.4: Withdrawals by lending programs: units, further outcomes and inference

	Programs	Agents	Index funds	All funds
Panel A. Balance: predetermined variables on the shock before purging				
Past quarter's return (%)	-0.083 (-0.49)	0.679 (4.38)	1.657 (8.73)	1.240 (11.22)
Past change in lendable supply	0.168 (8.22)	0.198 (10.41)	0.163 (8.34)	0.159 (12.92)
Past loans lost	-0.008 (-1.40)	-0.001 (-0.25)	0.003 (0.46)	-0.001 (-0.18)
R^2 of the shock on predetermined variables	0.15	0.32	0.32	0.42
Panel B. Further outcomes of a withdrawal of 1% of shares outstanding				
Loans (% of shares)	-0.269 (-16.77)	-0.229 (-15.28)	-0.157 (-8.82)	-0.128 (-12.04)
Short interest (% of shares)	-0.063 (-4.22)	-0.040 (-2.88)	0.074 (4.00)	0.035 (3.24)
Loans lost (% of shares)	0.068 (11.68)	0.072 (13.02)	0.042 (5.24)	0.070 (14.46)
Loans lost per share sold while on loan	3.341 (11.67)	3.491 (12.83)	0.924 (5.38)	1.647 (15.03)
first-stage F	305	332	355	605
Panel C. Recall event (pp): inference and samples				
IC rank as a control	1.91 (9.88)	1.94 (10.56)	2.68 (12.77)	3.13 (23.23)
Clustered by stock and quarter	1.84 (7.50)	1.85 (10.48)	2.71 (7.41)	3.09 (11.98)
Clustered by stock and largest unit	1.84 (8.33)	1.85 (14.70)	2.71 (2.10)	3.09 (4.95)
Excluding quarters with the Russell reconstitution	2.01 (9.20)	1.84 (8.89)	3.10 (12.32)	2.72 (16.98)
Excluding 2020	1.82 (7.98)	1.80 (8.20)	3.17 (12.77)	3.44 (21.63)
Previous quarter's withdrawal added: current	1.86 (9.53)	1.96 (10.60)	2.79 (12.86)	3.16 (23.04)
previous	-0.16 (-0.81)	-0.37 (-2.09)	-0.29 (-1.46)	0.13 (1.04)
Stock-quarters	58,170	55,721	56,884	64,452
Median units per stock	23	10	10	12

Notes. The withdrawal built from lending programs (non-index funds, as in Table 3), from lending agents, from index funds and from all funds. Panel A regresses each predetermined variable on the shock z_s before purging, not signed as a withdrawal (a positive value means that units with large holdings grew their holdings relatively more), with the equal-weighted growth, log market capitalization, utilization, the fee and loans relative to shares outstanding as controls and quarter fixed effects; the last row is the R^2 of the regression of the shock on all predetermined variables. Panel B: loans lost per share sold while on loan, instrumented by the withdrawal. Panel C: the specification of Table 3, with IC as an additional control, with standard errors clustered as stated, without the quarters that contain the Russell reconstitution (March to June) or 2020, and with the previous quarter's withdrawal as an additional regressor. Standard errors clustered by stock unless stated; t-statistics in parentheses.

Table D.5: Withdrawals by lending programs: robustness

	Recall event (pp)		URR (pp of loans)		
	Withdrawal	Large withdrawal by the largest program × IC	Withdrawal	Large withdrawal by the largest program × IC	Obs.
Panel A. Controls and fixed effects					
Main specification	1.84 (9.5)	4.72 (3.4)	1.17 (17.3)	2.06 (3.2)	58,170
Return during the quarter and past 12-month return	1.88 (9.7)	4.55 (3.2)	1.20 (18.1)	1.89 (2.9)	56,333
Programs' holdings relative to shares outstanding	1.73 (9.0)	5.32 (3.8)	1.14 (17.0)	2.23 (3.5)	58,170
Log number of programs	2.00 (10.4)	4.31 (3.1)	1.20 (17.7)	1.99 (3.1)	58,170
Industry × quarter fixed effects	1.80 (9.1)	4.37 (3.0)	1.22 (17.9)	1.66 (2.6)	56,280
Stock and quarter fixed effects	1.75 (9.0)	2.23 (1.6)	1.13 (16.9)	0.53 (0.9)	57,907
Main specification, stock-quarters with 13F data	1.90 (8.5)	6.24 (3.4)	1.32 (16.9)	0.69 (0.9)	43,943
Size, IO and ownership HHI interacted with the shock		-0.03 (-0.0)		-0.26 (-0.3)	43,943
IC residualized on size, IO and ownership HHI		1.74 (1.0)		0.32 (0.5)	43,943
Panel B. Definition of a large withdrawal					
Cut at least 15 points more than other programs		3.76 (3.1)		1.91 (3.5)	58,170
Cut at least 50 points more than other programs		2.45 (1.3)		3.16 (3.7)	58,170
Own holdings fall by at least 25%		8.92 (6.6)		3.10 (5.0)	58,170
Own holdings fall by at least 50%		9.04 (5.0)		2.87 (3.5)	58,170
Other programs: at least 5% of the holdings		5.25 (3.7)		2.28 (3.6)	58,170
Other programs: at least 20% of the holdings		4.44 (3.2)		1.87 (2.9)	58,170
Panel C. Stock and quarter fixed effects: effect within terciles of the stock's average IC					
Bottom tercile		1.33 (2.1)		1.41 (6.6)	57,907
Middle tercile		2.71 (3.6)		1.15 (5.1)	
Top tercile		3.63 (4.7)		1.58 (4.8)	

Notes. Programs (non-index funds). Withdrawal: coefficient on the withdrawal of equation (14), 1% of shares outstanding, as in Panel A of Table 3. Large withdrawal by the largest program × IC: interaction of the indicator of a large withdrawal by the largest program (equation (15)) with the within-quarter percentile rank of IC, as in Panel B of Table 3. Panel A adds controls or changes the fixed effects; the return and industry rows use the stock-quarters with these data. The number of programs falls steeply with IC, so holding it fixed removes part of the variation in concentration that the test uses. The last three rows of Panel A use the stock-quarters with 13F data. The second of them adds the within-quarter ranks of market capitalization, institutional ownership and ownership HHI and their interactions with the indicator; the third replaces the IC rank with the within-quarter rank of the residual from a quarterly cross-sectional regression of the IC rank on the three ranks. Panel B changes the definition of a large withdrawal. Panel C: stock and quarter fixed effects, with the effect of a large withdrawal by the largest program estimated separately within terciles of the stock's average IC rank over the sample. Observations: the regressions with the large withdrawal by the largest program. Standard errors clustered by stock; t-statistics in parentheses.

E Additional pricing results

This appendix supports Section 5. Appendix E.1 reports DGTW-adjusted returns and lending income on lent shares, Appendix E.2 the anomalies without selection, Appendix E.3 size-neutral sorts, and Appendix E.4 compares IC with Markit's lender concentration. Appendix E.5 reports the response of prices to earnings news.

E.1 DGTW-adjusted returns and lending income on lent shares

DGTW-adjusted returns. Table E.1 repeats the average-anomaly comparison of Table 6 with each stock's return measured relative to its DGTW benchmark portfolio of stocks with similar size, book-to-market and momentum (Daniel et al., 1997). The High-minus-Low difference is 0.40% a month ($t = 3.6$), and 0.30% net of fees ($t = 2.7$). By cluster, the net-of-fee difference is positive in all ten clusters and significant for short-term reversal (0.62, $t = 3.0$), profit growth (0.67, $t = 3.6$), momentum (0.52, $t = 2.5$), and investment (0.41, $t = 3.0$; Tables E.2 and E.3). In the NetLeg portfolios, the Q5-minus-Q1 spread is 124 basis points a month at high IC ($t = 3.5$) and 102 net of fees ($t = 2.9$), against 32 at low IC ($t = 1.3$; Table E.4).

Lending income on lent shares. Following Muravyev et al. (2025), Tables E.1 and E.5 credit the long leg only for the shares that are actually lent, 0.7× utilization × fee instead of 0.7× fee. The net-of-fee difference for the average anomaly is then 0.27% a month ($t = 2.2$) in excess returns and 0.24% ($t = 2.1$) DGTW-adjusted, and the Q5-minus-Q1 spread at high IC is 93 basis points a month ($t = 2.0$).

Table E.1: Average anomaly: DGTW-adjusted returns and lending income on lent shares

	High − Low	Long leg	Short leg
Excess returns			
Net of fees, income on lent shares	0.27	0.04	−0.23
	(2.2)	(0.3)	(−1.2)
DGTW-adjusted returns			
Before fees	0.40	0.08	−0.32
	(3.6)	(0.5)	(−1.7)
Net of fees	0.30	0.16	−0.14
	(2.7)	(1.0)	(−0.8)
Net of fees, income on lent shares	0.24	0.10	−0.14
	(2.1)	(0.6)	(−0.8)

Notes. As in Table 6. Entries are the High-minus-Low difference for the average anomaly in the long-short return, the long leg and the short leg, in percent a month, with t-statistics in parentheses. DGTW-adjusted returns are measured relative to benchmark portfolios of stocks with similar size, book-to-market and momentum (Daniel et al., 1997). Income on lent shares credits long positions with 0.7× utilization × fee instead of 0.7× fee.

Table E.2: Anomaly returns by cluster and inventory concentration: DGTW-adjusted returns

Cluster	High LS Ret.	Low LS Ret.	High–Low LS Ret.	Long Contri.	Short Contri.
Short-Term Reversal	0.89***	0.20	0.69***	0.15	−0.54**
	(4.39)	(1.42)	(3.30)	(0.73)	(-2.55)
Profit Growth	0.73***	0.02	0.71***	0.25	−0.46**
	(4.05)	(0.23)	(3.83)	(1.31)	(-2.37)
Value	0.62**	0.18	0.45**	0.04	−0.40*
	(2.20)	(1.05)	(1.98)	(0.23)	(-1.87)
Momentum	0.62***	0.04	0.58***	0.15	−0.43**
	(3.38)	(0.35)	(2.83)	(0.89)	(-1.98)
Investment	0.60***	0.12	0.48***	0.08	−0.40**
	(4.64)	(1.01)	(3.43)	(0.40)	(-2.47)
Profitability	0.51*	0.13	0.38	0.11	−0.27
	(1.69)	(0.83)	(1.50)	(0.73)	(-1.05)
Low Risk	0.50*	0.11	0.39**	0.06	−0.33
	(1.83)	(0.66)	(2.02)	(0.33)	(-1.63)
Quality	0.49**	0.26**	0.23	0.03	−0.20
	(2.40)	(1.96)	(1.18)	(0.21)	(-0.84)
Seasonality	0.43***	0.10	0.33**	0.30*	−0.03
	(3.15)	(1.12)	(2.06)	(1.75)	(-0.15)
Debt Issuance	0.16	0.07	0.09	−0.05	−0.14
	(1.48)	(0.95)	(0.70)	(-0.26)	(-0.86)

Notes. As in Table 4, with each stock's return measured relative to its DGTW benchmark portfolio (Daniel et al., 1997).

Table E.3: Net-of-fee anomaly returns by cluster and inventory concentration: DGTW-adjusted returns

	Long-short return			CAPM α		
Cluster	High	Low	High–Low	High	Low	High–Low
Short-Term Reversal	0.81^{***}	0.19	0.62^{***}	0.83^{***}	0.17	0.66^{***}
	(4.01)	(1.33)	(2.99)	(4.03)	(1.20)	(3.11)
Profit Growth	0.68^{***}	0.01	0.67^{***}	0.62^{***}	−0.00	0.63^{***}
	(3.76)	(0.08)	(3.62)	(3.42)	(-0.01)	(3.34)
Momentum	0.53^{***}	0.02	0.52^{**}	0.56^{***}	0.13	0.43^{**}
	(2.90)	(0.14)	(2.52)	(2.97)	(1.14)	(2.09)
Investment	0.52^{***}	0.10	0.41^{***}	0.56^{***}	0.13	0.43^{***}
	(3.98)	(0.85)	(2.95)	(4.29)	(1.08)	(3.01)
Value	0.44	0.15	0.29	0.70^{***}	0.20	0.49^{**}
	(1.57)	(0.90)	(1.30)	(2.59)	(1.20)	(2.29)
Seasonality	0.37^{***}	0.09	0.28^{*}	0.37^{***}	0.10	0.27^{*}
	(2.71)	(1.01)	(1.75)	(2.68)	(1.06)	(1.69)
Low Risk	0.37	0.08	0.29	0.81^{***}	0.35^{***}	0.46^{**}
	(1.36)	(0.45)	(1.53)	(3.83)	(2.65)	(2.54)
Quality	0.34^{*}	0.25^{*}	0.10	0.41^{**}	0.31^{**}	0.10
	(1.67)	(1.83)	(0.50)	(2.00)	(2.33)	(0.52)
Profitability	0.32	0.11	0.22	0.53^{*}	0.19	0.34
	(1.06)	(0.67)	(0.85)	(1.77)	(1.20)	(1.33)
Debt Issuance	0.11	0.06	0.05	0.14	0.09	0.05
	(0.95)	(0.76)	(0.36)	(1.21)	(1.12)	(0.37)

Notes. As in Table 5, with each stock's return measured relative to its DGTW benchmark portfolio (Daniel et al., 1997). Short positions pay the holding-month fee, and long positions earn 70% of the fee. CAPM α is the intercept from a regression of the cluster's monthly net-of-fee long-short return on the market excess return. Parentheses report t-statistics for the monthly time series.

Table E.4: NetLeg portfolio returns by inventory concentration: DGTW-adjusted returns

Metric	Group	1	2	3	4	5	H–L
r	Low-IC	-24.67	-1.76	0.65	2.99	7.42	32.10
		(-1.28)	(-0.20)	(0.10)	(0.56)	(0.95)	(1.33)
	High-IC	-81.88	-43.89	-8.58	27.36	41.86	123.74
		(-2.65)	(-2.06)	(-0.66)	(1.56)	(3.04)	(3.47)
Avg. Fee	Low-IC	6.01	3.96	3.60	3.39	3.33	–
	High-IC	29.72	21.05	14.82	14.00	11.67	–
SR	Low-IC	-0.343	-0.049	0.024	0.125	0.242	0.348
	High-IC	-0.651	-0.503	-0.122	0.331	0.539	0.860
r^{feeadj}	Low-IC	-18.67	1.01	3.16	5.37	9.75	28.42
		(-0.97)	(0.12)	(0.51)	(1.01)	(1.25)	(1.18)
	High-IC	-52.16	-29.15	1.80	37.17	50.03	102.19
		(-1.70)	(-1.38)	(0.14)	(2.11)	(3.62)	(2.88)
SR^{feeadj}	Low-IC	-0.260	0.028	0.118	0.224	0.318	0.308
	High-IC	-0.416	-0.334	0.026	0.449	0.644	0.711
α_{CAPM}	Low-IC	-43.10	-11.60	-2.33	1.82	14.32	57.42
		(-2.43)	(-1.37)	(-0.37)	(0.33)	(2.03)	(2.70)
	High-IC	-88.54	-41.22	12.98	53.71	73.04	161.58
		(-2.90)	(-1.98)	(1.04)	(2.91)	(5.25)	(4.86)
α_{CAPM}^{feeadj}	Low-IC	-37.06	-8.81	0.19	4.20	16.65	53.71
		(-2.09)	(-1.04)	(0.03)	(0.75)	(2.37)	(2.53)
	High-IC	-58.90	-26.40	23.45	63.53	81.23	140.13
		(-1.94)	(-1.29)	(1.89)	(3.42)	(5.84)	(4.24)
Num. Months	Low-IC	209	209	209	209	209	–
	High-IC	209	209	209	209	209	–
Avg. Num. Stocks	Low-IC	127	127	126	126	126	–
	High-IC	126	125	125	126	126	–

Notes. As in Table 7, with each stock's return measured relative to its DGTW benchmark portfolio (Daniel et al., 1997).

Table E.5: NetLeg portfolio returns by inventory concentration: lending income on lent shares

Metric	Group	1	2	3	4	5	H–L
$r^{feeadj,util}$	Low-IC	69.15	89.17	88.57	90.78	94.23	25.08
		(1.20)	(1.96)	(2.29)	(2.62)	(3.21)	(0.68)
	High-IC	30.89	42.71	76.41	110.45	123.70	92.81
		(0.45)	(0.73)	(1.76)	(2.70)	(3.33)	(2.04)
$SR^{feeadj,util}$	Low-IC	0.298	0.475	0.547	0.601	0.737	0.172
	High-IC	0.118	0.200	0.486	0.797	1.013	0.507
$\alpha_{CAPM}^{feeadj,util}$	Low-IC	-55.35	-18.73	-5.91	2.43	19.49	74.83
		(-2.10)	(-1.24)	(-0.51)	(0.24)	(2.28)	(2.66)
	High-IC	-92.48	-63.81	-1.76	41.20	61.55	154.03
		(-2.38)	(-2.25)	(-0.08)	(1.75)	(2.95)	(4.00)

Notes. As in Table 7, with quintile 5 credited with 0.7× utilization × fee, the lending income on the shares actually lent, instead of 0.7× fee.

E.2 Anomalies without selection

Table E.6 repeats Table 6 for every characteristic of Jensen et al. (2023) with enough stocks in each IC group, 147 in all, without the selection rule of Section 3. The High-minus-Low difference is 0.27% a month ($t = 3.8$), and 0.20% net of fees ($t = 2.8$). It is smaller than for the selected anomalies, because many characteristics do not predict returns in this sample, but it has the same sign, so the result does not depend on the selection rule. Appendix G lists the 70 selected anomalies.

Table E.6: Average anomaly without selection: all JKP characteristics

	Long (5)	4	3	2	Short (1)	Long − Short
Panel A. Excess returns (% a month)						
High IC	0.84	0.89	0.81	0.69	0.51	0.33
	(2.11)	(2.37)	(2.13)	(1.69)	(1.07)	(3.18)
Low IC	0.87	0.87	0.85	0.83	0.81	0.06
	(2.20)	(2.29)	(2.24)	(2.10)	(1.84)	(0.84)
High − Low	-0.03	0.02	-0.05	-0.15	-0.31	0.27
	(-0.23)	(0.14)	(-0.31)	(-0.89)	(-1.76)	(3.81)
Panel B. Net of fees (% a month)						
High IC	0.95	0.89	0.81	0.69	0.71	0.24
	(2.41)	(2.37)	(2.13)	(1.69)	(1.51)	(2.32)
Low IC	0.90	0.87	0.85	0.83	0.86	0.04
	(2.27)	(2.29)	(2.24)	(2.10)	(1.94)	(0.59)
High − Low	0.05	0.02	-0.05	-0.15	-0.15	0.20
	(0.34)	(0.14)	(-0.31)	(-0.89)	(-0.84)	(2.79)
Panel C. Fee (% a year)						
High IC	2.00	1.75	1.78	1.91	2.49	
Low IC	0.49	0.43	0.43	0.45	0.56	

Notes. As in Table 6, for every characteristic of Jensen et al. (2023) with enough stocks in each IC group, without the CAPM-alpha selection. t-statistics of the monthly time series in parentheses.

E.3 Size

IC groups within size terciles. Table E.7 forms the IC groups within terciles of market capitalization, so that each group draws about the same number of stocks from each size tercile. The High-minus-Low difference for the average anomaly is 0.25% a month ($t = 2.6$), and the High-minus-Low difference in the NetLeg Q5-minus-Q1 spread is 58 basis points a month ($t = 2.4$).

A fitted squeeze probability. Table E.7 also sorts on a fitted squeeze probability (SQP) instead of IC. SQP is the prediction of a logit of the next-month squeeze indicator on the variables that determine π in equation (A.3): IC, the largest lender's share of inventory s, utilization u and u^2, $\max(0, s + u - 1)$ and $IC \times u$. The logit is refit each January on all prior data after a 24-month burn-in, so SQP is out of sample and available from 2009. The High-minus-Low difference is 0.48% a month for the average anomaly ($t = 2.6$), against 0.45% for IC over the same period ($t = 3.4$). Because SQP uses utilization, which rises with shorting demand, it serves as a check on the channel rather than as the main sorting variable.

Table E.7: Size-neutral concentration and recall risk: anomaly and NetLeg spreads

	Average anomaly, High−Low				NetLeg	
Sorting variable	EW long-short	EW long leg	EW short leg	VW long-short	Q5−Q1, High−Low	Months
IC (main sort)	0.43	0.02	-0.40	0.32	0.91	209
	(3.57)	(0.16)	(-2.10)	(1.92)	(3.28)	
IC within size terciles	0.25	-0.10	-0.35	0.18	0.58	209
	(2.55)	(-0.97)	(-2.19)	(1.26)	(2.35)	
IC, 2009 onward	0.45	0.11	-0.34	0.42	0.97	179
	(3.36)	(0.65)	(-1.58)	(2.55)	(3.12)	
Recall risk (SQP), 2009 onward	0.48	-0.28	-0.76	0.36	1.11	179
	(2.64)	(-1.04)	(-1.87)	(1.71)	(2.55)	

Notes. Each month stocks are split into Low (bottom quintile), Mid and High (top quintile) groups of the sorting variable, and anomaly portfolios are formed within each group. Columns 1 to 4 report the average across anomalies of the High-group minus Low-group difference in the long-short return, in the long leg and in the short leg (where a negative value means the short leg earns less in the High group), in percent per month, equal- (EW) and value-weighted (VW). Column 5 reports the difference between the High and Low groups in the return spread between the top and bottom NetLeg quintiles. IC within size terciles ranks IC within NYSE-based size terciles. Recall risk (SQP) starts in 2009, and the IC row for 2009 onward is the matching comparison. Excess returns. Newey-West t-statistics with three lags in parentheses.

E.4 Lender concentration

Markit's lender concentration measures the concentration of the shares on loan across lenders, while IC measures the concentration of lendable inventory, including lenders with no shares on loan. The two differ because a small loan book is concentrated even when inventory is dispersed. Table E.8 compares them on the stock-months for which both are available. In the recall regressions of Panel A, IC retains 91% of its recall-event coefficient when lender concentration is added (2.07 against 2.28 percentage points). Lender concentration predicts URR more strongly than IC, consistent with URR being measured relative to loans. Panel B sorts stocks on each measure, with DGTW-adjusted returns from 2007 to 2023. Sorting on IC gives a High-minus-Low difference in the Q5-minus-Q1 spread of 96 basis points a month ($t = 3.6$), and sorting on lender concentration 19 basis points ($t = 0.8$). Ranking IC within terciles of lender concentration leaves 82 basis points ($t = 3.1$), whereas ranking lender concentration within terciles of IC gives -42 basis points ($t = -1.5$).

Table E.8: Inventory concentration versus Markit lender concentration

Panel A. Next-month recall outcomes, controls of Table 2					
	Recall event	URR	Supply drop	Squeeze	Supply vol.
IC alone	2.284	1.267	2.245	0.317	0.043
	(9.11)	(6.58)	(7.15)	(6.72)	(12.05)
Lender concentration alone	1.085	1.971	1.051	0.099	0.025
	(7.13)	(16.21)	(6.16)	(4.65)	(14.16)
Both: IC	2.068	0.702	2.038	0.303	0.038
	(8.37)	(3.69)	(6.43)	(6.70)	(10.43)
Both: lender concentration	0.704	1.842	0.672	0.044	0.019
	(4.74)	(15.46)	(3.94)	(2.53)	(10.62)
Panel B. NetLeg portfolios, High minus Low group (bp a month, DGTW-adjusted)					
	NetLeg spread	Short leg	Long leg		
IC	96	-60	36		
	(3.55)	(-2.41)	(2.26)		
Lender concentration	19	20	39		
	(0.76)	(0.80)	(3.03)		
IC within lender-concentration terciles	82	-74	9		
	(3.13)	(-2.89)	(0.64)		
Lender concentration within IC terciles	-42	69	27		
	(-1.54)	(2.66)	(2.85)		

Notes. Lender concentration is Markit's concentration of the shares on loan across lenders, averaged over the month; IC is the concentration of lendable inventory. Panel A: coefficients on each measure, standardized within month, with the controls and fixed effects of Table 2, on the stock-months with both measures; standard errors clustered by firm and month. Panel B: each month, stocks in the top and bottom quintile of the grouping variable are sorted into NetLeg quintiles; the columns report the High-minus-Low difference in the NetLeg spread (quintile 5 minus 1), in the short leg (quintile 1) and in the long leg (quintile 5). In the last two rows each measure is ranked within terciles of the other before grouping. Newey-West t-statistics in parentheses. 2007 to 2023.

E.5 Earnings announcements

If recall risk deters short selling, negative news should enter prices more slowly where IC is high, while positive news should not. Incorporating negative news may require investors without a position to borrow shares and sell short; incorporating positive news requires no borrowing. Prices drift after earnings announcements (Bernard and Thomas, 1989), more so when arbitrage is costly or risky (Mendenhall, 2004). I test whether high IC predicts greater drift after negative but not after positive earnings news.

Design. Day 0 is the announcement day of each earnings announcement from 2006 to 2023. Daily abnormal returns are stock returns minus the value-weighted return of the matching Fama–French 5×5 size and book-to-market portfolio (Livnat and Mendenhall, 2006). The announcement return $\mathrm{CAR}_i[-1,+1]$ sums abnormal returns from day -1 to day $+1$, and the drift $\mathrm{CAR}_i[+2,+h]$ sums them from day $+2$ to day $+h$, for horizons up to 60 trading days. Each month, announcements with a negative return at or below the median of negative returns are negative news, and announcements with a positive return at or above the median of positive returns are positive news. Following Chan et al. (1996), I classify news by the market reaction rather than by the surprise relative to analyst forecasts, because the reaction also reflects guidance, revisions and conference calls. Separately for negative and positive news, I estimate

$$\begin{aligned}\mathrm{CAR}_i[+2,+h] = \beta_h\,\mathrm{CAR}_i[-1,+1]\times IC_i + b\,\mathrm{CAR}_i[-1,+1] + c\,IC_i \\ + \sum_k \big(d_k + e_k\,\mathrm{CAR}_i[-1,+1]\big)Z_{k,i} + \delta_t + \varepsilon_i,\end{aligned} \tag{E.1}$$

where IC is standardized and measured in the month before the announcement, and δ_t are month fixed effects. The controls Z are the fee, log market capitalization, idiosyncratic volatility, institutional ownership, short interest, Amihud illiquidity and lendable supply, each also interacted with the announcement return. β_h measures the additional continuation of the announcement return for a one-standard-deviation higher IC; after negative news, a positive β_h means a larger subsequent decline.

Results. Table E.9 reports the estimates. After negative news (Panel A), a one-standard-deviation increase in IC raises the continuation coefficient by 0.040 at 20 days ($t = 2.6$), 0.051 at 30 days ($t = 2.5$) and 0.083 at 60 days ($t = 2.6$). For the average negative announcement return of -9.9%, the 60-day estimate implies an additional decline of about 0.8 percentage points. After positive news (Panel B), the interaction is insignificant at every horizon, including 60 days (0.018, $t = 0.6$). Figure E.1 shows these estimates as additional drift in the direction of the news. For the average stock, announcement returns continue after positive news (0.077, $t = 3.3$) but not after negative news (-0.005, $t = -0.2$).

The role of the controls. High-IC stocks are small, and returns adjusted with size and book-to-market portfolios still differ in how fast they respond to news. With month fixed effects only (block i), the 60-day interaction is therefore positive after both negative news (0.101, $t = 4.1$) and positive news (0.049, $t = 2.1$). Once the response to news may vary with size and the other controls (block ii), only the negative-news interaction remains significant. This asymmetry points to a constraint on short selling rather than to a friction that slows all information. The fee does not predict additional drift after negative news (0.022, $t = 1.3$).

Sample and market-adjusted returns. Table E.10 describes the announcements. Among negative news, the 60-day drift is 0.09% in the bottom IC tercile and −0.74% in the top, and top-tercile stocks are smaller, have higher fees, lower institutional ownership, higher volatility and less lendable supply. With market-adjusted returns (Table E.11), the 60-day interaction is 0.092 ($t = 2.7$) after negative news and 0.015 ($t = 0.5$) after positive news.

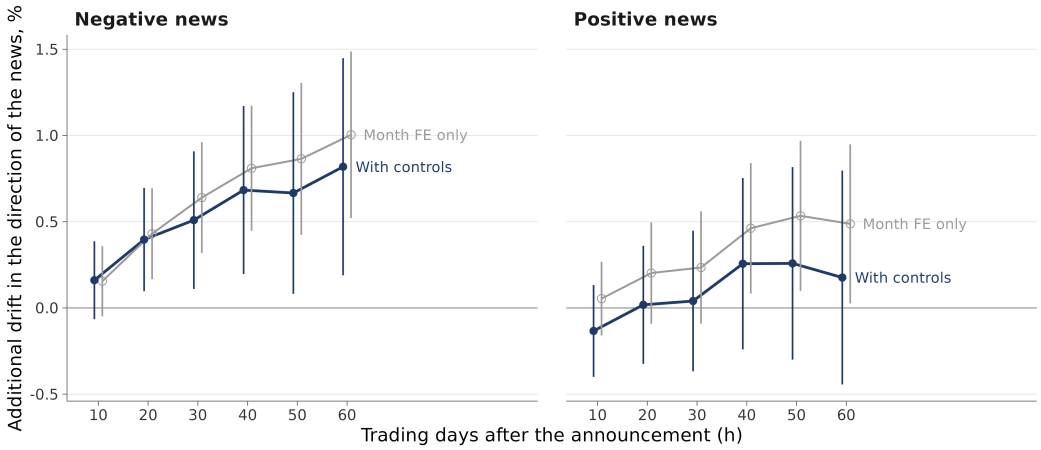


Figure E.1: Post-announcement drift and inventory concentration. Additional drift in the direction of the news, in percent, for one standard deviation higher IC after an average negative or positive announcement: the coefficient on CAR$[-1,+1]$×IC in Table E.9 times the absolute mean announcement return of the group, with 95% intervals. Dark: with controls (block ii); grey: month fixed effects only (block i).

Table E.9: Post-announcement drift and inventory concentration

	Dependent variable: CAR[+2, +h]					
	$h = 10$	$h = 20$	$h = 30$	$h = 40$	$h = 50$	$h = 60$
Panel A. Negative news (mean CAR[−1, +1] = -9.9%)						
(i) Month fixed effects only						
CAR[−1, +1] × IC	0.016	0.043	0.065	0.082	0.087	0.101
	(1.49)	(3.20)	(3.90)	(4.38)	(3.85)	(4.07)
CAR[−1, +1]	-0.017	-0.022	-0.034	-0.032	-0.031	-0.018
	(-1.44)	(-1.37)	(-1.71)	(-1.33)	(-1.18)	(-0.59)
IC	0.120	0.254	0.255	0.342	0.337	0.423
	(1.22)	(1.74)	(1.41)	(1.56)	(1.29)	(1.48)
Adjusted R^2	0.017	0.016	0.016	0.024	0.029	0.031
(ii) With controls						
CAR[−1, +1] × IC	0.016	0.040	0.051	0.069	0.067	0.083
	(1.39)	(2.60)	(2.50)	(2.75)	(2.23)	(2.55)
CAR[−1, +1]	-0.022	-0.017	-0.024	-0.014	-0.015	-0.005
	(-2.05)	(-1.16)	(-1.47)	(-0.73)	(-0.70)	(-0.19)
IC	0.338	0.433	0.433	0.456	0.379	0.478
	(2.82)	(2.49)	(1.89)	(1.64)	(1.14)	(1.35)
CAR[−1, +1] × fee	-0.001	-0.005	0.004	0.006	0.013	0.022
	(-0.10)	(-0.50)	(0.27)	(0.40)	(0.76)	(1.28)
CAR[−1, +1] × log size	-0.008	-0.008	0.000	0.009	0.018	0.013
	(-1.13)	(-0.91)	(0.02)	(0.61)	(1.08)	(0.69)
Adjusted R^2	0.018	0.017	0.018	0.027	0.032	0.035
Observations	41,753	41,753	41,753	41,753	41,753	41,753
Panel B. Positive news (mean CAR[−1, +1] = 10.0%)						
(i) Month fixed effects only						
CAR[−1, +1] × IC	0.005	0.020	0.023	0.046	0.053	0.049
	(0.49)	(1.35)	(1.41)	(2.39)	(2.41)	(2.07)
CAR[−1, +1]	0.058	0.086	0.107	0.119	0.121	0.131
	(6.15)	(6.44)	(6.95)	(6.41)	(5.17)	(5.23)
IC	0.097	-0.036	-0.150	-0.293	-0.231	-0.147
	(0.94)	(-0.23)	(-0.82)	(-1.47)	(-1.04)	(-0.59)
Adjusted R^2	0.011	0.011	0.012	0.012	0.015	0.017
(ii) With controls						
CAR[−1, +1] × IC	-0.013	0.002	0.004	0.026	0.026	0.018
	(-0.98)	(0.10)	(0.19)	(1.01)	(0.91)	(0.56)
CAR[−1, +1]	0.030	0.052	0.064	0.071	0.069	0.077
	(3.06)	(3.62)	(3.98)	(4.11)	(3.34)	(3.28)
IC	0.102	-0.107	-0.235	-0.490	-0.463	-0.385
	(0.74)	(-0.55)	(-0.99)	(-1.83)	(-1.60)	(-1.18)
CAR[−1, +1] × fee	-0.003	-0.007	-0.011	-0.012	-0.002	0.005
	(-0.42)	(-0.78)	(-1.09)	(-1.09)	(-0.13)	(0.28)
CAR[−1, +1] × log size	-0.025	-0.032	-0.029	-0.032	-0.035	-0.030
	(-3.72)	(-3.91)	(-2.85)	(-2.75)	(-2.58)	(-1.78)
Adjusted R^2	0.015	0.014	0.016	0.016	0.019	0.021
Observations	42,851	42,851	42,851	42,851	42,851	42,851

Notes. Regressions of the size and book-to-market adjusted cumulative abnormal return over days [+2, +h] after an earnings announcement on the announcement return CAR[−1, +1], IC and their interaction, estimated separately for negative and positive news. Within each month, negative (positive) news are announcements whose CAR[−1, +1] is negative (positive) and at or below the median of the negative (at or above the median of the positive) announcement returns. IC is standardized (one standard deviation). Block (i) includes only CAR[−1, +1], IC, their interaction and month fixed effects. In block (ii), the controls are the fee, log size, idiosyncratic volatility, institutional ownership, short interest, Amihud illiquidity and lendable supply (% of shares outstanding), measured at the end of the month before the announcement and centered at their sample means; each also enters interacted with CAR[−1, +1], and the table reports the interactions with the fee (in percent a year) and log size. The coefficient on CAR[−1, +1] is therefore the continuation for a stock with average characteristics. The regressions do not include firm fixed effects. The concern they would address is that a persistent trait of concentrated stocks slows the response to news; that is a difference in the slope on CAR[−1, +1], which a firm fixed effect does not absorb, and the interactions of CAR[−1, +1] with the controls address it. With firm fixed effects added, the negative-news coefficient at $h = 60$ is 0.061 (t = 1.65). Standard errors are clustered by firm and month; t-statistics in parentheses. 2006 to 2023. The daily abnormal return is the stock's return minus the value-weighted return of its Fama-French 5 × 5 size and book-to-market portfolio (Kenneth French's data library, NYSE breakpoints, formed each June), summed over the window. Table E.11 reports the same regressions with market-adjusted returns.

Table E.10: Earnings announcements: summary statistics

Panel A. Distribution over all announcements

	N	Mean	SD	P10	Median	P90
CAR[−1, +1] (%)	171,392	0.11	8.40	-9.11	0.08	9.44
CAR[+2, +20] (%)	171,392	0.18	10.04	-10.53	-0.03	11.01
CAR[+2, +60] (%)	171,392	0.34	17.83	-18.82	0.24	19.41
IC	171,392	0.213	0.105	0.137	0.183	0.312
Market capitalization ($m)	171,392	8,348	43,708	106	869	14,917
Fee (bp)	171,392	79.6	149.7	28.4	37.5	130.1
Lendable supply (% of shares)	171,392	23.4	12.3	6.4	23.7	39.6
Short interest (% of shares)	171,392	4.4	5.0	0.4	2.8	10.1
Institutional ownership (%)	171,392	64.3	27.0	21.4	71.6	93.8
Idiosyncratic volatility (%, daily)	171,392	1.91	1.53	0.75	1.52	3.44
Amihud illiquidity	171,392	0.446	6.062	0.000	0.003	0.143

Panel B. Means by news group, and negative news by IC tercile

	All announcements				Negative news, by IC tercile		
	Negative	Other	Positive	All	Low	Mid	High
Events	41,753	86,788	42,851	171,392	13,648	14,494	13,611
Firms	5,859	6,208	5,698	6,641	3,183	3,823	3,745
Events per firm, median	5	9	5	18	3	3	2
CAR[−1, +1], mean (%)	-9.92	0.06	10.00	0.11	-9.49	-10.04	-10.21
CAR[−1, +1], median (%)	-7.94	0.04	8.11	0.08	-7.59	-8.05	-8.20
CAR[+2, +20], mean (%)	-0.18	0.12	0.64	0.18	-0.15	0.00	-0.39
CAR[+2, +60], mean (%)	-0.15	0.19	1.11	0.34	0.09	0.17	-0.74
IC, mean	0.209	0.217	0.208	0.213	0.148	0.185	0.296
Market cap, median ($m)	777	1,003	785	869	2,885	870	203
Fee, mean (bp)	84.8	78.4	77.0	79.6	52.0	65.9	137.7
Lendable supply, mean (% of shares)	23.7	22.8	24.3	23.4	28.8	26.1	16.2
Short interest, mean (%)	5.1	3.8	4.9	4.4	5.5	5.9	4.0
Institutional ownership, mean (%)	65.3	62.7	66.7	64.3	76.7	70.2	48.5
Idiosyncratic volatility, mean (%)	2.12	1.75	2.04	1.91	1.67	2.00	2.69

Notes. Earnings announcements in the regression sample of Table E.9, 2006 to 2023. Within each month, negative (positive) news are announcements whose CAR[−1, +1] is negative (positive) and at or below the median of the negative (at or above the median of the positive) announcement returns. Other are the rest. The last three columns of Panel B split the negative-news events by IC tercile within the month. CARs are size and book-to-market adjusted and winsorized at 0.5% and 99.5%. IC, market capitalization, the fee, lendable supply (Markit lendable quantity over shares outstanding), short interest, institutional ownership, idiosyncratic volatility (daily, Fama-French three-factor residuals over 21 days) and Amihud illiquidity are measured at the end of the month before the announcement.

Table E.11: Post-announcement drift and inventory concentration: market-adjusted returns

	Dependent variable: CAR[+2, +h]					
	$h = 10$	$h = 20$	$h = 30$	$h = 40$	$h = 50$	$h = 60$
Panel A. Negative news (mean CAR[−1, +1] = -9.9%)						
(i) Month fixed effects only						
CAR[−1, +1] × IC	0.015	0.040	0.061	0.076	0.086	0.105
	(1.46)	(2.98)	(3.76)	(3.92)	(3.68)	(3.94)
CAR[−1, +1]	-0.012	-0.021	-0.036	-0.031	-0.024	-0.008
	(-1.00)	(-1.33)	(-1.83)	(-1.30)	(-0.90)	(-0.25)
IC	0.071	0.158	0.152	0.243	0.260	0.375
	(0.77)	(1.18)	(0.97)	(1.13)	(0.95)	(1.23)
Adjusted R^2	0.049	0.060	0.068	0.073	0.078	0.080
(ii) With controls						
CAR[−1, +1] × IC	0.015	0.032	0.042	0.064	0.066	0.092
	(1.30)	(2.10)	(2.16)	(2.51)	(2.15)	(2.72)
CAR[−1, +1]	-0.020	-0.020	-0.028	-0.014	-0.008	0.003
	(-1.89)	(-1.43)	(-1.71)	(-0.75)	(-0.39)	(0.11)
IC	0.338	0.352	0.267	0.390	0.366	0.638
	(2.91)	(2.01)	(1.24)	(1.36)	(1.05)	(1.68)
CAR[−1, +1] × fee	-0.004	-0.007	-0.001	-0.003	0.003	0.011
	(-0.58)	(-0.73)	(-0.06)	(-0.21)	(0.16)	(0.63)
CAR[−1, +1] × log size	-0.015	-0.018	-0.014	-0.002	0.001	-0.001
	(-2.08)	(-1.90)	(-1.26)	(-0.15)	(0.05)	(-0.07)
Adjusted R^2	0.051	0.061	0.070	0.075	0.081	0.084
Observations	42,595	42,595	42,595	42,595	42,595	42,595
Panel B. Positive news (mean CAR[−1, +1] = 10.1%)						
(i) Month fixed effects only						
CAR[−1, +1] × IC	0.009	0.023	0.024	0.043	0.048	0.052
	(0.83)	(1.56)	(1.48)	(2.24)	(2.12)	(2.24)
CAR[−1, +1]	0.049	0.082	0.108	0.127	0.127	0.132
	(4.81)	(5.62)	(6.58)	(6.33)	(4.63)	(4.29)
IC	0.051	-0.039	-0.099	-0.182	-0.081	-0.136
	(0.45)	(-0.25)	(-0.58)	(-0.95)	(-0.37)	(-0.57)
Adjusted R^2	0.034	0.051	0.057	0.053	0.057	0.058
(ii) With controls						
CAR[−1, +1] × IC	-0.011	0.004	0.004	0.018	0.013	0.015
	(-0.82)	(0.24)	(0.21)	(0.72)	(0.44)	(0.47)
CAR[−1, +1]	0.025	0.050	0.070	0.080	0.077	0.081
	(2.41)	(3.28)	(4.16)	(4.52)	(3.65)	(3.27)
IC	0.130	-0.082	-0.151	-0.322	-0.177	-0.214
	(0.89)	(-0.41)	(-0.66)	(-1.23)	(-0.62)	(-0.69)
CAR[−1, +1] × fee	-0.007	-0.012	-0.016	-0.014	-0.007	-0.005
	(-1.07)	(-1.28)	(-1.52)	(-1.26)	(-0.54)	(-0.31)
CAR[−1, +1] × log size	-0.024	-0.031	-0.024	-0.032	-0.035	-0.033
	(-3.69)	(-3.49)	(-2.19)	(-2.52)	(-2.37)	(-1.83)
Adjusted R^2	0.036	0.054	0.061	0.057	0.060	0.061
Observations	43,199	43,199	43,199	43,199	43,199	43,199

Notes. As Table E.9, with abnormal returns measured against the market: the daily abnormal return is the stock's return minus the value-weighted market return of the CRSP daily file, summed over the window. The events are those of Table E.9; news is classified by the market-adjusted announcement return. Within each month, negative (positive) news are announcements whose CAR[−1, +1] is negative (positive) and at or below the median of the negative (at or above the median of the positive) announcement returns. IC is standardized (one standard deviation). Block (i) includes only CAR[−1, +1], IC, their interaction and month fixed effects. In block (ii), the controls are the fee, log size, idiosyncratic volatility, institutional ownership, short interest, Amihud illiquidity and lendable supply (% of shares outstanding), measured at the end of the month before the announcement and centered at their sample means; each also enters interacted with CAR[−1, +1], and the table reports the interactions with the fee (in percent a year) and log size. The coefficient on CAR[−1, +1] is therefore the continuation for a stock with average characteristics. Month fixed effects; standard errors clustered by firm and month; t-statistics in parentheses.

F Additional evidence on short positions

This appendix supports Section 6: the timing of the short-position regressions, the full regression of the entry event study, and the robustness of the Russell 3000 results.

F.1 Timing of the outcome

Table 8 measures short interest and utilization at the end of month $t+1$, after the month in which NetShort, IC and the controls are measured. Table F.1 measures them at the end of month t. The NetShort × IC coefficient barely changes: -2.70 ($t = -8.6$) in column 2, -0.90 ($t = -2.8$) with all interactions in column 3, and -7.75 ($t = -7.3$) for utilization in column 6.

Table F.1: Short positions and inventory concentration: outcomes in month t

	Short interest (% of shares)				Utilization (%)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
NetShort × IC, outcome in $t+1$	-5.83	-2.68	-0.86	-1.05	-3.26	-7.08	-6.55
	(-17.52)	(-8.64)	(-2.67)	(-2.86)	(-3.61)	(-6.58)	(-5.34)
NetShort × IC, outcome in t	-5.79	-2.70	-0.90	-1.13	-3.54	-7.75	-7.41
	(-17.49)	(-8.57)	(-2.82)	(-3.09)	(-3.94)	(-7.28)	(-6.07)
NetShort, outcome in t	3.37	2.24	2.13	1.98	6.83	7.73	7.62
	(26.60)	(19.35)	(19.61)	(17.47)	(21.17)	(24.64)	(20.85)
Observations, outcome in t	639,265	639,265	583,116	449,545	651,900	594,895	456,459

Notes. The specifications of Table 8, with short interest and utilization measured at the end of month t, the month in which NetShort, NetLong, IC and the controls are measured, instead of month $t+1$. The first row repeats the coefficients of Table 8. Controls, fixed effects and samples are those of the corresponding column; standard errors clustered by firm and month; t-statistics in parentheses.

F.2 Entry into the anomaly short leg: the full regression

Table F.2 reports every coefficient of equation (17) at 21 and 42 trading days after the end of the formation month, for loans and utilization, for entries into the short leg and for the placebo. IC and the controls are centered at 0.5 and the size quintile at the middle quintile, so the Entry coefficient is the response of the median stock in the middle size quintile. Within two months, entry raises the loans of the median stock by 0.52% of shares outstanding ($t = 3.3$), about 0.9% at the bottom of the IC distribution and 0.1% at the top. Among the characteristics interacted with entry, only IC changes the response: the interactions with the fee, lendable supply, Amihud illiquidity, idiosyncratic volatility, institutional ownership and ownership HHI have t-statistics between -1.4 and 1.4.

The rows without the entry indicator relate each characteristic to the change among the comparison stocks. Among the comparison stocks of the placebo, loans rise with IC by

0.23% of shares outstanding over two months ($t = 4.6$), so heavily shorted low-IC stocks shed loans faster whether or not they enter the long leg. The difference-in-differences removes this drift, which is why the raw gap and the IC rows of the placebo in Table 9 are positive while the Entry × IC rows are close to zero.

F.3 Russell 3000 inclusion

Robustness. Table F.3 varies the bandwidth, excludes ranks near the cutoff, uses a quadratic running variable, moves the cutoff to placebo ranks and splits the sample period. At the true cutoff, the effect of entry on the probability of a recall event falls by between 8 and 12 percentage points in every specification; at the placebo cutoffs, it is not significant. Figure F.1 shows that lendable supply, passive ownership and IC change after reconstitution, followed by the decline in recall events, without changes before it.

The lender base after inclusion. Table F.4 reports further outcomes. Inclusion raises passive ownership by 1.54% of shares outstanding ($t = 12.4$) and lowers Markit's lender concentration by 0.113 ($t = -7.8$). Fund filings for the 2020 and 2021 reconstitutions show that inclusion raises the number of funds holding the stock by 0.43 log points ($t = 4.1$) and the number lending it by 0.51 ($t = 3.8$), and lowers the largest lender's share of loan value by 0.17 ($t = -3.5$). The fraction of holdings that funds lend and the probability that a loan continues into the next quarter do not change. Because the index-fund share of loan value also rises (0.22, $t = 2.8$), these data do not separate a more dispersed lender base from a larger share of passive lenders.

Effects by IC before inclusion. Table F.5 splits entrants at the median IC before inclusion. Inclusion lowers the probability of a recall event by 13.1 percentage points ($t = -3.7$) where IC was above the median and by 6.4 ($t = -2.1$) where it was below, although lendable supply rises less where IC was above the median (1.94 against 2.92% of shares outstanding).

Effects by utilization before inclusion. Table F.6 splits entrants at the median utilization before inclusion. Short interest and loans rise in both halves: by 1.62 ($t = 6.8$) and 0.88 ($t = 6.2$) percentage points of shares outstanding where utilization was below the median, and by 2.00 ($t = 3.4$) and 1.16 ($t = 3.7$) where it was above. In the lower half, lenders had lent out only 1.2% of their inventory before inclusion, so the additional supply relaxed no binding constraint, yet short positions rose by a similar amount.

Table F.2: Entry into the anomaly short leg: the difference-in-differences regression

	Loans, percent of shares outstanding				Utilization, percentage points			
	Short leg		Long leg, placebo		Short leg		Long leg, placebo	
Trading day	21	42	21	42	21	42	21	42
Entry	0.49	0.52	-0.20	-0.19	1.96	1.95	-0.37	-0.13
	(3.41)	(3.33)	(-2.18)	(-1.72)	(2.69)	(2.40)	(-0.98)	(-0.30)
Entry × IC	-0.61	-0.77	0.09	0.03	-2.98	-3.07	0.07	-0.25
	(-2.50)	(-2.61)	(0.58)	(0.13)	(-2.55)	(-2.13)	(0.09)	(-0.29)
Entry × Fee	-0.09	-0.18	0.04	0.23	-0.60	-1.02	0.89	1.75
	(-0.40)	(-0.65)	(0.32)	(1.47)	(-0.53)	(-0.74)	(1.34)	(2.35)
Entry × Lendable supply	-0.05	-0.63	0.42	0.60				
	(-0.12)	(-1.39)	(1.98)	(2.53)				
Entry × Amihud	-0.29	-0.28	0.58	0.46	-0.97	-0.24	2.49	2.45
	(-1.24)	(-0.94)	(3.90)	(2.63)	(-0.89)	(-0.19)	(3.39)	(2.94)
Entry × IVOL	0.28	0.15	-0.28	-0.20	1.40	1.67	-2.01	-1.83
	(1.39)	(0.71)	(-1.88)	(-1.24)	(1.43)	(1.59)	(-2.83)	(-2.46)
Entry × Inst. ownership	-0.16	0.14	-0.07	-0.05	-1.14	-0.83	0.68	1.16
	(-0.60)	(0.45)	(-0.42)	(-0.22)	(-0.93)	(-0.57)	(1.06)	(1.38)
Entry × Ownership HHI	0.33	0.39	0.07	0.14	1.25	1.64	-0.16	0.68
	(0.98)	(0.99)	(0.37)	(0.66)	(0.89)	(1.06)	(-0.19)	(0.68)
IC	0.04	0.08	0.16	0.23	0.40	0.57	1.35	1.72
	(1.71)	(2.45)	(3.98)	(4.61)	(3.57)	(3.94)	(7.08)	(7.35)
Fee	-0.23	-0.29	-0.38	-0.50	-1.49	-1.89	-3.68	-4.70
	(-9.65)	(-9.83)	(-11.69)	(-12.63)	(-13.66)	(-13.91)	(-20.45)	(-22.25)
Lendable supply	-0.19	-0.29	-0.53	-0.75				
	(-5.91)	(-6.93)	(-9.33)	(-10.63)				
Amihud	-0.07	-0.08	-0.10	-0.08	0.02	0.14	0.03	0.42
	(-2.56)	(-2.16)	(-2.58)	(-1.66)	(0.19)	(1.07)	(0.16)	(1.75)
IVOL	0.14	0.21	0.44	0.57	0.10	0.26	1.31	1.65
	(7.61)	(9.20)	(14.86)	(15.98)	(1.33)	(2.66)	(8.00)	(8.47)
Inst. ownership	-0.15	-0.17	-0.27	-0.35	-0.67	-0.79	-1.61	-2.06
	(-6.19)	(-5.47)	(-7.19)	(-7.12)	(-7.56)	(-6.90)	(-9.12)	(-9.42)
Ownership HHI	-0.20	-0.25	-0.30	-0.42	-0.94	-1.18	-1.58	-2.03
	(-8.97)	(-8.98)	(-8.20)	(-8.74)	(-8.52)	(-8.16)	(-8.07)	(-8.49)
Entry × size quintile	Yes							
Month × size-quintile FE	Yes							
Stock-months	237,140	241,982	216,403	221,191	237,140	241,982	216,403	221,191
R^2	0.064	0.068	0.073	0.080	0.057	0.061	0.056	0.061

Notes. Every coefficient of the regression behind the Entry × IC rows of Table 9, at 21 and 42 trading days after the end of the formation month. The sample pools the entrants with the comparison stocks; the outcome is the change in loans or in utilization relative to the base day, the last trading day of month $t-2$. IC and the controls are within-month ranks at the end of month $t-2$, centered at 0.5, and the size quintile is centered at the middle quintile, so the Entry coefficient is the response to entry of the median stock in the middle size quintile; centering leaves the other coefficients unchanged. The rows without the entry indicator are the relation between each characteristic and the change among the comparison stocks. Lendable supply is omitted when utilization is the outcome. Changes winsorized at 0.5% and 99.5% by day; standard errors clustered by firm and month; t-statistics in parentheses.

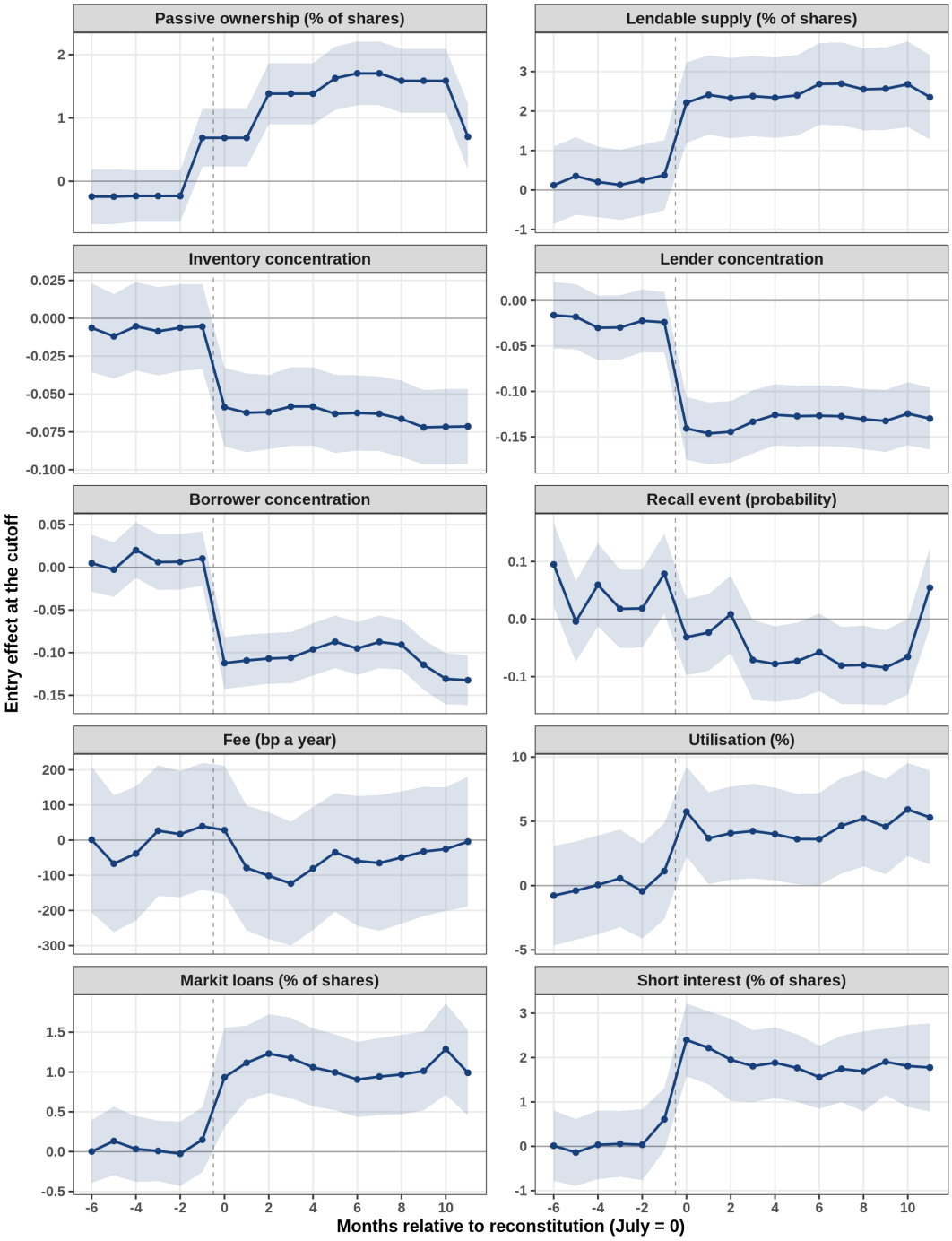


Figure F.1: Lending and short selling around Russell 3000 inclusion. Monthly estimates relative to June, with 95% confidence intervals, for prior non-members within 250 ranks of the reconstructed cutoff, 2007–2021. Outcomes include lendable supply, passive ownership, inventory concentration, lender and borrower concentration in outstanding loans, recall-event probability, fees, and short interest.

Table F.3: Russell entry robustness

Specification	Recall event	IC	Supply (pp)
Baseline, bandwidth 250	−0.096 (-4.1)	−0.064 (-6.0)	+2.37 (9.4)
Bandwidth 150	−0.082 (-2.7)	−0.039 (-2.8)	+1.92 (5.9)
Bandwidth 350	−0.093 (-4.6)	−0.065 (-7.1)	+2.63 (12.1)
Bandwidth 500	−0.080 (-4.6)	−0.077 (-10.0)	+2.86 (15.5)
Donut 25 ranks	−0.121 (-4.1)	−0.079 (-6.1)	+2.86 (9.0)
Donut 50 ranks	−0.115 (-3.1)	−0.083 (-5.1)	+3.03 (7.6)
Quadratic running variable, bandwidth 350	−0.084 (-2.8)	−0.048 (-3.5)	+1.91 (6.0)
Placebo cutoff −500	−0.062 (-1.6)	−0.016 (-0.9)	+0.50 (0.9)
Placebo cutoff +500	+0.014 (0.5)	+0.021 (1.9)	+0.04 (0.2)
Placebo cutoff −650	+0.034 (0.8)	+0.001 (0.1)	−0.42 (-0.6)
Placebo cutoff +650	+0.005 (0.2)	−0.003 (-0.2)	+0.25 (0.9)
Placebo cutoff −800	−0.074 (-1.6)	−0.019 (-0.9)	+0.11 (0.1)
Placebo cutoff +800	+0.018 (0.5)	+0.029 (2.1)	−0.09 (-0.3)
2007 to 2012	−0.099 (-3.3)	−0.060 (-4.1)	+2.56 (6.4)
2013 to 2021	−0.092 (-2.7)	−0.068 (-4.5)	+2.26 (7.1)

Notes. Effect of entry, design as Table 10, 2007 to 2021. The effect on recall events is negative in 13 of 15 years.

Table F.4: Russell 3000 entry: further outcomes and the lender base

Panel A. Further outcomes, diff-in-RD at the entry cutoff				
Outcome	Effect	t	Pre-entry mean (entrants)	N
Recall events removing $\geq 0.5\%$ of shares	−0.033	-1.8	0.149	
Recall events removing $\geq 1\%$ of shares	−0.008	-0.5	0.087	
Passive ownership (% of shares)	+1.54	12.4	2.70	38,149
Lender concentration	−0.113	-7.8	0.615	47,465
Borrower concentration	−0.110	-8.1	0.479	49,368
Panel B. Lender base in N-PORT data, entry in 2020 and 2021 (479 stock-years, 209 entrants)				
Outcome	Effect	t	Pre-entry mean (entrants)	Stock-years
log funds holding the stock	+0.43	4.1	2.34	462
log funds lending the stock	+0.51	3.8	0.94	462
Index-fund share of loan value	+0.22	2.8	0.39	323
Largest lender's share of loan value	−0.17	-3.5	0.73	323
Herfindahl of loans across funds	−0.19	-3.3	0.64	323
Number of lending programs	+1.1	2.9	2.5	321
Herfindahl of loans across programs	−0.17	-3.5	0.79	321
Share of holders lending	+0.03	1.0	0.18	462
Loan value / held value	+0.02	0.7	0.12	462
Loan continuation (fund-stock, next quarter)	+0.01	0.2	0.68	314
New lenders' share	+0.05	0.6	0.59	323

Notes. Panel A: equation (18) on prior non-members within 250 ranks of the rebuilt Russell 3000 cutoff, event months −6 to +11 around June, June and July dropped, stock-year and month fixed effects, standard errors clustered by stock; the table reports $-\beta$. Panel B: the same design on quarterly N-PORT holdings of all mutual funds and ETFs, quarters −3 to +4 around the June quarter, stock-year and quarter fixed effects. Lending programs are the parent groups of funds' securities-lending agents from N-CEN.

Table F.5: Entry effects by pre-entry concentration

	Low pre-entry IC	High pre-entry IC	High − Low
Recall event	−0.064 (-2.1)	−0.131 (-3.7)	−0.067 (-1.4)
URR (% of loans)	−7.82 (-4.0)	−5.84 (-2.4)	+1.99 (0.6)
Inventory concentration	−0.051 (-6.3)	−0.066 (-3.7)	−0.015 (-0.8)
Lendable supply (pp)	+2.92 (7.7)	+1.94 (5.9)	−0.98 (-2.0)
Passive ownership (pp)	+1.73 (10.1)	+1.44 (7.8)	−0.28 (-1.1)
Pre-entry IC, median split	below 0.35	above 0.35	

Notes. The entry sample of Table 10 split at the median IC in April before reconstitution. Each cell is the addition effect from equation (18) estimated within the group, June and July dropped, stock-year and month fixed effects, clustered by stock; t-statistics in parentheses. High − Low is the coefficient on the interaction of every term of equation (18) with the high pre-entry IC indicator, with month effects by group.

Table F.6: Russell 3000 entry by pre-entry utilization

	Low utilization		High utilization	
Pre-entry utilization (%)	1.2		34.2	
Outcome	Effect (t)	Pre-mean	Effect (t)	Pre-mean
Short interest (% of shares)	+1.62 (6.8)	0.54	+2.00 (3.4)	3.75
Markit loans (% of shares)	+0.88 (6.2)	0.20	+1.16 (3.7)	2.37
Lendable supply (% of shares)	+2.06 (6.2)	8.00	+2.67 (7.1)	6.36
Inventory concentration	−0.052 (-3.7)	0.401	−0.070 (-4.4)	0.392
Recall event (prob.)	−0.072 (-2.2)	0.310	−0.112 (-3.4)	0.418

Notes. The entry sample of Table 10 split at the median utilization in April before reconstitution. Each cell is the entry effect from equation (18) estimated within the half, June and July dropped, stock-year and month fixed effects, clustered by stock. Pre-mean is the pre-entry mean among added stocks.

G Selected anomalies

Table G.1 lists the 70 anomalies selected from the library of Jensen et al. (2023) by the rule of Section 3.

Table G.1: Anomalies selected from the JKP library

Anomaly	JKP name	Mean	CAPM α	$t(\alpha)$
Debt Issuance (3 of 7)				
Abnormal corporate investment	`capex_abn`	0.21	0.22	2.58
Growth in book debt (3 years)	`debt_gr3`	0.12	0.25	2.10
Change in financial liabilities	`fnl_gr1a`	0.14	0.22	2.07
Investment (16 of 22)				
Mispricing factor: Management	`mispricing_mgmt`	0.64	0.76	5.16
Change PPE and Inventory	`ppeinv_gr1a`	0.43	0.52	3.65
CAPEX growth (1 year)	`capx_gr1`	0.39	0.41	3.54
Change in net operating assets	`noa_gr1a`	0.46	0.48	3.44
CAPEX growth (2 years)	`capx_gr2`	0.38	0.41	3.12
Change in net noncurrent operating assets	`nncoa_gr1a`	0.42	0.43	2.96
Inventory growth	`inv_gr1`	0.33	0.38	2.79
Inventory change	`inv_gr1a`	0.27	0.32	2.74
Asset Growth	`at_gr1`	0.55	0.53	2.74
Change in noncurrent operating assets	`ncoa_gr1a`	0.44	0.41	2.61
Change in long-term net operating assets	`lnoa_gr1a`	0.34	0.35	2.54
Change in common equity	`be_gr1a`	0.46	0.39	2.14
Hiring rate	`emp_gr1`	0.37	0.38	2.07
Sales Growth (1 year)	`sale_gr1`	0.34	0.37	1.95
Liquidity of book assets	`aliq_at`	0.35	0.41	1.81
CAPEX growth (3 years)	`capx_gr3`	0.22	0.25	1.68
Low Risk (15 of 18)				
Highest 5 days of return	`rmax5_21d`	0.43	1.03	3.43
Return volatility	`rvol_21d`	0.34	1.06	3.23
Maximum daily return	`rmax1_21d`	0.31	0.86	3.08
Idiosyncratic volatility from the CAPM (21 days)	`ivol_capm_21d`	0.33	0.91	2.91
Idiosyncratic volatility from the q-factor model	`ivol_hxz4_21d`	0.31	0.85	2.87
Idiosyncratic volatility from the Fama-French 3-factor model	`ivol_ff3_21d`	0.31	0.85	2.85
Number of zero trades with turnover as tiebreaker (12 months)	`zero_trades_252d`	0.03	0.59	2.70
Downside beta	`betadown_252d`	-0.12	0.64	2.68
Cash flow volatility	`ocfq_saleq_std`	0.44	0.50	2.61
Years 6-10 lagged returns, nonannual	`seas_6_10na`	0.27	0.33	2.56
Number of zero trades with turnover as tiebreaker (6 months)	`zero_trades_126d`	-0.02	0.53	2.35
Dimson beta	`beta_dimson_21d`	-0.02	0.54	2.31
Share turnover	`turnover_126d`	-0.02	0.52	2.29
Idiosyncratic volatility from the CAPM (252 days)	`ivol_capm_252d`	0.12	0.76	2.19
Frazzini-Pedersen market beta	`betabab_1260d`	-0.26	0.56	2.08
Momentum (7 of 8)				
Current price to high price over last year	`prc_highprc_252d`	0.16	0.94	2.51

continued

Anomaly	JKP name	Mean	CAPM α	$t(\alpha)$
Price momentum t-6 to t-1	ret_6_1	0.41	0.72	2.42
Year 1-lagged return, nonannual	seas_1_1na	0.38	0.76	2.40
Price momentum t-3 to t-1	ret_3_1	0.31	0.58	2.33
Price momentum t-9 to t-1	ret_9_1	0.37	0.76	2.28
Residual momentum t-6 to t-1	resff3_6_1	0.21	0.32	1.97
Price momentum t-12 to t-1	ret_12_1	0.23	0.62	1.83
Profit Growth (1 of 12)				
Standardized earnings surprise	niq_su	0.23	0.29	2.58
Profitability (5 of 11)				
Return on net operating assets	ebit_bev	0.51	0.81	3.08
Operating cash flow to assets	ocf_at	0.58	0.74	2.71
Quarterly return on equity	niq_be	0.42	0.70	2.59
Ohlson O-score	o_score	0.22	0.54	1.95
Operating profits-to-book equity	ope_be	0.39	0.52	1.76
Quality (14 of 17)				
Assets turnover	sale_bev	0.66	0.60	3.82
Cash-based operating profits-to-book assets	cop_at	0.74	0.70	3.72
Cash-based operating profits-to-lagged book assets	cop_atl1	0.64	0.59	3.18
Mispricing factor: Performance	mispricing_perf	0.57	0.92	2.99
Operating profits-to-book assets	op_at	0.65	0.75	2.86
Quality minus Junk: Profitability	qmj_prof	0.51	0.72	2.81
Gross profits-to-assets	gp_at	0.64	0.63	2.71
Quarterly return on assets	niq_at	0.42	0.72	2.53
Operating profits-to-lagged book assets	op_atl1	0.55	0.63	2.46
Quality minus Junk: Safety	qmj_safety	-0.10	0.51	2.36
Quality minus Junk: Composite	qmj	0.12	0.54	2.31
Gross profits-to-lagged assets	gp_atl1	0.51	0.47	2.10
Capital turnover	at_turnover	0.57	0.43	2.02
Operating leverage	opex_at	0.55	0.34	1.90
Seasonality (3 of 12)				
Years 16-20 lagged returns, annual	seas_16_20an	0.35	0.31	2.55
Years 6-10 lagged returns, annual	seas_6_10an	0.33	0.31	2.34
Taxable income-to-book income	pi_nix	0.16	0.16	1.68
Short-Term Reversal (1 of 6)				
Highest 5 days of return scaled by volatility	rmax5_rvol_21d	0.42	0.43	2.42
Value (6 of 17)				
Net stock issues	chcsho_12m	0.51	0.71	3.05
Net equity issuance	eqnetis_at	0.56	0.73	2.80
Free cash flow-to-price	fcf_me	0.55	0.70	2.76
Equity net payout	eqnpo_12m	0.43	0.66	2.63
Net payout yield	eqnpo_me	0.50	0.63	2.24
Net total issuance	netis_at	0.52	0.54	2.23

Notes. Each of the 152 JKP characteristics with enough history is sorted monthly into equal-weighted quintiles in the main sample, with the JKP sign convention. An anomaly is selected when the CAPM alpha of its long-short return is positive with $t > 1.645$ (10% level, two-sided). Mean and alpha in percent per month; 71 anomalies are selected. In parentheses after each cluster: selected out of sorted.