Lendable Inventory Concentration, Borrow Fragility, and Equity Pricing Anomalies

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Abstract

Borrowing fees measure the spot price of borrowing shares, but short arbitrage requires durable borrow access. I study this non-price dimension of short-sale constraints through the lens of borrow fragility: the risk that borrow access deteriorates after a short position is initiated. Using IHS Markit securities-lending data, I show that lendable inventory concentration predicts greater borrow fragility. Stocks whose lendable supply is concentrated among fewer lenders experience more frequent lendable-quantity disruptions, greater fee instability, more severe fee and utilization tail events, and shorter loan tenure. High-concentration stocks incorporate negative earnings news more slowly and exhibit larger fee-adjusted anomaly return spreads, with the difference driven primarily by the short leg. The evidence suggests that concentrated lendable inventory is a structural source of borrow fragility, limiting short arbitrage beyond borrowing fees and helping sustain anomaly-related mispricing.

Keywords: lendable inventory concentration; borrow fragility; short-selling risk; limits to arbitrage; equity anomalies.

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1 Introduction

Borrowing fees are the standard measure of short-sale constraints, but a fee is a spot price: it captures the cost of borrowing shares today, not whether that access will hold. Short arbitrage is a dynamic trade. An arbitrageur must borrow shares, maintain the short position, and preserve borrow access until mispricing corrects, and over that horizon fees can rise, lenders can withdraw supply, and replacement borrow may be unavailable or available only on worse terms. I argue that this durability depends not only on the current fee, but on how lendable inventory is distributed across lenders. Because lending is specialized at the institution–stock level, lenders are not close substitutes: when inventory is dispersed across many active lenders, a withdrawal by one is absorbed by the others; when it is concentrated among a few, substitution is harder and borrow access is more fragile. This paper studies lendable inventory concentration as a state variable for borrow fragility: the risk that borrow access deteriorates after a short position is initiated.

This distinction implies that effective short-sale constraints have both a price component and a durability component. The price component is reflected in borrowing fees. The durability component is reflected in the stability of future borrow access. In this framework, inventory concentration (IC) is not itself the realized trading friction. Rather, IC measures the substitutability of lendable supply across lenders and predicts whether borrow access is likely to remain stable or become fragile.

I study this mechanism using IHS Markit securities-lending data for U.S. equities from 2006 to 2023. The central variable is *lendable inventory concentration* (IC), measured as the Herfindahl index of lendable shares across lenders for each stock-month. The analysis proceeds in three steps. First, I show that IC predicts future borrow fragility: more frequent lendable-quantity disruptions, greater fee instability, more severe fee and utilization tail events, and shorter loan tenure. Second, I show that high-IC stocks incorporate negative earnings news more slowly, even after controlling for the borrowing fee, while their response to positive news is largely unaffected. Third, I show that anomaly profitability is concentrated among high-IC stocks, that the spread is driven by the short leg, and that it survives explicit borrowing-fee adjustment.

The first set of tests validates IC as a state variable for borrow fragility. High-IC stocks experience more frequent lendable-quantity disruptions, greater fee instability, more severe fee and utilization tail events, and shorter loan tenure. These patterns hold after controlling for shorting demand, firm characteristics, lendable supply, stable-lender supply, and borrowing fees, indicating that IC contains information about future borrow-access stability beyond the current fee.

Event evidence from the Janus–Henderson merger supports this interpretation. I com-

pare stocks in which both Janus and Henderson were large pre-merger institutional holders, and therefore potential suppliers of lendable inventory, with stocks in which neither institution held a large position before the merger. The identifying assumption is that, absent the merger, these two groups would have followed similar lending-market trends. The event is useful because it plausibly reorganizes a large institutional ownership base that can supply lendable shares, while it does not directly create firm-specific negative information or a mechanical increase in borrowing demand for the affected stocks. Consistent with a supply-side reorganization, treated stocks experience an increase in inventory concentration and a decline in normalized lendable quantity after the merger. By contrast, normalized quantity on loan shows no clear post-merger increase. Borrowing-fee variance rises after the event, and utilization-tail pressure increases more noisily. This pattern is consistent with a supply-side interpretation: lendable supply becomes more concentrated and less abundant, without a corresponding increase in borrowing demand. The resulting increase in lending-market tightness is therefore consistent with greater borrow fragility rather than a demand-driven rise in shorting pressure.

Second, I examine whether this lending-market structure matters for price discovery. Earnings announcements provide information events with a natural asymmetry. If borrow fragility limits short-side arbitrage, negative news should be incorporated more slowly when short positions are difficult to maintain, whereas the response to positive news should be less affected. Consistent with this prediction, post-announcement drift after negative news is substantially stronger among high-IC stocks, even after controlling for borrowing fees and other market conditions. The corresponding effect after positive news is weak. This asymmetry is difficult to reconcile with symmetric explanations such as general inattention or illiquidity and is consistent with concentrated lendable supply impairing price discovery through a short-sale-constraint channel beyond borrowing costs.

Third, I study a broad set of equity anomalies. If borrow fragility limits arbitrage, anomaly return spreads should be larger among high-IC stocks and the difference should be concentrated on the short leg. The evidence is consistent with this prediction. Long–short anomaly returns are larger among high-IC stocks across major anomaly clusters, and the High–Low difference is driven primarily by the short leg. Importantly, these are not only gross return differences: after explicitly adjusting for borrowing fees, anomaly profits remain economically large and statistically significant among high-IC stocks. Cross-sectional regressions further show that realized short-selling risk predicts subsequent returns beyond loan fees, with predictive content concentrated among stocks that anomaly strategies classify as short candidates.

This paper makes three contributions. First, it identifies lendable inventory concen-

tration as a structural source of borrow fragility. Prior work emphasizes borrowing fees as the price component of short-sale constraints; this paper shows that the cross-lender structure of lendable supply predicts the durability of short-sale financing. Second, it contributes to research on price discovery by showing that high-IC stocks incorporate negative earnings news more slowly, while the corresponding effect for positive news is weak. Third, it contributes to the anomaly literature by showing that anomaly profitability remains economically large after fee adjustment precisely where borrow access is fragile and where arbitrage requires maintaining short positions.

The remainder of the paper is organized as follows. Section 2 reviews the related literature. Section 3 provides institutional background on the securities-lending market and motivates the role of lender-side concentration. Section 4 describes the data and variable construction. Section 5 establishes IC as a state variable for borrow fragility. Section 6 examines price adjustment around earnings announcements. Section 7 analyzes how lending-market structure conditions anomaly return spreads. Section 8 concludes.

2 Related Literature

This paper connects three literatures: lender structure in equity-lending markets, short-sale constraints and securities lending, and cross-sectional anomalies and limits to arbitrage. Each literature establishes part of the picture: ownership and lender structure shape the supply of borrowable shares, borrowing fees and short-selling risk are priced, and short-sale constraints limit anomaly arbitrage. What remains less understood is the structural source of borrow instability. I study this margin by measuring the concentration of actual lendable inventory across lenders and showing that it predicts borrow fragility, slower incorporation of negative information, and larger after-fee anomaly return spreads.

Lender structure, ownership, and lendable supply. A first strand studies how ownership and lending-market structure shape the borrowable-share supply. Nagel (2005) and Porras Prado et al. (2016) show that institutional ownership affects lending supply and that ownership concentration is associated with higher fees and stronger mispricing; more broadly, lower institutional ownership, more concentrated ownership, or shorter-horizon ownership can reduce lendable supply and raise arbitrage risk, delaying the correction of mispricing. A more recent line shows that lending markets are granular rather than competitive: supply is concentrated and persistent, with a few lenders supplying much of the inventory and stable lender–stock relationships (Dong and Zhu, 2022); market power and strategic behavior affect fees and quantities (Chen et al., 2022; Atmaz et al., 2024);

and lender identity shapes supply stability (Palia and Sokolinski, 2024). The common implication is that lenders are not perfectly substitutable. I depart from the ownership papers on the object of measurement: they ask whether a stock's *holders* make shares available, whereas I measure the cross-lender concentration of *actual lendable inventory*. The two need not coincide—a widely held stock may be lent by a small set of active lenders, and a stock with ample lendable quantity may still have poor substitutability across them. Building on the granularity evidence, I use this cross-lender concentration as a direct state variable for borrow fragility.

Borrowing fees and short-selling risk. A second strand connects securities-lending frictions directly to the maintenance of short positions. Fees need not fully summarize the constraint. Engelberg et al. (2018) measure short-selling risk through the variation and uncertainty of lending fees and show it is priced even after controlling for the fee level, and Ma (2019) shows that hedge funds bearing more short-selling risk earn higher performance. The relevant constraint is therefore not only the expected cost of borrowing but the risk that borrowing conditions change while a short is outstanding. This paper differs by identifying *why* that instability arises. Prior work documents short-selling risk and shows that it matters. I identify a structural source of this risk: the limited substitutability of lendable supply across lenders.

Cross-sectional anomalies and limits to arbitrage. A third strand studies cross-sectional return predictors and the limits to arbitrage that allow them to persist. A large literature debates whether anomaly returns reflect mispricing, risk compensation, or statistical artifacts. Some predictors are sensitive to data-snooping, microcap influence, and post-publication decay (Harvey et al., 2016; Linnainmaa and Roberts, 2018; Green et al., 2017; Hou et al., 2020), while other work documents that predictability persists out of sample, internationally, and after correcting for selective reporting (McLean and Pontiff, 2016; Jacobs and Müller, 2020; Y. Chen and Zimmermann, 2022; Jensen et al., 2023). If anomaly returns reflect mispricing, their persistence requires limits to arbitrage. Arbitrageurs face funding risk, margin requirements, price impact, and forced-unwind risk (Shleifer and Vishny, 1997; Vayanos and Gromb, 2010). These limits are especially important on the short side, where correcting overpricing requires borrowing shares, posting collateral, and maintaining the position while borrowing conditions change (Miller, 1977; Diamond and Verrecchia, 1987).

Empirically, short-sale constraints are closely related to anomaly profitability. High borrowing fees, limited lending supply, and short-sale restrictions are associated with overpricing and abnormal subsequent returns (Jones and Lamont, 2002; Hong and Stein,

2003; Cohen et al., 2007). Borrowing costs can substantially reduce, and sometimes eliminate, the profitability of anomaly long–short strategies (Muravyev et al., 2025), and institutional investors often do not trade aggressively on anomaly signals (Lewellen, 2011; Edelen et al., 2016). Da et al. (2025) show that lenders charge higher fees to more informed short sellers, so that equilibrium fees reflect the informativeness of short-sale demand, and that fee-adjusted anomaly profits survive primarily among the most profitable shorting opportunities, especially when lenders lack market power. A common premise across this work is that the borrowing fee is the relevant summary statistic for the short-sale constraint, whether the fee is treated as an exogenous cost or, as in Da et al. (2025), as an equilibrium price that impounds the informativeness of borrowers.

My paper contributes by showing that borrowing fees, however they are determined, are not a sufficient statistic for short-side limits to anomaly arbitrage. Prior work emphasizes the level of fees. I study a complementary margin: whether the lender base is sufficiently substitutable to support stable borrow access over the life of a short position. I show that fee-adjusted anomaly profits remain large precisely among high-concentration stocks, where this fragility is greatest, and that the short-leg return predictability is driven by the instability of borrow access beyond the level of fees. The relevant margin in my paper is therefore distinct from the price of borrowing emphasized in prior work, including Da et al. (2025): it is the substitutability of lenders and the stability of borrow access, rather than the level or informational content of the fee.

Taken together, prior work shows that lender structure affects lendable supply, that borrowing conditions are risky, and that short-sale constraints shape anomaly returns. This paper connects these insights by treating lendable inventory concentration as a state variable for borrow fragility. I show that IC predicts instability in borrow access and that high-IC stocks exhibit the pricing patterns implied by a short-side arbitrage channel: slower incorporation of negative news and larger after-fee anomaly return spreads. This durability margin is distinct from, and complementary to, the fee-based limits to arbitrage emphasized in prior work.

3 Institutional Background

The mechanism in this paper starts from a simple feature of short selling: borrow access must be maintained over the life of the position. A short seller who loses access to borrowed shares must either replace the loan or unwind the position. In the securities lending market, this replacement problem depends on the structure of lender-side supply. Lendable shares are supplied by different lender-side institutions, and these institutions

differ in their willingness and ability to lend particular stocks. This section describes that market structure and explains why the distribution of lendable inventory across lenders can affect the durability of short positions.

The relevant object for this paper is the supply side of the securities-lending market. Lendable inventory ultimately comes from beneficial owners, such as mutual funds, pension funds, insurers, ETFs, and other asset managers. These owners decide whether and under what conditions their holdings are made available for lending, often through custodians or agent lenders that administer lending programs on their behalf. Although short sellers typically access borrowed shares through prime brokers, the concentration measure used in this paper is defined on the lender side: it captures how actual lendable inventory is distributed across the institutions that make shares available to lend.

Figure 1 illustrates this market structure. Borrowers access lendable shares through prime brokers, while prime brokers source inventory from lender-side institutions. The key economic point is that lendable shares supplied through different lender-side institutions are not necessarily perfect substitutes. Lenders differ in their lending programs, collateral requirements, risk-management rules, tax and regulatory constraints, and willingness to lend particular stocks. As a result, the effective supply of borrow depends not only on the aggregate number of shares available to lend, but also on which lenders supply those shares.

Beneficial owners do not lend all shares mechanically. Their lending decisions reflect a trade-off between lending revenue and the costs and constraints of making shares available. Owners restrict lending for a range of reasons documented by practitioners and studied in Dong and Zhu (2022), including relationship concerns, counterparty risk, insider or restricted-stock constraints, liquidity-management needs, tax considerations, voting and corporate-governance concerns, and ESG restrictions. Custodians and agent lenders also face regulatory, compliance, operational, reputational, and risk-management constraints that affect which stocks are made available to borrow. These institutional frictions imply that the relevant lending supply for a stock is not simply institutional ownership, but the subset of shares actually made available through specific lender-side relationships.

This specialized-supply view is supported by prior evidence and by the data. Dong and Zhu (2022) show that securities lending is shaped by persistent lender–stock specialization: some institutions repeatedly lend particular stocks, while other institutions holding the same stocks do not. Consistent with this interpretation, Appendix Table 17 shows that persistent fund–stock relationships explain a substantial share of variation in both the extensive margin of lending and the intensive loan share. These patterns suggest that lender identity is economically relevant for borrow access: two stocks with

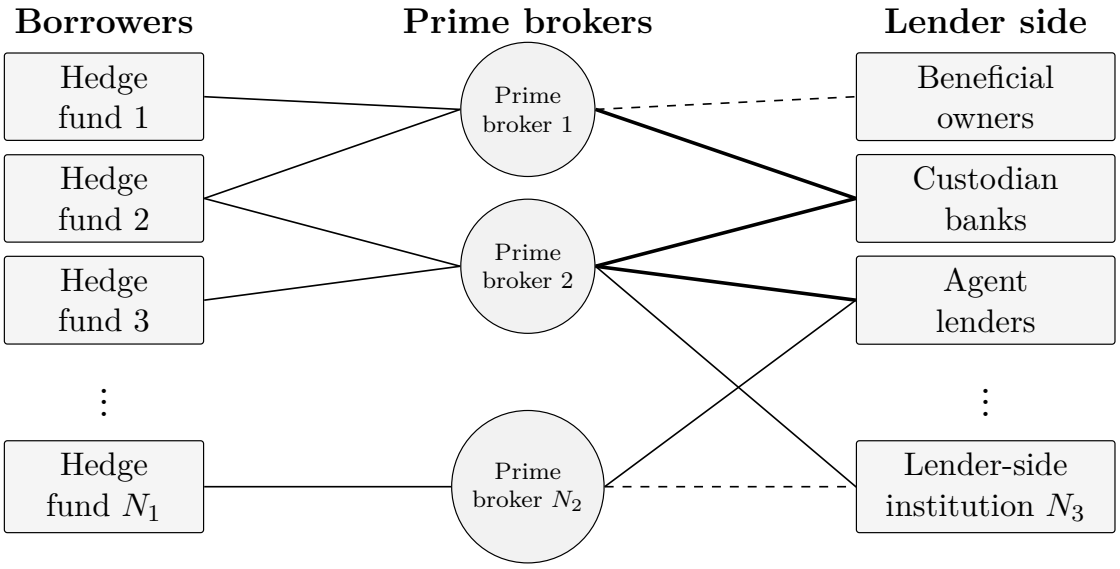


Figure 1: Securities Lending Market Structure

Notes: This figure illustrates the securities-lending market structure. Lendable inventory ultimately comes from beneficial owners, including mutual funds, pension funds, insurers, ETFs, and other asset managers. Custodians and agent lenders often administer securities-lending programs on behalf of these owners. Although borrowers typically access shares through prime brokers, the empirical measure in this paper is lender-side inventory concentration: the concentration of actual lendable inventory across the institutions that make shares available to lend. Relationships with lender-side institutions can be regular, occasional, or infrequent, represented by thick solid, thin solid, and dashed lines, respectively. Because borrow access depends on these lender-side relationships, lendable shares supplied through different institutions may not be perfect substitutes.

similar institutional ownership or aggregate lendable quantity can differ sharply in the substitutability of their lender-side supply.

This institutional structure matters because short arbitrage requires durable borrow access. A short seller must maintain the loan over the life of the position. If one source of lendable supply becomes unavailable, the short seller must replace that borrow through another source. In a frictionless market, replacement would be immediate and lender identity would be irrelevant. In a specialized lending market, however, replacement depends on whether alternative lender-side institutions are willing and able to supply the same stock on comparable terms.

The durability margin studied here extends the search-and-bargaining view of securities lending in Duffie et al. (2002). In their framework, short sellers do not draw shares from a centralized pool; they must locate a lender and bargain over the lending fee, so that securities which are harder to locate carry higher fees and prices that can stand above fundamental value and decline as the search friction resolves. That analysis prices the constraint at the point a short is *established*. The margin studied in this paper arises one step later. Once a position is on, an arbitrageur who loses a lender must re-locate borrow, and the cost of that re-search is governed by the same friction: when many comparable lenders are available, replacement is a short search over close substitutes; when lendable inventory is concentrated among a few institutions, the same withdrawal forces a costly search over few alternatives. Lender-side concentration is therefore the state variable that determines how severe this replacement problem is, and it need not be reflected in the current fee, which prices only the spot cost of borrowing today.

The distinction is about concentration. Suppose two stocks have the same aggregate lendable quantity and the same borrowing fee, but one has supply spread across many lenders while the other rests on one or two dominant lenders. When a lender exits, the first stock's shortfall is easily covered by others; the second's dominant lender leaves few substitutes, so borrow access is far more fragile even though the fee looks identical. Proxy record dates make this concrete: lenders routinely recall shares to vote, and if one large index fund's program supplies most of the borrow, that scheduled recall removes it all at once with no ready alternative, whereas dispersed supply absorbs the same recall with little effect.

This market structure makes lender composition economically relevant for the durability of borrow access. When active lenders are substitutable, a supply withdrawal by one lender can be absorbed by others, and borrow access is stable. When lendable inventory is concentrated among a few institution–stock lending relationships, the replacement problem is more severe. Another institution may hold the same stock but may not be willing

or able to lend it on comparable terms. The withdrawal of a dominant lender is therefore more likely to disrupt existing short positions. This is the institutional rationale for treating lender-side concentration as a determinant of borrow-access durability: concentration is precisely the condition under which supply shocks cannot be readily absorbed.

4 Data

This section describes the data sources, sample construction, and main variable definitions. I combine information from five sources: (i) quarterly institutional holdings from Thomson Reuters 13F, (ii) stock returns and market equity from CRSP, (iii) accounting fundamentals from Compustat, (iv) monthly anomaly signals from Jensen et al. (2023), and (v) daily securities lending data from IHS Markit Securities Finance. The securities lending sample runs from July 2006 to December 2023. Unless otherwise stated, the unit of observation is a stock–month.

4.1 Sample Construction and Filters

I begin with the intersection of CRSP common stocks and IHS Markit securities lending coverage. I restrict the sample to U.S. common stocks, defined as CRSP share codes 10 and 11, and merge the lending data to CRSP using standard security identifiers.

I apply two baseline filters throughout the analysis. First, I exclude microcaps, defined as stocks with lagged market equity below \$50 million and lagged price below \$1. Second, I exclude stock-months whose monthly average borrowing fee exceeds 1%. These observations correspond to extreme special-borrowing environments in which short-sale constraints are already directly reflected in posted borrowing fees. The purpose of the paper is to study whether borrow fragility matters in the economically relevant region where short positions are potentially implementable and where borrowing fees alone do not mechanically reveal the constraint. I apply the same filters consistently across the lending-condition tests, the earnings-announcement tests, and the anomaly portfolio analyses.

4.2 Securities Lending Data

The core lending data come from IHS Markit Securities Finance, which provides daily information on securities lending activity. I use daily observations on borrowing fees, quantity on loan, lendable inventory, utilization, and lender-level inventory shares. I aggregate daily variables to the stock–month level by averaging within each month, unless

otherwise stated.

Borrowing fees. The borrowing fee is IHS Markit's *Indicative Fee*. IHS Markit interprets this variable as the annualized expected borrowing cost faced by a representative hedge fund. In the empirical tests, I use both the level of the borrowing fee and fee-based measures of short-selling risk.

Utilization and lending supply. Utilization measures the intensity with which lendable supply is already being used. IHS Markit defines utilization as the value or quantity on loan divided by total lendable value or quantity. High utilization indicates that a larger share of available lendable inventory has already been borrowed, leaving less residual capacity for additional short demand.

Lendable supply. I define LQ as the quantity of stock inventory available to lend, scaled by total shares outstanding:

$$LQ_{i,t} = \frac{\text{Inventory available to lend}_{i,t}}{\text{Shares outstanding}_{i,t}}.$$

Lendable inventory concentration. I obtain inventory concentration, IC, directly from IHS Markit. The measure is based on the Herfindahl concentration of lender-level lendable inventory. Let $w_{i\ell d}$ denote lender ℓ's share of total lendable inventory in stock i on day d. Inventory concentration is given by

$$IC_{id} = \sum_{\ell} w_{i\ell d}^2.$$

IC therefore measures concentration among the lender-side institutions that supply lendable shares, as illustrated in Figure 1. In the data, these lenders are underlying lender-side institutions, including institutional owners, custodian banks, and agent lenders, but do not include the prime brokers that intermediate borrowing demand. I aggregate daily IC to the stock-month level by averaging within each month. Higher values indicate that lendable inventory is concentrated among fewer lender-side institutions.

Lendable Quantity Stability. I use Markit's lender classification to construct $\text{LQS}_{i,t}$, the share of lendable quantity supplied by stable, low-turnover lending funds. Markit classifies funds using a proprietary stability algorithm that evaluates, on a quarterly basis, the movement of securities into and out of each fund. Funds whose portfolio composition changes slowly relative to other lending funds are classified as stable. Thus, $\text{LQS}_{i,t}$

captures the stability composition of a stock's lending base.

4.3 Short-Selling Risk Measures

To capture instability in borrowing conditions, I construct short-selling risk measures from daily lending data. The goal is to measure the risk that borrowing conditions deteriorate after a short position has been initiated. This risk is conceptually distinct from the average borrowing fee. A stock can have a moderate average fee but still be risky to short if borrowing costs are volatile or lendable inventory is unstable.

Following the short-selling risk literature (Engelberg et al., 2018; Palia and Sokolinski, 2024), I compute rolling-window volatility and tail measures over the prior 21 trading days.

Fee instability and fee tail risk. FeeVar is the natural logarithm of the variance of daily borrowing fees over the prior 21 trading days:

$$\text{FeeVar}_{it} = \log\left(\text{Var}(\text{Fee}_{i,d})\right).$$

FeeTail captures extreme fee pressure:

$$\text{FeeTail}_{it} = \overline{\text{Fee}}_{it} + 2.33 \times \sigma(\text{Fee}_{i,d}),$$

where $\overline{\text{Fee}}_{it}$ and $\sigma(\text{Fee}_{i,d})$ are computed over the same rolling window.

Utilization instability and utilization pressure. UtilVar is the natural logarithm of the variance of daily utilization over the prior 21 trading days:

$$\text{UtilVar}_{it} = \log\left(\text{Var}(\text{Util}_{i,d})\right).$$

UtilTail captures utilization pressure:

$$\text{UtilTail}_{it} = \overline{\text{Util}}_{it} + 2.33 \times \sigma(\text{Util}_{i,d}).$$

High values of UtilVar indicate instability in lending-market tightness. UtilTail captures extreme states in which a large share of lendable inventory is already on loan and residual borrowing capacity is limited. Because utilization measures borrowing demand relative to lending supply, high utilization pressure indicates that short sellers have less spare inventory available to absorb supply withdrawals or additional shorting demand.

It also implies greater exposure to recall-like disruptions, since a withdrawal of lendable shares is harder to replace when most available inventory is already on loan.

Composite short-selling risk. In the anomaly regressions in Section 7.6, I also use a composite short-selling risk measure, denoted SSR. I first transform the fee-instability, fee-tail, utilization-instability, and utilization-pressure measures into within-month percentile ranks. I then average the available non-missing ranked components:

$$\mathrm{SSR}_{it} = \frac{1}{|\mathcal{K}_{it}|} \sum_{k \in \mathcal{K}_{it}} Z_{it}^{k},$$

where

$$\mathcal{K}_{it} = \{\mathrm{FeeVar}, \mathrm{FeeTail}, \mathrm{UtilVar}, \mathrm{UtilTail}\}_{it}^{\mathrm{nonmissing}},$$

and Z_{it}^{k} denotes the within-month percentile rank of component k. If all four components are missing for a stock-month observation, I set SSR_{it} to missing. Higher values of SSR_{it} indicate more unstable shorting conditions relative to other stocks in the same month.

Average tenure. I use Markit's average loan tenure variable, denoted AT, as an additional measure of lending-market stability. AT measures the average duration of outstanding securities loans. I aggregate this variable to the stock–month level. Longer average tenure indicates that existing loans remain outstanding for longer periods, suggesting more stable lending relationships and more persistent access to lendable shares. Conversely, shorter tenure is consistent with a more fragile borrowing environment in which loans turn over more quickly and short sellers face greater uncertainty about maintaining positions.

4.4 Returns, Firm Characteristics, and Earnings Announcements

Stock returns, prices, shares outstanding, market capitalization, and share codes are from CRSP. Accounting variables are from Compustat and are merged to CRSP using standard links. I construct standard firm characteristics used in asset-pricing tests, including size, book-to-market, momentum, bid–ask spread, institutional ownership, short interest, turnover, and idiosyncratic volatility. Continuous variables are winsorized at conventional percentiles to reduce the influence of outliers. Earnings announcement dates are from Compustat RDQ and are used only for the price-discovery tests. Institutional ownership (IOR) is constructed from Thomson Reuters 13F holdings and is used as a control variable.

4.5 Equity Pricing Anomalies

I use the monthly signed anomaly signals from Jensen et al. (2023) and merge them with CRSP returns and Markit securities-lending data. Because lending-market variables are observed only for securities covered by Markit, the investable universe is narrower than the full anomaly library. All anomaly tests are therefore conducted within the merged CRSP–Jensen–Markit universe.

I apply the baseline tradability screens used throughout the paper. I restrict the sample to common stocks with market capitalization above $50 million, share price above $1, non-missing securities-lending variables, and monthly borrowing fees below 1%. These screens focus the analysis on economically meaningful stocks for which inventory concentration, borrowing fees, and borrow fragility are well measured.

Within this universe, I retain anomaly signals whose long–short returns earn a positive CAPM alpha that is statistically significant at the 10% level. This restriction focuses the analysis on anomaly strategies that remain present in the tradable universe where lending-market frictions are observed. The final sample contains 69 anomaly signals over July 2006 to December 2023, comprising 730,404 stock-month observations.

4.6 Summary Statistics

Table 1 reports summary statistics for the main variables. Panel A reports firm characteristics and ownership variables, while Panel B reports securities-lending variables and short-selling risk measures. Borrowing conditions display substantial heterogeneity. The mean annualized borrowing fee is 0.99 percent, but the distribution is skewed, and both fee-based and utilization-based risk measures vary substantially across stock-months.

Table 2 reports pairwise correlations among the main ownership, lending-structure, cost, and risk variables. Two patterns are useful for interpreting the empirical tests. First, lendable inventory concentration is related to, but distinct from, both institutional ownership concentration and the borrowing fee. The correlation between IC and institutional ownership concentration is 0.37, while the correlation between IC and the borrowing fee is 0.35. Thus, IC is not simply a repackaging of either concentrated ownership or the current price of borrowing. Second, IC is more strongly related to fee-based risk measures than to utilization-based instability: its correlations with log(FeeVar) and FeeTail are 0.38 and 0.36, compared with 0.13 for both log(UtilVar) and UtilTail. This pattern is consistent with IC capturing a distinct dimension of lending-market fragility.

Table 3 then decomposes the relation between borrowing fees and short-selling risk measures into pooled, cross-sectional, and within-stock time-series correlations. The fee

is highly correlated with FeeTail, which is expected because the tail measure embeds extreme fee realizations. By contrast, the fee is less strongly related to utilization-based risk. The pooled correlation between fees and log(UtilVar) is 0.27, and the average within-stock time-series correlation is 0.22. The corresponding correlations with UtilTail are 0.46 and 0.34. These results show that borrowing fees contain information about shorting conditions, but do not fully summarize the instability and utilization-pressure dimensions of short-selling risk.

Table 1: Summary statistics

Variable	N	Mean	SD	P25	Median	P75
Panel A: Firm characteristics						
ME ($ millions)	742,461	7,421	39,951	261	887	3,453
BM	701,405	0.658	0.712	0.268	0.508	0.842
Short Interest	651,574	0.050	0.058	0.014	0.031	0.066
BidAsk	739,912	0.010	0.007	0.006	0.008	0.013
Turnover (%)	733,613	0.915	1.147	0.297	0.664	1.276
IOR	606,336	0.630	0.277	0.435	0.704	0.861
Panel B: Securities lending characteristics and short-selling risk						
IC	742,461	0.240	0.151	0.157	0.189	0.250
LQS	742,459	0.522	0.263	0.399	0.587	0.711
LQ	742,461	0.217	0.149	0.101	0.219	0.314
Average Tenure (Days)	742,461	76.234	71.861	33.471	59.200	96.760
Utilization (%)	742,461	15.802	19.153	1.670	7.985	27.139
BorrowFee (annualized, %)	742,461	0.985	1.762	0.330	0.375	0.506
FeeVar	586,895	-5.332	2.646	-7.203	-5.699	-4.191
FeeTail	586,895	1.552	2.813	0.399	0.527	0.967
UtilVar	586,895	-0.073	2.590	-1.736	0.042	1.691
UtilTail (%)	586,895	22.003	24.609	3.761	12.129	32.216

5 Lendable Inventory Concentration and Borrow Fragility

This section tests the first implication of the mechanism: stocks with more concentrated lendable inventory should experience less stable borrow access in the future. I measure IC before fragility is realized and ask whether it predicts subsequent lendable-quantity disruptions, fee instability, fee and utilization tail events, and shorter loan tenure. Because IC is lagged relative to these outcomes, the tests ask whether the structure of lendable supply forecasts future borrow fragility, not whether the two move together contemporaneously.

Table 2: Correlations among ownership, lending structure, and borrow-fragility measures

	ME	BidAsk	IOR	HHI	IC	Fee	FeeVar	FeeTail	UtilVar	UtilTail
ME	1.00	-0.11	0.04	-0.08	-0.08	-0.06	-0.06	-0.06	-0.17	-0.11
BidAsk	-0.11	1.00	-0.22	0.21	0.09	0.23	0.24	0.23	0.26	0.26
IOR	0.04	-0.22	1.00	-0.52	-0.44	-0.33	-0.42	-0.36	-0.17	-0.21
HHI	-0.08	0.21	-0.52	1.00	0.37	0.27	0.31	0.29	0.15	0.17
IC	-0.08	0.09	-0.44	0.37	1.00	0.35	0.38	0.36	0.13	0.13
Fee	-0.06	0.23	-0.33	0.27	0.35	1.00	0.61	0.91	0.27	0.46
FeeVar	-0.06	0.24	-0.42	0.31	0.38	0.61	1.00	0.72	0.29	0.38
FeeTail	-0.06	0.23	-0.36	0.29	0.36	0.91	0.72	1.00	0.26	0.41
UtilVar	-0.17	0.26	-0.17	0.15	0.13	0.27	0.29	0.26	1.00	0.70
UtilTail	-0.11	0.26	-0.21	0.17	0.13	0.46	0.38	0.41	0.70	1.00

Notes: This table reports pairwise Pearson correlations among firm characteristics, ownership variables, lending-market structure, and realized borrow-fragility measures over the July 2006–December 2023 sample. ME is market equity; BidAsk is the bid–ask spread; IOR is institutional ownership; HHI is institutional ownership concentration; IC is lendable inventory concentration; Fee is the borrowing fee; FeeVar and UtilVar are the logged variances of daily borrowing fees and utilization; FeeTail and UtilTail are the corresponding tail-event measures. Two patterns are central to the paper. First, IC is only modestly correlated with the borrowing fee (0.35) and with ownership concentration (HHI, 0.37), indicating that it is not a repackaging of either the price of borrowing or the concentration of a stock's holders. Second, IC correlates more strongly with the fee-instability and fee-tail measures (0.38 and 0.36) than with the utilization-volatility measure (0.13), consistent with concentration mapping into fragility rather than into routine variation in lending-market tightness.

Table 3: Decomposed Correlations between Borrowing Fees and Short-Selling Risk Measures

Risk measure	Pooled	Avg. monthly cross-section	Avg. within-stock time-series
FeeVar	0.611	0.649	0.569
FeeTail	0.910	0.914	0.879
UtilVar	0.268	0.281	0.220
UtilTail	0.461	0.482	0.339

Notes: This table reports correlations between the borrowing fee and the main borrow-fragility measures. The pooled column reports correlations in the stock-month panel. The cross-sectional column reports the average monthly correlation across firms. The time-series column reports the average within-stock correlation over time, computed among stocks with at least 24 valid monthly observations for the pair. Fee is the annualized borrowing fee. log(FeeVar) is the logged rolling variance of daily borrowing fees. FeeTail denotes fee-tail risk. log(UtilVar) is the logged rolling variance of daily utilization. UtilTail denotes utilization pressure.

I proceed in two steps. First, I test whether lagged IC predicts future lendable-quantity disruptions, including events in which available lendable quantity and quantity on loan fall together. These events capture contractions in effective lending supply that are more likely to affect existing short positions. Second, I test whether lagged IC predicts realized borrow fragility more broadly: higher fee instability, more severe fee and utilization tail events, and shorter loan tenure. Together, these tests ask whether IC captures a dimension of borrow fragility that is distinct from the current amount of lendable supply and the current borrowing fee.

5.1 Inventory Concentration and Lendable Quantity Fragility

The first outcome is abrupt contraction in lendable quantity. If IC captures weak substitutability across lenders, high-IC stocks should experience more frequent and more severe drops in active lendable quantity.

I measure quantity fragility using daily IHS Markit securities lending data. For each stock-month t, I compute average inventory concentration during month $t-1$ and sort stocks into quintiles within month t based on this lagged concentration measure. I then measure lendable quantity fragility during month t by counting the number of days on which active lendable quantity (ALQ) falls by more than 5% or 10% from the previous trading day. I also construct a joint event, defined as a day on which both ALQ and quantity on loan (OLQ) fall by more than the same threshold. The joint ALQ–OLQ measure is a conservative proxy for quantity disruptions that are more likely to affect existing short positions: a decline in available supply coinciding with a decline in outstanding loans is more indicative of a binding quantity constraint than a supply contraction alone.

Table 4 reports the sorting evidence. Panel A shows a strong monotonic pattern. Higher lagged inventory concentration predicts substantially more quantity-drop days in the following month. In the lowest IC quintile, the average stock-month has 0.21 days on which ALQ falls by more than 5%; in the highest IC quintile, this rises to 2.14 days. The joint-drop measures are especially informative. The average number of days with joint 5% ALQ–OLQ drops rises from 0.07 to 1.27 across quintiles, and the average number of joint 10% drops rises from 0.03 to 0.95. Panel B reports the extensive-margin version. In the lowest IC quintile, 12.49% of stock-months experience at least one ALQ drop greater than 5%; in the highest quintile, this probability rises to 64.09%. For joint 10% ALQ–OLQ drops, the probability increases from 2.26% to 39.16%.

These patterns show that high-IC stocks are not only more expensive to borrow and more heavily utilized; they are also more exposed to abrupt quantity disruptions. The sorting evidence therefore links inventory concentration to the stability of borrow access,

rather than only to the level of borrowing costs.

To verify that the sorting patterns are not driven by differences in firm characteristics or lending-market conditions, I estimate stock-month regressions of future lendable-quantity disruptions on lagged inventory concentration. The full specifications control for utilization, borrowing fees, size, book-to-market, institutional ownership, prior returns, turnover, bid–ask spreads, and lendable quantity, with month and FF49 industry fixed effects. Tables 5 and 6 confirm the sorting evidence using the 10% disruption threshold. Lagged IC predicts more frequent ALQ disruptions, more frequent joint ALQ–OLQ disruptions, a higher probability of at least one joint disruption, and larger conditional ALQ drops. These relations remain positive and statistically significant in the full specifications. Appendix Tables 19 and 20 show that the same conclusions hold using a 5% threshold.

The sorting and regression evidence supports the borrow-fragility interpretation for three reasons. First, IC is measured before the disruptions occur. Second, the joint ALQ–OLQ outcome is directly relevant for existing short positions because it combines a contraction in available supply with a decline in shares on loan. Third, the relation survives controls for utilization, borrowing fees, and lendable quantity. IC therefore predicts future disruptions beyond current borrowing demand, supply, and price. The evidence therefore links lender-base concentration to future disruptions in borrow access, rather than only to contemporaneous borrowing demand, aggregate lendable quantity, or borrowing fees.

5.2 Inventory Concentration and Borrow Fragility

I next examine broader measures of borrow fragility. Quantity disruptions are one manifestation of unstable borrow access; the same instability can also appear as volatile fees, tail fee realizations, utilization pressure, and shorter loan tenure. The hypothesis is that IC predicts these outcomes even after conditioning on the current borrowing fee, utilization, lendable supply, and firm characteristics.

I measure this borrow fragility using four complementary proxies. FeeVar captures volatility in borrowing fees and therefore measures uncertainty about the future cost of maintaining a short position. FeeTail captures extreme fee realizations, representing sudden borrowing-cost spikes. UtilVar captures volatility in utilization and therefore measures instability in lending-market tightness. UtilTail captures extreme utilization events, indicating sudden pressure on available lending capacity. I also examine average loan tenure, AT: shorter tenure indicates less persistent borrowing relationships and less stable access to borrowed shares. Appendix C.1 reports the corresponding results for the

Table 4: Lendable Supply Fragility by Lagged Inventory Concentration

Panel A. Number of large quantity-drop days within next month

IC Quintile	Stock-month obs.	Avg. IC	Fee	Util.	Δ ALQ $< -5\%$	Δ ALQ & Δ OLQ $< -5\%$	Δ ALQ $< -10\%$	Δ ALQ & Δ OLQ $< -10\%$
1	197,637	0.14	0.50	14.24	0.21	0.07	0.09	0.03
2	197,713	0.17	0.60	17.17	0.30	0.11	0.16	0.05
3	197,707	0.21	0.90	20.75	0.57	0.22	0.34	0.11
4	197,713	0.32	1.93	32.04	1.53	0.74	1.10	0.47
5	197,803	0.69	3.53	50.59	2.14	1.27	1.72	0.95

Panel B. Probability of at least one large quantity-drop day within next month

IC Quintile	Any Δ ALQ $< -5\%$	Any Δ ALQ & Δ OLQ $< -5\%$	Any Δ ALQ $< -10\%$	Any Δ ALQ & Δ OLQ $< -10\%$
1	12.49	5.12	5.69	2.26
2	15.89	6.81	8.71	3.36
3	24.75	12.00	16.67	6.83
4	50.61	31.59	42.10	22.60
5	64.09	46.52	58.77	39.16

Notes: This table reports next-month lendable-supply fragility by lagged inventory concentration. For each stock-month t, stocks are sorted into quintiles based on average inventory concentration in month $t-1$. Panel A reports the average number of days in month t on which active lendable quantity (ALQ), or both ALQ and quantity on loan (OLQ), fall by more than 5% or 10% from the previous trading day. Panel B reports the percentage of stock-months with at least one such drop day. Joint ALQ–OLQ drops are interpreted as recall-like quantity disruptions; they need not identify literal lender recalls one-for-one. Fee and utilization are monthly averages.

level of borrowing costs.

Hypothesis. *Inventory concentration predicts greater realized borrow fragility, conditional on shorting demand, borrowing fees, lendable supply, and standard stock characteristics.*

5.3 Empirical Specifications

I estimate stock–month panel regressions that relate short-selling risk to the concentration of lendable inventory. The baseline specification is

$$\text{Risk}_{i,t} = \lambda_{j(i)} + \tau_t + \gamma_1 \text{IC}_{i,t-1} + \gamma_2 \text{LQS}_{i,t-1} + \Gamma' X_{i,t-1} + u_{i,t}, \tag{1}$$

where i indexes stocks, t indexes calendar months, and $\lambda_{j(i)}$ denotes FF49 industry fixed effects, with $j(i)$ indexing the Fama–French 49 industry of stock i. The term τ_t denotes calendar-month fixed effects. The dependent variable, $\text{Risk}_{i,t}$, is one of the monthly measures of short-selling risk: borrowing-fee volatility, fee-tail risk, utilization volatility, utilization-tail risk, and average loan tenure.

I use industry rather than stock fixed effects because inventory concentration is a

Table 5: Inventory Concentration and Next-Month Lendable-Quantity Disruptions

Dep. var.:	(1) ALQ ct (10%)	(2) ALQ ct (10%)	(3) Joint ct (10%)	(4) Joint ct (10%)	(5) Any joint (10%)	(6) Any joint (10%)
IC	2.733***	2.199***	1.294***	1.164***	0.585***	0.491***
	(0.101)	(0.138)	(0.065)	(0.093)	(0.024)	(0.032)
LQS	−0.429***	−0.336***	−0.154***	−0.153***	−0.081***	−0.069***
	(0.048)	(0.057)	(0.028)	(0.040)	(0.009)	(0.012)
Utilization		0.178***		−0.130***		0.007
		(0.050)		(0.031)		(0.012)
BorrowFee		−0.101		0.128**		−0.059**
		(0.149)		(0.062)		(0.029)
Log(ME)		0.044***		0.023***		0.009***
		(0.009)		(0.007)		(0.002)
BM		−0.000		0.000		0.000
		(0.000)		(0.000)		(0.000)
IOR		−0.203***		−0.063***		−0.029***
		(0.028)		(0.016)		(0.007)
Ret(−6, −1)		0.027**		0.018***		0.008***
		(0.012)		(0.007)		(0.003)
Turnover		0.018***		0.006***		0.004***
		(0.005)		(0.002)		(0.001)
BidAsk		0.068***		0.008		0.009***
		(0.009)		(0.005)		(0.002)
LQ		−1.403***		−0.647***		−0.277***
		(0.094)		(0.048)		(0.018)
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
FF49 FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	710,928	517,268	710,928	517,268	710,928	517,268
Within adj. R^2	0.121	0.166	0.078	0.099	0.094	0.117

This table reports panel regressions of next-month lendable-quantity disruptions using the 10% threshold. ALQ ct (10%) counts the number of days in month t on which active lendable quantity falls by more than 10% from the previous trading day. Joint ct (10%) counts the number of days on which both active lendable quantity and quantity on loan fall by more than 10%. Any joint (10%) is an indicator for whether the stock-month has at least one joint ALQ–OLQ disruption greater than 10%. Odd-numbered columns include only IC and LQS as regressors; even-numbered columns additionally control for utilization, borrowing fee, size, book-to-market, institutional ownership, prior six-month returns, turnover, bid–ask spread, and lendable quantity. All specifications include month and FF49 fixed effects. Standard errors are clustered by month and stock. *, **, and *** denote significance at the 10%, 5%, and 1% levels.

Table 6: Inventory Concentration and Next-Month Lendable-Quantity Disruptions: Conditional Size

	(1)	(2)
Dep. var.:	ALQ drop size (%)	ALQ drop size (%)
IC	39.701***	22.427***
	(1.775)	(2.677)
LQS	4.825***	4.283***
	(0.939)	(1.253)
Utilization		−45.028***
		(2.269)
Borrowing fee		5.290
		(4.313)
Log(ME)		0.699***
		(0.261)
BM		0.000
		(0.002)
IOR		−5.228***
		(1.380)
Ret(−6, −1)		0.607***
		(0.232)
Turnover		−0.389***
		(0.083)
BidAsk		−0.625**
		(0.247)
LQ		−30.520***
		(5.063)
Month FE	Yes	Yes
FF49 FE	Yes	Yes
Observations	119,922	71,331
Within adj. R^2	0.069	0.207

This table reports panel regressions of next-month ALQ disruption size using the 10% threshold. The dependent variable is the stock-month average absolute percentage drop in ALQ, computed over all days in month t on which ALQ falls by more than 10% from the previous trading day. The sample is restricted to stock-months with at least one such ALQ drop, so the estimates capture the intensive margin conditional on a disruption. Column (1) includes only IC and LQS as regressors; column (2) additionally controls for utilization, borrowing fee, size, book-to-market, institutional ownership, prior six-month returns, turnover, bid–ask spread, and lendable quantity. All specifications include month and FF49 fixed effects. Standard errors are clustered by month and stock. *, **, and *** denote significance at the 10%, 5%, and 1% levels.

persistent, primarily cross-sectional characteristic. Its one-month autocorrelation is 0.95 and declines only to 0.73 at one year, and roughly two-thirds of its total variance is between stocks rather than within a stock over time (Table 16). This persistence reflects the slow-moving structure of a stock's lender base, which is shaped by institutional ownership and custodial lending arrangements that do not adjust rapidly month to month. Stock fixed effects would absorb this dominant cross-sectional variation and identify γ_1 from the small within-stock component alone; industry and month fixed effects instead retain the structural cross-sectional variation that the concept is designed to capture, while controlling for sectoral composition and aggregate lending conditions. I nonetheless re-estimate all specifications with stock fixed effects in Appendix C.3; the disruption, fee-instability, and loan-tenure results are robust.

The coefficient of interest is γ_1. For fee- and utilization-based risk measures, a positive estimate of γ_1 indicates that stocks with more concentrated lendable inventory subsequently experience greater instability in borrowing conditions. For average loan tenure, the predicted sign is negative, since shorter loan duration indicates less stable short-sale financing.

The main specifications include controls for shorting demand, firm characteristics, ownership, trading activity, liquidity, lendable supply, and the current borrowing cost. The vector $X_{i,t-1}$ includes utilization, borrowing fee, log market equity, book-to-market, institutional ownership, past six-month returns, turnover, bid–ask spread, and lendable quantity. I also control for $\mathrm{LQS}_{i,t-1}$, the percentage of lendable quantity supplied by stable, low-turnover lending funds. Including the borrowing fee separates the spot-cost component of short-sale constraints from the borrow-access stability captured by IC. Standard errors are two-way clustered by month and stock.

5.4 Results

Fee risk. Table 7 reports results for fee-based measures of short-selling risk. The evidence shows a strong positive relation between inventory concentration and subsequent borrowing-fee instability. Columns (1) and (3) report specifications that include IC with month and FF49 industry fixed effects. Columns (2) and (4) add the full set of controls. Across both specifications, IC is positive, economically large, and statistically significant.

In the full specification, the coefficient on IC is 2.776 when the dependent variable is FeeVar and 1.812 when the dependent variable is FeeTail. Thus, stocks with more concentrated lendable inventory experience substantially greater subsequent volatility in borrowing fees and more severe fee-tail realizations. Importantly, these estimates are obtained after controlling for utilization, borrowing fee, firm size, book-to-market, insti-

tutional ownership, prior returns, turnover, bid–ask spreads, lendable quantity, month fixed effects, and FF49 industry fixed effects. The result indicates that IC contains information about future borrowing-cost instability beyond the borrow fee and standard lending-market controls.

The coefficient on LQS is negative in both fee-risk specifications. In the full specification, LQS enters with a coefficient of -0.282 for FeeVar and -0.176 for FeeTail, both statistically significant at the one-percent level. This pattern is consistent with the interpretation that a more stable lendable supply base dampens future fee instability. Overall, the fee-risk evidence supports the borrow-fragility mechanism: when lendable inventory is concentrated, borrowing conditions are less stable and extreme borrowing-cost outcomes become more likely.

Utilization pressure and loan tenure. Table 8 examines utilization-based risk and loan stability. The results show that inventory concentration is especially related to tail pressure in lending capacity and to shorter loan duration. Columns (1), (3), and (5) report specifications with IC and fixed effects, while columns (2), (4), and (6) add the full set of controls.

For utilization volatility, the unconditional relation is positive: column (1) shows that IC is associated with higher UtilVar. However, after controlling for utilization, borrowing fee, firm characteristics, liquidity, ownership, trading activity, and lendable quantity, the coefficient becomes small and statistically insignificant. This suggests that IC does not primarily operate by increasing ordinary month-to-month utilization volatility once other lending-market conditions are held fixed.

The evidence is much stronger for utilization-tail pressure. In column (4), the full-specification coefficient on IC is 5.763 with a standard error of 0.507. This indicates that concentrated lendable inventory predicts substantially greater tail pressure in utilization. The distinction between utilization volatility and utilization-tail pressure is important. Inventory concentration does not merely proxy for smooth variation in borrowing demand; rather, it is associated with extreme states in which lending capacity becomes strained.

Column (6) provides additional evidence from average loan tenure. The full-specification coefficient on IC is -38.981 with a standard error of 5.227, indicating that stocks with more concentrated lendable inventory have significantly shorter average loan duration. Shorter loan tenure is consistent with less durable short-sale financing: short sellers must roll over positions more frequently and face greater exposure to recall or funding disruptions. At the same time, LQS is positively related to average tenure, consistent with the idea that stable lendable supply supports more durable borrowing relationships.

Taken together, the fee-risk, utilization-pressure, and tenure results show that IC

predicts multiple dimensions of future borrow-access instability. The relation is not driven solely by high borrowing costs, since IC remains economically and statistically significant after controlling for the borrowing-fee level, utilization, lendable quantity, and standard firm characteristics.

Table 7: Inventory Concentration and Borrowing-Fee Risk

	FeeVar		FeeTail	
	(1)	(2)	(3)	(4)
IC	7.316***	2.776***	6.900***	1.812***
	(0.187)	(0.156)	(0.222)	(0.088)
LQS		−0.282***		−0.176***
		(0.081)		(0.048)
Utilization		0.005***		0.004***
		(0.001)		(0.001)
BorrowFee		0.576***		1.110***
		(0.011)		(0.005)
Log(ME)		−0.081***		−0.026***
		(0.012)		(0.004)
BM		0.083***		0.023***
		(0.016)		(0.007)
IOR		−0.385***		−0.212***
		(0.066)		(0.024)
Ret(-6,-1)		0.049***		0.007
		(0.014)		(0.018)
Turnover		0.075***		−0.006
		(0.011)		(0.006)
BidAsk		0.045***		0.003
		(0.016)		(0.008)
LQ		−3.873***		−0.582***
		(0.230)		(0.053)
Controls	No	Yes	No	Yes
Month FE	Yes	Yes	Yes	Yes
FF49 FE	Yes	Yes	Yes	Yes
Observations	571,590	437,258	571,590	437,258
R^2	0.264	0.520	0.176	0.769
Within adj. R^2	0.155	0.438	0.131	0.756

Notes: Standard errors clustered by month and stock are reported in parentheses. All specifications include month and FF49 industry fixed effects. *, **, and *** denote significance at the 10%, 5%, and 1% levels.

Table 8: Inventory Concentration, Utilization Pressure, and Loan Tenure

	UtilVar		UtilTail		AT	
	(1)	(2)	(3)	(4)	(5)	(6)
IC	2.316***	−0.064	15.666***	5.763***	−28.402***	−38.981***
	(0.206)	(0.177)	(1.803)	(0.507)	(4.244)	(5.227)
LQS		−1.072***		−4.075***		53.890***
		(0.075)		(0.300)		(3.008)
Utilization		0.059***		1.049***		0.842***
		(0.001)		(0.003)		(0.032)
BorrowFee		−0.056***		−0.036		−2.466***
		(0.007)		(0.024)		(0.322)
Log(ME)		−0.090***		−0.005		−5.345***
		(0.014)		(0.021)		(0.514)
BM		−0.068***		−0.095**		0.455
		(0.017)		(0.041)		(0.580)
IOR		0.512***		−0.277*		−0.998
		(0.074)		(0.153)		(2.090)
Ret(-6,-1)		0.082***		0.093		0.436
		(0.026)		(0.084)		(0.690)
Turnover		0.262***		0.639***		−9.778***
		(0.027)		(0.059)		(0.925)
BidAsk		0.185***		0.499***		−1.239*
		(0.021)		(0.061)		(0.633)
LQ		−3.614***		−6.781***		78.395***
		(0.220)		(0.517)		(6.948)
Controls	No	Yes	No	Yes	No	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
FF49 FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	571,590	437,258	571,590	437,258	719,504	559,315
R^2	0.143	0.429	0.133	0.887	0.030	0.091
Within adj. R^2	0.016	0.334	0.008	0.869	0.003	0.063

Standard errors clustered by month and stock are reported in parentheses. All specifications include month and FF49 industry fixed effects. *, **, and *** denote significance at the 10%, 5%, and 1% levels.

5.5 Janus–Henderson Merger-Induced Changes in Borrow Fragility

The panel evidence shows that inventory concentration predicts future borrow fragility, but much of the variation is cross-sectional. As complementary event-based evidence, I use the Janus–Henderson merger, which consolidated two large asset managers with overlapping pre-merger equity holdings. Janus Capital Group and Henderson Group were two large, independent active asset managers that announced an all-stock merger in October 2016 and completed it on May 30, 2017. Because both legacy institutions were large equity holders, the transaction consolidated two previously separate ownership bases into a single organization, plausibly concentrating the inventory available to lend without a stock-specific shock to short-selling demand. I therefore treat the merger as a shock to the structure of lending supply and define June 2017 as the first full post-merger month.

I construct treatment from pre-merger 13F holdings. For each stock, I compute average ownership by Janus and by Henderson separately over June 2016 through May 2017, rolling quarterly positions forward to monthly frequency and scaling by shares outstanding. Treated stocks are those in the top quartile of both the Janus and the Henderson pre-merger ownership distributions; control stocks have zero pre-merger ownership by both institutions on average. Stocks with intermediate exposure are excluded. One limitation should be stated at the outset: treatment is defined from ownership, not from lender identity, because the data do not link specific lendable inventory to Janus or Henderson. The design tests whether the consolidation of two large ownership bases is associated with changes in lending-market conditions.

I estimate the difference-in-differences specification

$$Y_{i,t} = \beta \, \text{Treated}_i \times \text{Post}_t + \alpha_i + \gamma_t + \varepsilon_{i,t}, \tag{2}$$

where $Y_{i,t}$ is a monthly securities-lending outcome for stock i, Treated_i equals one for high-exposure stocks and zero for controls, and Post_t equals one from June 2017 onward. Unlike the cross-sectional panel, which uses industry and month fixed effects to preserve the persistent cross-sectional variation in IC, the difference-in-differences design identifies the effect from event timing. Stock fixed effects are therefore appropriate here: they absorb fixed treated–control differences, and β compares changes within the same calendar month. Standard errors are two-way clustered by stock and month. The treated group contains 100 stocks and the control group 355, and the design rests on a modest sample of about 9,850 stock-months; I therefore read the event as complementary to the panel rather than as the paper's primary identification.

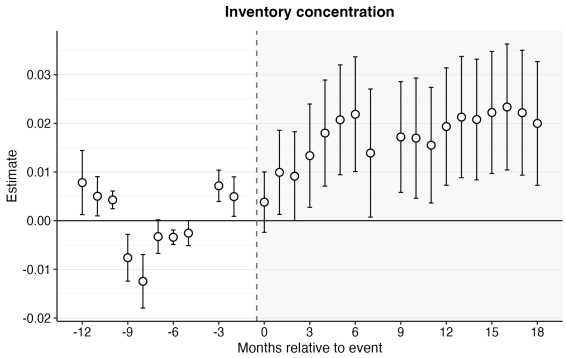
Table 9 reports the results. The merger is followed by a significant increase in borrow fragility among treated stocks. The clearest evidence is on the supply side. Inventory concentration rises by 0.0158 and normalized lendable quantity falls by 0.0397, both significant at the 1 percent level, while normalized quantity on loan is essentially unchanged and insignificant. These three coefficients are the heart of the design: they establish that the ownership consolidation propagated into the lending market, raising concentration and reducing available supply, and they do so in the pattern of a supply-side contraction rather than a demand-driven increase in borrowing. Because lendable quantity and quantity on loan are both scaled by shares outstanding, a demand-driven story would raise the quantity on loan; the flat on-loan series is difficult to reconcile with a purely demand-driven interpretation.

The fragility measures move accordingly. Fee variance increases by 0.870 (significant at 1 percent) and fee tail risk by 1.217 (significant at 5 percent), so borrowing costs become both more volatile and more prone to spikes once supply tightens. Utilization-based fragility moves in the same direction, with utilization variance rising by 0.310 and utilization tail risk by 2.849; these estimates are noisier and I read them as corroborating the fee-based and quantity-based results rather than as primary. The within-R^2 values are small, as is standard in a saturated difference-in-differences design where stock and month fixed effects absorb most of the variation and the treatment effect is a marginal contribution.

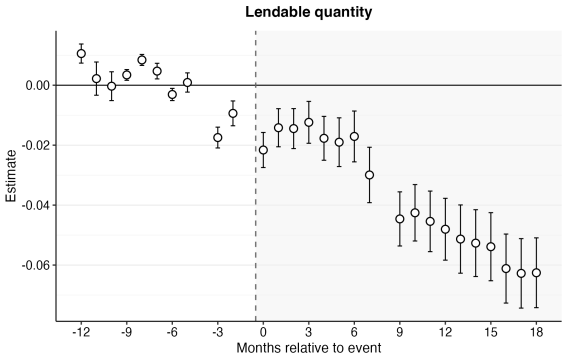
Figure 2 presents the main event-study estimates. Across all four outcomes, the pre-merger coefficients fluctuate around zero and show no systematic differential trend toward the event, so the treated–control divergence emerges only after the merger rather than continuing a pre-existing gap. For lendable quantity, the pre-period estimates are, if anything, slightly positive, which runs against the post-merger decline and therefore cannot mechanically generate it. After the merger, inventory concentration rises and lendable quantity falls, both persistently, while fee variance increases. Quantity on loan remains flat throughout the window. This combination is the signature of a supply-side contraction rather than a demand-driven increase in borrowing. Appendix Figure 8 reports additional fee-tail and utilization-based outcomes.

Taken together, the evidence in this section is consistent with the paper's mechanism. In the broad stock-month panel, inventory concentration predicts future borrow fragility, including fee instability, tail events, and disruptions to lendable supply. The Janus–Henderson merger provides complementary event-based evidence: the consolidation of two large ownership bases raised inventory concentration, reduced measured lendable supply, and increased borrowing instability, while leaving the quantity on loan unchanged.

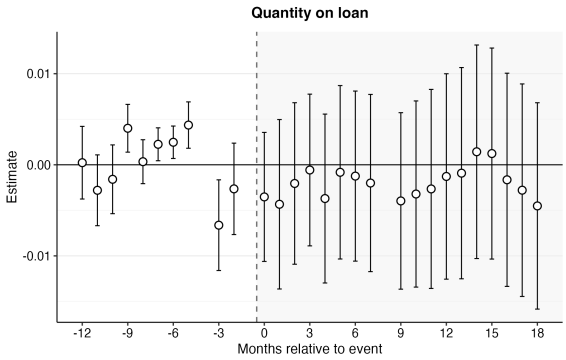
Figure 2: Janus–Henderson Merger: Lender Concentration and Borrowing Conditions



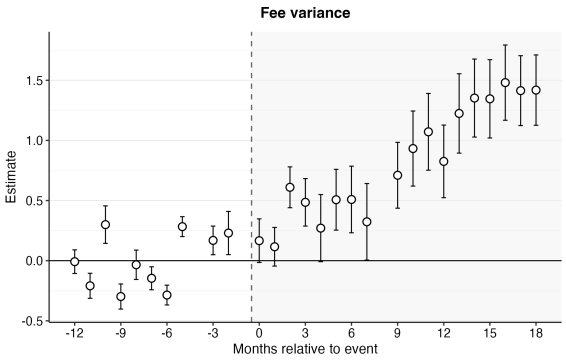
(a) Inventory concentration



(b) Lendable quantity



(c) Quantity on loan



(d) Fee variance

Notes: This figure plots event-study estimates around the Janus–Henderson merger. Treated stocks have large pre-merger ownership by both Janus and Henderson; control stocks have zero pre-merger ownership by both institutions. Panels report inventory concentration, lendable quantity normalized by shares outstanding, quantity on loan normalized by shares outstanding, and fee variance. The omitted month is May 2017, and June 2017 is the first full post-merger month. The shaded region denotes the post-merger period. Regressions include stock and month fixed effects. Standard errors are two-way clustered by stock and month.

Table 9: Janus–Henderson Merger and Contemporaneous Borrow Fragility

	FeeVar	FeeTail	UtilVar	UtilTail	IC	LQ	QOL
Treated × Post	0.870***	1.217**	0.310**	2.849**	0.0158***	-0.0397***	-0.0011
	(0.163)	(0.578)	(0.130)	(1.379)	(0.0052)	(0.0062)	(0.0044)
Stock FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	9,851	9,851	9,851	9,851	9,850	9,848	9,848
R^2	0.659	0.436	0.613	0.770	0.653	0.897	0.750
Within R^2	0.0148	0.0015	0.0016	0.0026	0.0047	0.0337	0.0000

Notes: This table reports difference-in-differences estimates around the Janus–Henderson merger. Treated stocks are those in the top quartile of both pre-merger Janus ownership and pre-merger Henderson ownership. Control stocks are those with zero average pre-merger ownership by both Janus and Henderson. The pre-merger period is June 2016 through May 2017. Post equals one from June 2017 onward. LQ and QOL denote lendable quantity and quantity on loan, respectively, both normalized by shares outstanding. The regressions include stock and month fixed effects. Standard errors are two-way clustered by stock and month and reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Because the data do not identify whether the supply decline comes from specific Janus or Henderson lending decisions, I interpret the event as complementary to the panel rather than as standalone identification. These findings motivate the asset-pricing tests that follow. If concentrated lendable supply makes short positions harder to maintain, price adjustment should be most impaired where arbitrage requires short selling. I test this prediction in two settings: the incorporation of negative earnings news (Section 6) and anomaly returns, with particular attention to the short leg (Section 7). The prediction is not that IC mechanically predicts returns, but that the borrow fragility it generates weakens arbitrage on the short side, where correcting overpricing requires maintaining a position as borrowing conditions change.

6 Lendable Inventory Concentration and Earnings News Incorporation

This section examines whether the structure of the securities-lending market affects the speed with which earnings news is incorporated into prices. A large literature documents post–earnings-announcement drift (PEAD): stock prices continue to rise after positive news and continue to fall after negative news (Bernard and Thomas, 1989). One interpretation is that PEAD reflects limits to arbitrage. When trading against mispricing is costly or risky, informed traders respond less aggressively on impact and prices adjust more slowly (Mendenhall, 2004; Pontiff, 2006). Because correcting overpricing after negative news often requires short selling, short-sale constraints should matter disproportionately for negative earnings news.

I test whether the durability margin matters for price discovery. If borrow fragility limits short-side arbitrage, negative news should be incorporated more slowly among high-IC stocks, even after controlling for borrowing fees. The corresponding effect should be weaker for positive news, where trading does not require establishing or maintaining a short position.

6.1 Earnings Announcement Events and Abnormal Return Measures

I identify earnings announcements using Compustat quarterly report dates (RDQ) and measure the market's reaction with CAPM-adjusted cumulative abnormal returns in event time. The announcement-window reaction is $CAR^{CAPM}_{i,t,[-1,+1]}$, which I use as a market-based measure of the total information released around the announcement. Unlike SUE, which captures only the earnings surprise relative to analyst forecasts, the price response also reflects guidance, expectation revisions, and conference-call information. Since the question is whether short-sale frictions slow the incorporation of negative information, the relevant object is the market's assessment of *all* news at the announcement, so I classify news by the announcement-window return rather than by standardized unexpected earnings.

I measure post-announcement drift using $CAR^{CAPM}_{i,t,[+2,+h]}$, the cumulative abnormal return after the immediate window, where h denotes the horizon. Each month, positive- (negative-) news events are those in the top (bottom) 30% of the announcement-window return distribution, and High- and Low-IC stocks are the top and bottom quintiles of lendable inventory concentration.

Appendix Table 28 and Appendix Figure 9 provide descriptive evidence. The announcement-window reactions are nearly identical across IC groups within each news category (neg-

ative news: −4.08% for High-IC versus −4.11% for Low-IC; positive news: 4.51% versus 4.07%), confirming that the classification separates comparable information events. The post-announcement paths, however, diverge sharply after negative news: by $h = 60$, cumulative abnormal returns reach −27.54% for High-IC stocks versus −10.91% for Low-IC stocks, and the gap widens to −43.40% versus −16.85% by $h = 120$. The corresponding pattern after positive news is much weaker and shows no such divergence; the IC-related drift is therefore concentrated in negative-news events.

This asymmetry is consistent with a short-sale-constraint channel: when lendable inventory is concentrated, short positions are harder to initiate and maintain, and this friction binds most after negative news, when correcting overpricing requires shorting. Because the descriptive evidence does not condition on other determinants of drift—size, liquidity, volatility, institutional ownership, shorting demand, or borrowing fees—I estimate local-projection regressions that test whether inventory concentration predicts delayed price adjustment beyond these characteristics, and in particular beyond the borrowing-fee level.

6.2 Empirical Specification

I study post-announcement price adjustment using event-time local projections. For each horizon h, the dependent variable is the post-announcement abnormal return $CAR^{CAPM}_{i,t,[+2,+h]}$, and the main news measure is the announcement-window abnormal return $CAR^{CAPM}_{i,t,[-1,+1]}$. Appendix Tables 29 and 30 report benchmark specifications with and without lagged controls, showing that post-announcement drift is present in the sample.

The main specification allows the post-announcement response to vary with pre-announcement inventory concentration:

$$\begin{aligned} CAR^{CAPM}_{i,t,[+2,+h]} = \eta_t &+ \beta_h CAR^{CAPM}_{i,t,[-1,+1]} + \theta_h IC_{i,t-1} + \delta_h' Z_{i,t-1} \\ &+ \gamma_h \left(CAR^{CAPM}_{i,t,[-1,+1]} \times IC_{i,t-1} \right) \\ &+ \sum_{Z \in \mathcal{Z}} \psi_{h,Z} \left(CAR^{CAPM}_{i,t,[-1,+1]} \times Z_{i,t-1} \right) + \varepsilon_{i,t,h}. \end{aligned} \tag{3}$$

The vector $Z_{i,t-1}$ includes lagged market capitalization, institutional ownership, idiosyncratic volatility, illiquidity, short interest, and the borrowing fee. The interaction set $\mathcal{Z}$ contains the same variables, so the specification controls not only for differences in firm and lending-market characteristics, but also for whether these characteristics affect the mapping from announcement-window returns to subsequent returns. Including both the borrowing-fee level and its interaction with the announcement-window return is central to the design. The borrowing fee captures the current price of borrowing shares, while IC

captures the concentration of the lendable supply base. The coefficient on the interaction between announcement-window news and IC therefore asks whether lendable-inventory concentration predicts delayed price adjustment beyond the effect of current borrowing costs.

The coefficient of interest is γ_h. It measures whether inventory concentration changes the mapping from the announcement-window return into subsequent abnormal returns over horizon h. I estimate the specification separately for positive- and negative-news announcements. In the negative-news subsample, $CAR^{CAPM}_{i,t,[-1,+1]} < 0$. Therefore, a positive γ_h implies that higher IC makes post-announcement abnormal returns more negative following bad news. This pattern is consistent with slower incorporation of negative information when lendable inventory is more concentrated.

6.3 Results: Asymmetric Drift under High Inventory Concentration

Table 10 reports the interaction coefficient γ_h from equation (3). The results show a sharp asymmetry. For positive-news events, the interaction between announcement-window news and inventory concentration is generally small and statistically insignificant. The coefficients are negative at longer horizons, but their statistical significance is weak; for example, the coefficient is -0.803 at $h = 60$ with a t-statistic of -1.82, and -1.651 at $h = 120$ with a t-statistic of -1.75.

In contrast, the interaction is positive, economically large, and statistically significant for negative-news events. The coefficient is 0.367 at $h = 20$ with a t-statistic of 2.05, 0.601 at $h = 30$ with a t-statistic of 2.47, and 1.609 at $h = 60$ with a t-statistic of 3.15. The effect continues to increase at longer horizons, reaching 2.998 at $h = 90$ and 4.408 at $h = 120$, with t-statistics of 3.72 and 3.77, respectively. Because the announcement-window return is negative in the negative-news subsample, these positive interaction coefficients imply more negative post-announcement abnormal returns when inventory concentration is high.

The specification controls directly for the borrowing-fee level and for the interaction between the announcement-window return and the borrowing fee. Thus, the positive γ_h estimates after negative news are not simply a fee-level effect. Instead, they show that the concentration of lendable supply has incremental explanatory power for delayed price adjustment beyond the current price of borrowing shares. This evidence supports the paper's central mechanism: because the structure of lendable supply affects whether short positions can be maintained after negative information arrives, the borrowing fee alone does not fully capture the short-sale constraint. The asymmetry across news signs is also informative. If the results reflected a general slow-information-processing channel,

one would expect inventory concentration to affect positive and negative news more symmetrically. Instead, the effect is concentrated in negative-news events, where correcting overpricing is more likely to require short selling. This asymmetry is consistent with a short-sale-constraint channel in which concentrated lendable inventory makes short-side arbitrage more fragile, slowing the incorporation of negative information into prices.

Table 10: Inventory concentration and post-announcement drift: local-projection interaction estimates

News Group	5	10	15	20	30	40	50	60	90	120
Positive	-0.076	0.029	0.050	-0.088	-0.362	-0.322	-0.534	-0.803	-0.912	-1.651
	(-0.85)	(0.22)	(0.31)	(-0.48)	(-1.44)	(-0.98)	(-1.31)	(-1.82)	(-1.46)	(-1.75)
Negative	0.083	0.132	0.230	0.367	0.601	0.940	1.031	1.609	2.998	4.408
	(0.89)	(1.10)	(1.45)	(2.05)	(2.47)	(2.96)	(2.47)	(3.15)	(3.72)	(3.77)

Notes: This table reports γ_h, the coefficient on $CAR^{CAPM}_{i,t,[-1,+1]} \times IC_{i,t-1}$ from equation (3). The dependent variable is $CAR^{CAPM}_{i,t,[+2,+h]}$. The specification includes calendar-month fixed effects and controls for the borrowing fee, size, idiosyncratic volatility, institutional ownership, short interest, and illiquidity, as well as interactions between the announcement-window return and each of these controls. Estimates are reported separately for positive- and negative-news events. t-statistics are in parentheses. Standard errors are clustered by stock and month.

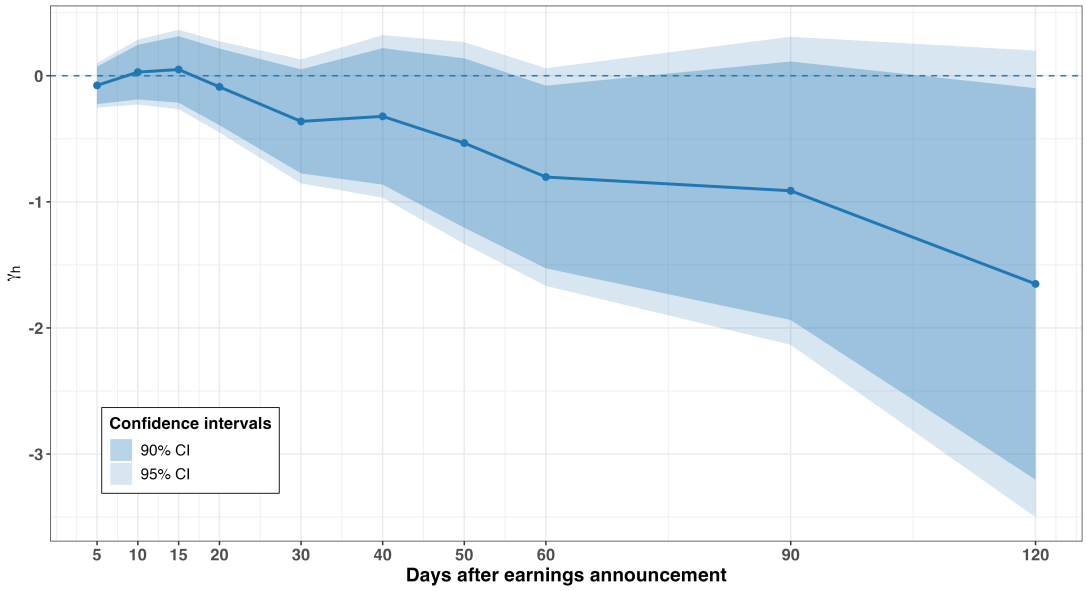


Figure 3: Inventory concentration and post-announcement response to positive news. This figure plots γ_h, the horizon-h coefficient on $CAR^{CAPM}_{i,t,[-1,+1]} \times IC_{i,t-1}$ from equation (3), where the dependent variable is $CAR^{CAPM}_{i,t,[+2,+h]}$. The estimates show how the post-announcement response to positive news varies with pre-announcement lendable inventory concentration.

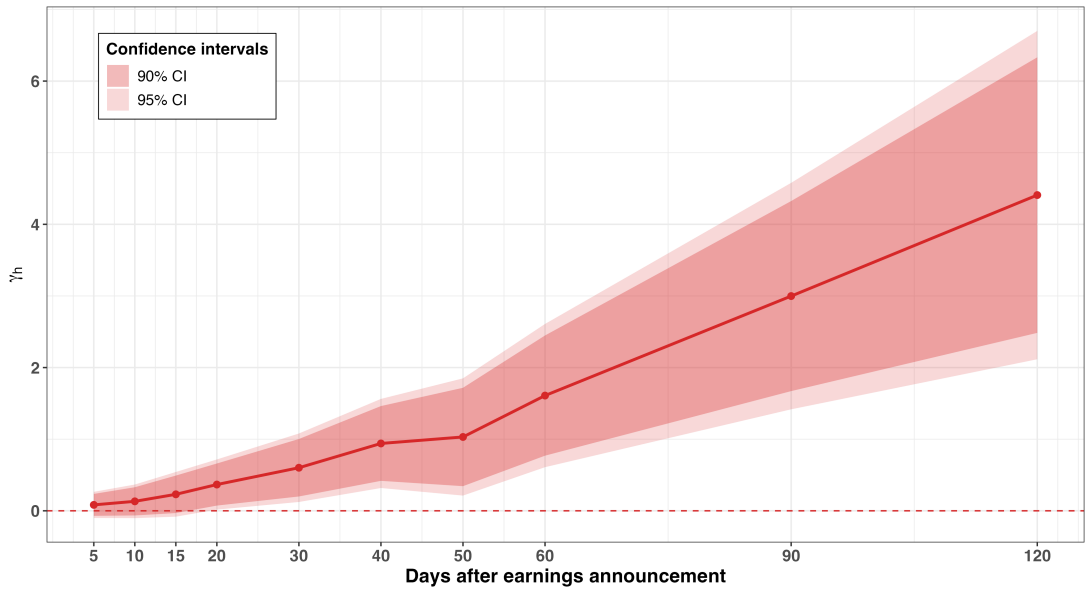


Figure 4: Inventory concentration and post-announcement response to negative news. This figure plots γ_h, the horizon-h coefficient on $CAR^{CAPM}_{i,t,[-1,+1]} \times IC_{i,t-1}$ from equation (3), where the dependent variable is $CAR^{CAPM}_{i,t,[+2,+h]}$. The estimates show how the post-announcement response to negative news varies with pre-announcement lendable inventory concentration.

6.4 Implications for Price Discovery

The earnings-announcement evidence indicates that lending-market structure is related to the speed of information incorporation. The effect is asymmetric: negative news is incorporated more slowly when lendable inventory is concentrated, while the corresponding effect after positive news is weak. This asymmetry is difficult to reconcile with symmetric frictions such as general inattention, slow information diffusion, or illiquidity. It is instead consistent with a short-sale-constraint channel in which concentrated lendable supply makes short-side arbitrage more fragile.

7 Lendable Inventory Concentration and Equity Pricing Anomalies

This section tests whether the durability margin is reflected in anomaly returns. If borrow fragility limits arbitrage against overpricing, anomaly long–short returns should be larger among high-IC stocks, concentrated on the short leg, and remain economically meaningful after borrowing fees are taken into account.

This prediction follows from the earlier evidence. Section 5 shows that inventory concentration predicts realized short-selling risk, while Section 6 shows that high-IC stocks

incorporate negative earnings information more slowly. I now test whether the same lending-market structure matters more broadly for anomaly portfolios, where the short leg requires borrowing shares to trade against overpricing.

I first show that gross anomaly spreads are larger among high-IC stocks and that the High–Low IC difference is mainly driven by the short leg. I then turn to the main implementation test, fee-adjusted anomaly returns, which show that borrowing fees reduce but do not eliminate high-IC anomaly profitability. Throughout, I confirm that the results survive characteristic adjustment for size and illiquidity; the DGTW size–illiquidity-adjusted results are collected in Appendix E.1, which also details the benchmark construction.

7.1 Data Inputs and Portfolio Construction

The anomaly tests use the 69 signed anomaly signals selected from the merged CRSP–Jensen–Markit universe described in Section 4.5. For each retained signal, I sort stocks each month into equal-weighted signal quintiles and compute long–short returns using the sign convention from Jensen et al. (2023), so high signal values correspond to the long leg and low signal values correspond to the short leg.

The anomaly selection rule is applied unconditionally, before sorting on inventory concentration. It depends only on each signal's unconditional CAPM alpha in the merged tradable universe and not on its relation to IC, borrowing fees, or short-selling risk. The subsequent tests ask whether the strength of these surviving anomaly signals varies systematically with lending-market conditions.

The baseline tests use excess returns. To ensure that cross-IC differences in anomaly payoffs do not simply reflect the size and liquidity composition of high-IC stocks, I also construct DGTW-style characteristic-adjusted returns following Daniel et al. (1997): each month I assign stocks to ten size portfolios using NYSE breakpoints and then to ten illiquidity portfolios within each size portfolio, and subtract the value-weighted benchmark-portfolio excess return from each stock's excess return. The construction is detailed in Appendix E.1. These adjusted returns remove the component of returns attributable to the stock's size–illiquidity benchmark, allowing the analysis to compare anomaly payoffs across IC groups after accounting for mechanical differences in size and liquidity.

7.2 Double Sorts on Inventory Concentration and Anomaly Signals

The main portfolio construction is a monthly double sort that compares anomaly spreads across inventory-concentration groups, allowing me to test whether return predictability

is stronger when lendable supply is more concentrated. In month t, I first sort stocks into inventory-concentration groups based on $IC_{i,t}$: Low IC (bottom quintile), Mid IC (middle three quintiles), and High IC (top quintile). Within each IC group, I then sort stocks into quintiles based on the anomaly signal $X_{i,t}$ and compute equal-weighted portfolio returns. Let $r_{jq,t}$ denote the month-t return of characteristic quintile $j \in \{1, \ldots, 5\}$ within IC group $q \in \{L, M, H\}$. The within-group anomaly spread is

$$r_t^q = r_{5q,t} - r_{1q,t}, \qquad q \in \{L, M, H\}.$$

The key object is the High–minus–Low IC difference in anomaly returns,

$$\Delta r_t = r_t^H - r_t^L.$$

Because the long–short spread is formed separately within each IC group, r_t^H and r_t^L are each computed from stocks facing similar inventory-concentration conditions. As a result, Δr_t reflects differences in anomaly payoffs across IC states, rather than differences that arise simply because High-IC and Low-IC groups contain different types of stocks. I also require at least 20 stocks in both the long and short legs within each IC group-month.

Table 11: Double-sort design: inventory concentration and anomaly signals.

	Inventory Concentration (IC) groups		
Signal quintiles within IC group	Low IC (Q1)	Mid IC (Q2–Q4)	High IC (Q5)
Q1 (Low char)	r_{11}	r_{1m}	r_{15}
Q2	r_{21}	r_{2m}	r_{25}
Q3	r_{31}	r_{3m}	r_{35}
Q4	r_{41}	r_{4m}	r_{45}
Q5 (High char)	r_{51}	r_{5m}	r_{55}

Notes: Each month, stocks are first sorted into Low/Mid/High IC groups using $IC_{i,t}$. Within each IC group, stocks are sorted into characteristic quintiles using anomaly signal $X_{i,t}$ and equal-weighted returns $r_{jq,t}$ are computed. The within-group anomaly return is $r_t^q = r_{5q,t} - r_{1q,t}$.

7.3 Cluster-level evidence: anomaly return spreads are larger when lendable inventory is more concentrated

To summarize patterns across anomaly signals, I follow Jensen et al. (2023) and group the 69 anomalies into economically interpretable clusters, such as momentum, value, investment, profitability, and low risk. Within each cluster, I average anomaly-specific portfolio returns across all characteristics in the cluster.

The first set of results asks whether anomaly returns are larger when lendable inventory is more concentrated, and whether the difference comes from the short leg, where implementing the strategy requires borrowing shares. Table 12 reports raw excess returns from the inventory-concentration double sort. The pattern is broad-based. High-IC anomaly portfolios earn positive and economically large long–short returns across the main clusters, while the corresponding low-IC returns are much smaller. The High–Low IC differences are positive for most clusters, including momentum, value, profit growth, short-term reversal, low risk, and investment.

The leg decomposition shows that these differences are mainly short-side differences. The Long column is generally small and statistically weak. By contrast, the Short column is negative and economically large for the major clusters. Because the short leg is subtracted in a long–short portfolio, negative values in this column imply that high-IC short-leg stocks earn lower returns than low-IC short-leg stocks, thereby increasing the High–Low spread. For example, in the momentum cluster, the High–Low spread is 0.79% per month, while the short-leg contribution is −0.66%. For value, the High–Low spread is 0.63%, while the short-leg contribution is −0.62%. This pattern is consistent with high inventory concentration making arbitrage against overpriced stocks more difficult.

To ensure that these differences do not mechanically reflect the size or liquidity composition of high-IC stocks, I repeat the analysis using DGTW-adjusted excess returns. The conclusion is unchanged: high-IC anomaly returns remain large, the High–Low differences remain positive for the main clusters, and the leg decomposition continues to point to the short side (Appendix Table 31). The pattern is therefore not driven by a mechanical size or liquidity tilt.

The gross-return evidence shows that anomaly profits are larger among high-IC stocks, with the High–Low difference concentrated on the short side. Section 7.4 asks whether these profits survive borrowing fees. If observed fees fully captured the relevant short-sale constraint, fee-adjusted anomaly profits should largely disappear.

7.4 Fee-adjusted Implementations

Borrowing fees are a direct implementation cost for anomaly strategies that require short positions. A return spread that seems profitable on paper may therefore shrink or vanish once the cost of borrowing is considered. To assess net implementable performance, I construct fee-adjusted long–short returns using Markit indicative borrowing fees.

Notation. Let $r_{i,t+1}$ denote stock i's next-month excess return and $f_{i,t+1}$ the average buy-side borrowing fee over the same month, converted to monthly units. For each

Table 12: Anomaly return spreads by inventory concentration

Cluster	**High IC LS Ret.**	**Low IC LS Ret.**	**High–Low LS Ret.**	**Long Contri.**	**Short Contri.**
Value	0.88***	0.25	0.63**	0.01	-0.62**
	(2.68)	(1.04)	(2.42)	(0.05)	(-2.53)
Momentum	0.85***	0.06	0.79***	0.13	-0.66***
	(2.60)	(0.18)	(2.83)	(0.65)	(-2.76)
Quality	0.73**	0.38*	0.35	-0.10	-0.45
	(2.57)	(1.89)	(1.17)	(-0.53)	(-1.59)
Profit Growth	0.73***	0.02	0.70***	0.15	-0.55***
	(3.82)	(0.21)	(3.55)	(0.84)	(-2.87)
Short-Term Reversal	0.73***	0.21	0.51**	-0.08	-0.59***
	(3.18)	(1.08)	(2.27)	(-0.38)	(-2.97)
Profitability	0.70**	0.24	0.46	-0.07	-0.53*
	(1.97)	(1.00)	(1.62)	(-0.44)	(-1.92)
Low Risk	0.61*	0.10	0.51*	-0.02	-0.53**
	(1.69)	(0.39)	(1.96)	(-0.11)	(-2.18)
Investment	0.59***	0.15	0.43*	-0.14	-0.57***
	(2.68)	(0.86)	(1.81)	(-0.64)	(-2.81)
Debt Issuance	0.26	0.15	0.11	-0.21	-0.33*
	(1.12)	(1.01)	(0.48)	(-1.03)	(-1.75)
Accruals	0.25	0.07	0.18	-0.16	-0.34
	(1.26)	(0.59)	(0.82)	(-0.74)	(-1.54)
Seasonality	0.19	0.24	-0.05	0.17	0.22
	(0.89)	(1.36)	(-0.20)	(0.78)	(1.04)

Notes: Entries report monthly anomaly returns, with t-statistics in parentheses on the line below. High IC and Low IC are long–short anomaly portfolios formed separately within high- and low-inventory-concentration stocks. High–Low is the difference between the two long–short return spreads. Long and Short decompose this difference into the corresponding long- and short-leg components. Because the short leg is subtracted in a long–short portfolio, negative values in the Short Contri. column imply that high-IC short-leg stocks earn lower returns than low-IC short-leg stocks, thereby increasing the High–Low spread. *, **, and *** denote significance at the 10%, 5%, and 1% levels based on $|t|$.

anomaly strategy, let L_t denote the set of stocks in the long leg and S_t the set in the short leg, and define the leg-average returns and fees r^L_{t+1}, r^S_{t+1}, f^L_{t+1}, and f^S_{t+1} as the corresponding within-leg averages.

The short leg: stock return versus arbitrageur payoff. A key distinction is between the *return of the stocks* assigned to the short leg and the *payoff to an arbitrageur* who shorts them. The former is r^S_{t+1}. The latter has the opposite sign, since the arbitrageur profits when these stocks fall, and is further reduced by the borrowing fee paid to hold the position, $-\left(r^S_{t+1} + f^S_{t+1}\right)$. Two forces therefore erode short-side profitability: high realized returns on short-leg stocks (the stocks fail to underperform), and the borrowing fee paid to maintain the position.

The long leg and the fee-adjusted return. Long positions may also generate securities-lending income if the shares are lent out. Because this income applies only to the lent portion and is received net of intermediary spreads, I follow Muravyev et al. (2025) and add a fraction λ of the indicated borrowing fee to the long-leg return, setting $\lambda = 0.7$ in the baseline. Combining the two legs, the fee-adjusted long–short return is

$$r^{LS,\text{net}}_{t+1} = \underbrace{\left(r^L_{t+1} - r^S_{t+1}\right)}_{\text{gross spread}} + \underbrace{\lambda f^L_{t+1} - f^S_{t+1}}_{\text{net fee adjustment}}, \qquad \lambda = 0.7.$$

The fee adjustment adds a discounted lending yield to the long leg and subtracts the full borrowing fee from the short leg. Because short-leg fees typically exceed long-leg lending income, the adjustment lowers the long–short return; an anomaly that survives it therefore survives the main implementation cost of shorting. Fee-adjusted CAPM alphas regress these adjusted excess returns on the market. If fees fully explained anomaly profitability, fee-adjusted returns and alphas should weaken sharply among high-IC stocks, where borrowing is most expensive.

Tables 13 and 32 show that this is not the case: fee-adjusted profitability is much stronger among high-IC stocks. In Table 13, the leading clusters retain sizable and significant high-IC long–short returns after fees. These returns are 0.76% per month for momentum ($t = 2.34$), 0.71% for value ($t = 2.16$), 0.68% for short-term reversal ($t = 2.99$), and 0.67% for profit growth ($t = 3.56$). The corresponding low-IC returns collapse toward zero, at 0.04% for momentum, 0.01% for profit growth, and 0.20% for short-term reversal, none of which is statistically distinguishable from zero. The High$-$Low differences therefore capture nearly the entire fee-adjusted return and are significant for momentum (0.72%, $t = 2.60$), profit growth (0.67%, $t = 3.37$), short-term reversal (0.48%, $t = 2.12$),

and value (0.49%, $t = 1.86$).

The CAPM alphas reinforce this pattern. High-IC alphas reach 1.07% per month for momentum ($t = 3.37$), 1.02% for low risk ($t = 3.27$), 0.96% for value ($t = 3.01$), and 0.79% for short-term reversal ($t = 3.50$). The low-risk and profitability clusters are instructive: their high-IC raw returns are insignificant (0.48%, $t = 1.35$; 0.52%, $t = 1.47$), yet their alphas are large and significant (1.02%, $t = 3.27$; 0.74%, $t = 2.12$). Market adjustment thus uncovers high-IC profitability that the raw returns understate, rather than explaining it away. Across all eleven clusters, the high-IC alpha is positive in every case and significant in eight.

The conclusion is robust to characteristic adjustment. Repeating the fee-adjusted analysis on DGTW-adjusted returns leaves the magnitudes nearly unchanged: the high-IC momentum and value alphas are 1.06% and 0.90% (versus 1.07% and 0.96% under CAPM), and the High−Low differences are, if anything, slightly stronger, with the value spread rising to 0.52% ($t = 2.10$) and the low-risk spread to 0.52% ($t = 2.15$) (Appendix Table 32). Characteristic adjustment therefore does not absorb the IC effect; the high-IC premium is not a stale exposure to size or illiquidity benchmarks.

Two features of the results are informative about the mechanism. First, borrowing fees matter. They reduce anomaly profitability, and the weaker clusters, such as debt issuance, accruals, and seasonality, are insignificant in both IC groups. However, among clusters with economically large anomaly returns, fee adjustment does not eliminate profitability in high-IC stocks, whereas the corresponding low-IC returns are much smaller and generally insignificant. Second, the difference is cross-sectional. The same anomaly signal earns larger net returns precisely among stocks whose lendable supply is more concentrated. This pattern reinforces the distinction between borrowing costs and borrow-access durability. Fees reduce anomaly profitability, but the remaining after-fee spreads are largest where IC indicates more fragile borrow access.

7.5 A Summary Mispricing Measure: NetLeg

To aggregate information across many anomaly signals, I construct a NetLeg measure following Engelberg et al. (2018). In the full anomaly sample, which contains 69 signals and 730,404 stock-month observations, I count for each stock-month how often the stock appears in the long quintile and how often it appears in the short quintile across anomalies:

$$\text{NetLeg}_{i,t} = \text{NetLong}_{i,t} - \text{NetShort}_{i,t}.$$

Table 13: Fee-adjusted anomaly returns by inventory concentration.

Cluster	**High IC**		**Low IC**		**High–Low**
	LS Ret.	α_{CAPM}	**LS Ret.**	α_{CAPM}	**LS Ret.**
Momentum	0.76**	1.07***	0.04	0.38	0.72***
	(2.34)	(3.37)	(0.11)	(1.20)	(2.60)
Value	0.71**	0.96***	0.22	0.30	0.49*
	(2.16)	(3.01)	(0.94)	(1.27)	(1.86)
Short-Term Reversal	0.68***	0.79***	0.20	0.20	0.48**
	(2.99)	(3.50)	(1.03)	(1.00)	(2.12)
Profit Growth	0.67***	0.64***	0.01	0.06	0.67***
	(3.56)	(3.32)	(0.08)	(0.51)	(3.37)
Quality	0.58**	0.64**	0.37*	0.49**	0.22
	(2.07)	(2.20)	(1.81)	(2.35)	(0.73)
Profitability	0.52	0.74**	0.22	0.44*	0.30
	(1.47)	(2.12)	(0.90)	(1.91)	(1.07)
Investment	0.50**	0.56**	0.13	0.17	0.37
	(2.30)	(2.57)	(0.76)	(0.92)	(1.54)
Low Risk	0.48	1.02***	0.07	0.51**	0.42
	(1.35)	(3.27)	(0.27)	(1.98)	(1.59)
Debt Issuance	0.22	0.26	0.14	0.18	0.08
	(0.85)	(1.15)	(0.91)	(1.20)	(0.31)
Accruals	0.19	0.22	0.06	0.11	0.14
	(0.97)	(1.07)	(0.47)	(0.90)	(0.62)
Seasonality	0.14	0.20	0.22	0.19	-0.09
	(0.66)	(0.93)	(1.29)	(1.07)	(-0.36)

Notes: Entries report monthly fee-adjusted excess returns, with t-statistics in parentheses on the line below. High IC and Low IC denote anomaly portfolios formed separately within high- and low-inventory-concentration stocks. LS Ret. is the fee-adjusted long–short anomaly return. α_{CAPM} is the corresponding CAPM alpha. The High − Low column reports the difference between high-IC and low-IC fee-adjusted long–short returns. *, **, and *** denote significance at the 10%, 5%, and 1% levels based on $|t|$.

$\text{NetLong}_{i,t}$ is the number of anomaly signals that assign stock i to the long quintile in month t, and $\text{NetShort}_{i,t}$ is the number that assign it to the short quintile. Both components are nonnegative integers between 0 and 69, so $\text{NetLeg}_{i,t}$ ranges from -69 to 69. A high value indicates that a stock is classified as undervalued by many signals; a low value indicates that it is classified as overvalued by many signals.

Each month, I sort stocks into quintiles using the lagged NetLeg score and construct a zero-investment long–short portfolio that buys the top NetLeg quintile and shorts the bottom quintile. I repeat the construction within Low-, Mid-, and High-IC subsamples to test whether anomaly-related mispricing is stronger when lendable inventory is more concentrated, and again using DGTW-adjusted returns to ensure the results are not driven by size or liquidity differences across IC groups.

Figure 5 plots cumulative log returns of the NetLeg strategy across IC groups. A clear ordering emerges: the strategy performs best among High-IC stocks, is intermediate in the full sample, and performs weakest among Low-IC stocks. This ordering appears both before and after borrowing-fee adjustment. By the end of the sample, the High-IC portfolio accumulates 2.52 in log excess returns before fees and 2.12 after fees, well above the full sample (1.47 before fees, 1.30 after) and the Low-IC portfolio (0.516 before fees, 0.456 after). The fee wedge is largest in the High-IC portfolio, at about 0.40 log points, compared with 0.17 in the full sample and 0.07 in the Low-IC portfolio. Implementation costs are thus highest when inventory is concentrated, yet fee-adjusted performance remains strongest in high-IC stocks.

Table 14 reports portfolio-level statistics for the raw NetLeg portfolios. The state dependence is pronounced. In the High-IC subsample, average monthly excess returns rise from -27.50 bps in the lowest NetLeg quintile to 111.00 bps in the highest, generating a high-minus-low spread of 139.00 bps per month ($t = 3.09$). The high-minus-low CAPM alpha is 109.00 bps ($t = 2.45$). After borrowing-fee adjustment, the High-IC spread remains large and significant, at 119.00 bps per month ($t = 2.67$), with a fee-adjusted CAPM alpha of 89.40 bps ($t = 2.02$). The Low-IC subsample is much weaker: the raw high-minus-low spread is 37.70 bps ($t = 1.16$) and the fee-adjusted spread is 34.60 bps ($t = 1.07$). Borrowing fees are far lower in Low-IC stocks (3.33 to 5.49 bps across quintiles), yet the spread is also small and statistically weak; in the High-IC short leg, average fees reach 26.70 bps, but the fee-adjusted long–short strategy remains large and significant.

The same conclusion holds under DGTW adjustment. In the High-IC subsample, the DGTW-adjusted high-minus-low spread is 143.00 bps per month before fees and 123.00 bps after fees, with a fee-adjusted CAPM alpha of 94.70 bps ($t = 2.36$); in the Low-IC

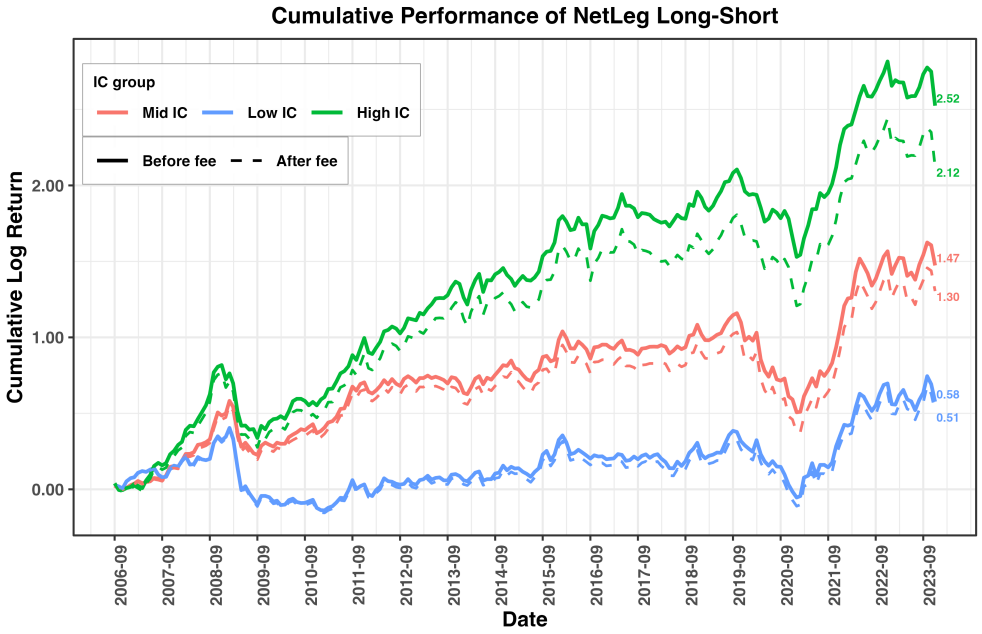


Figure 5: Cumulative log excess returns of NetLeg portfolios (borrowing-fee adjustment applied to both short and long legs), 2006:08–2023:12. The DGTW-adjusted counterpart is reported in Appendix Figure 12.

subsample the corresponding fee-adjusted spread is only 31.00 bps ($t = 1.16$) (Appendix Table 33). The High-IC–Low-IC contrast is therefore not explained by size or liquidity composition.

The NetLeg evidence aggregates the cluster-level results into a single mispricing measure: the aggregate anomaly signal is substantially more profitable when lendable inventory is concentrated. In the High-IC subsample, borrowing fees are higher and reduce long–short returns but do not eliminate the strategy's profitability; in the Low-IC subsample, fees are much lower yet the NetLeg spreads are small and statistically weak. The return difference is therefore not simply compensation for higher borrowing fees. It is consistent with more persistent anomaly-related mispricing when short-side arbitrage is constrained by fragile borrow access. Appendix Table 34 shows that short-leg stocks in the High-IC subsample also exhibit substantially higher fee-tail and utilization-tail risk than their Low-IC counterparts.

7.6 Short-Leg Anomaly Exposure, Borrow Fragility, and Expected Returns

The portfolio results show that anomaly return spreads are larger among high-IC stocks and concentrated on the short leg. I now test the mechanism in Fama–MacBeth regressions by interacting anomaly-leg exposure with borrowing fees and realized short-selling

Table 14: NetLeg portfolios: Low-IC vs. High-IC comparison. Returns, α, and borrow fees are in basis points.

Metric	Group	1	2	3	4	5	H–L
r	Low-IC	56.20	84.40	94.80	91.60	93.90	37.70
		(1.03)	(1.83)	(2.40)	(2.51)	(2.98)	(1.16)
	High-IC	-27.50	37.10	83.00	83.20	111.00	139.00
		(-0.40)	(0.68)	(1.89)	(2.10)	(2.91)	(3.09)
Avg. Fee	Low-IC	5.49	3.81	3.49	3.38	3.33	–
	High-IC	26.70	17.90	14.60	12.90	10.30	–
SR	Low-IC	0.254	0.452	0.573	0.592	0.695	0.293
	High-IC	-0.107	0.189	0.528	0.606	0.790	0.837
r^{feeadj}	Low-IC	61.70	87.00	97.20	93.90	96.20	34.60
		(1.13)	(1.89)	(2.46)	(2.58)	(3.05)	(1.07)
	High-IC	-0.78	49.60	93.20	92.20	118.00	119.00
		(-0.01)	(0.92)	(2.12)	(2.33)	(3.10)	(2.67)
SR^{feeadj}	Low-IC	0.279	0.466	0.588	0.607	0.713	0.269
	High-IC	-0.003	0.254	0.594	0.672	0.841	0.721
α_{CAPM}	Low-IC	-23.40	3.32	12.90	8.81	14.10	37.50
		(-0.84)	(0.18)	(1.01)	(0.72)	(1.44)	(1.27)
	High-IC	-48.60	-14.00	45.60	40.00	60.60	109.00
		(-1.03)	(-0.45)	(1.36)	(1.48)	(2.76)	(2.45)
$\alpha_{\text{CAPM}}^{\text{feeadj}}$	Low-IC	-18.00	6.04	15.30	11.20	16.40	34.40
		(-0.64)	(0.33)	(1.21)	(0.91)	(1.68)	(1.16)
	High-IC	-21.70	-1.49	55.70	49.00	67.80	89.40
		(-0.46)	(-0.05)	(1.66)	(1.81)	(3.09)	(2.02)
Num. Months	Low-IC	208	208	208	208	208	–
	High-IC	208	208	208	208	208	–
Avg. Num. Stocks	Low-IC	142	138	133	132	153	–
	High-IC	136	118	140	148	126	–

Notes: This table reports NetLeg portfolio returns by inventory-concentration group. Low-IC and High-IC denote portfolios formed within the low- and high-inventory-concentration subsamples, respectively. Columns 1–5 report anomaly-sorted portfolios, and H–L reports the high-minus-low spread. Returns, CAPM alphas, and average borrowing fees are in basis points. r denotes returns before borrowing-fee adjustment, while r^{feeadj} subtracts borrowing fees from the short leg and adds discounted lending income to the long leg, as described in Section 7.4. SR denotes the Sharpe ratio. Entries in parentheses are t-statistics. For Avg. Fee, the t-statistic is reported only for the H–L fee difference.

risk. The test asks whether short-leg predictability is stronger when borrow access is unstable, and whether this relation survives controls for the current borrowing fee.

I use the composite short-selling risk measure SSR defined in Section 4.3. It averages the within-month percentile ranks of fee-risk, fee-tail, utilization-risk, and utilization-tail components, using available non-missing components. Higher values indicate more unstable shorting conditions. Unlike the contemporaneous loan fee, SSR captures the risk that borrowing conditions deteriorate after a short position is initiated.

A useful first check is whether realized borrow fragility contains information beyond the contemporaneous borrowing fee. Appendix Table 35 reports panel and Fama–MacBeth regressions of next-month excess returns on borrowing fees and SSR . The coefficient on SSR is negative and statistically significant across specifications, while the coefficient on the borrowing fee becomes smaller and insignificant once standard controls are included. Consistent with prior work, short-selling risk is not fully summarized by the level of borrowing fees.

The main question is more specific: does borrow fragility matter precisely where anomaly arbitrage requires short selling? To answer it, I decompose anomaly exposure into long- and short-leg components. $\text{NetLong}_{i,t}$ measures how intensively a stock appears on the long side of anomaly strategies, and $\text{NetShort}_{i,t}$ how intensively it appears on the short side. I estimate the cross-sectional regression separately each month and average the slopes. Each regressor is a within-month percentile rank, so coefficients measure the effect of moving from the bottom to the top of the monthly distribution:

$$\begin{aligned} r^{e}_{i,t+1} = \alpha_t &+ \beta_t \text{NetLeg}_{i,t} \\ &+ \theta_t \text{SSR}_{i,t} + \phi^L_t \left(\text{NetLong}_{i,t} \times \text{SSR}_{i,t}\right) + \phi^S_t \left(\text{NetShort}_{i,t} \times \text{SSR}_{i,t}\right) \\ &+ \lambda_t \text{Fee}_{i,t} + \psi^L_t \left(\text{NetLong}_{i,t} \times \text{Fee}_{i,t}\right) + \psi^S_t \left(\text{NetShort}_{i,t} \times \text{Fee}_{i,t}\right) \\ &+ \Gamma'_t X_{i,t} + \varepsilon_{i,t+1}. \end{aligned} \tag{4}$$

The baseline specification includes NetLeg, SSR, Fee, size, market beta, and the corresponding long- and short-leg interactions for SSR, Fee, and size. Alternative specifications add institutional ownership, short interest, turnover, bid–ask spreads, and Amihud illiquidity, each with its long- and short-leg interactions. Inference is based on the time series of monthly slope estimates.

Table 15 reports the results. The standalone NetLeg coefficient is not robust across specifications, and the standalone SSR coefficient is small and insignificant. Neither aggregate anomaly exposure nor short-selling risk alone generates a uniform unconditional return premium.

The central evidence comes from $NetShort \times \text{SSR}$. The coefficient is negative in every

specification and significant in seven of the eight columns. It equals −173.12 bps in the baseline ($t = -2.06$) and remains large in the full specification, at −169.97 bps ($t = -2.39$). The estimates are stable across control sets, ranging from −155.64 to −206.62 bps, and the result is, if anything, strongest in the most saturated specifications. Stocks more heavily represented on anomaly short legs therefore earn especially low subsequent returns when borrowing conditions are fragile.

The borrowing-fee interaction shows a related but weaker pattern. The coefficient on $NetShort \times Fee$ is negative in every specification and equals −112.52 bps in the baseline ($t = -2.62$), but declines to −60.46 bps in the full model ($t = -1.52$). By contrast, the long-leg interactions with both SSR and Fee are small and insignificant throughout. This asymmetry is central: lending-market frictions operate primarily where arbitrage requires shorting overpriced stocks, and the instability of borrow access (SSR) retains explanatory power in the saturated specification where the fee interaction does not.

Overall, Table 15 links borrow fragility directly to anomaly arbitrage. Short-leg returns fall most sharply when short-selling risk is high, while borrowing fees capture part of the same pattern but are less robust in the most saturated specification. The weak long-leg interactions and strong short-leg interactions support the paper's central mechanism: anomaly-related overpricing is most persistent among stocks that arbitrageurs would need to short, but for which borrow access is most unstable.

7.7 Summary

The evidence in this section shows that anomaly return spreads are larger when borrow access is fragile, primarily where arbitrage requires short positions. Cluster-level double sorts show that anomaly spreads are larger among high-IC stocks, that the difference is concentrated on the short leg, and that the pattern survives DGTW size–liquidity benchmarking and explicit fee adjustment. The NetLeg portfolios aggregate this evidence into a single mispricing measure: the fee-adjusted high-minus-low spread is large and significant in the High-IC subsample but much smaller and statistically weak in the Low-IC subsample.

The Fama–MacBeth regressions sharpen the interpretation. The standalone NetLeg coefficient is weak, so the results are not driven by a broad unconditional anomaly premium. Instead, the predictive relation appears where the borrow-fragility mechanism predicts: on the short side. The interaction NetShort × SSR is negative and statistically significant across specifications, indicating that short-leg stocks earn especially low subsequent returns when borrowing conditions are fragile. Although NetShort × Fee is also negative in most specifications, the SSR interaction shows that the relevant friction is not

Table 15: Anomaly Exposure, Borrowing Fees, Short-Selling Risk

	Dependent variable: next-month excess return (in bps)							
	Base	+IOR	+IVOL	+ShortInt	+Turnover	+BidAsk	+Amihud	Full
Panel A. Anomaly exposure and lending-market frictions								
NetLeg	36.00	92.31**	5.33	50.71	40.70	-2.97	-3.75	53.24
	(0.98)	(2.12)	(0.14)	(1.31)	(1.09)	(-0.08)	(-0.06)	(0.93)
SSR	9.76	26.76	29.43	53.10	16.97	40.19	28.45	60.66
	(0.22)	(0.50)	(0.65)	(1.01)	(0.38)	(0.95)	(0.59)	(1.06)
NetLong × SSR	30.70	18.89	-4.94	32.36	30.15	-22.99	17.63	3.55
	(0.57)	(0.32)	(-0.10)	(0.57)	(0.62)	(-0.47)	(0.32)	(0.06)
NetShort × SSR	-173.12**	-197.32**	-155.64**	-202.52***	-178.82***	-164.49**	-206.62***	-169.97**
	(-2.06)	(-2.34)	(-2.17)	(-2.70)	(-2.87)	(-2.46)	(-2.61)	(-2.39)
Fee	45.13	29.94	34.79	34.54	37.16	41.62	37.86	21.05
	(1.57)	(0.96)	(1.28)	(1.12)	(1.27)	(1.47)	(1.30)	(0.72)
NetLong × Fee	3.60	0.78	10.87	4.76	1.87	4.25	0.47	4.28
	(0.11)	(0.02)	(0.34)	(0.14)	(0.06)	(0.13)	(0.01)	(0.12)
NetShort × Fee	-112.52***	-69.66	-93.43**	-111.53**	-93.95**	-101.39**	-85.71**	-60.46
	(-2.62)	(-1.63)	(-2.36)	(-2.50)	(-2.43)	(-2.46)	(-2.10)	(-1.52)
Panel B. Baseline controls and interactions								
β_{mkt}	47.97	52.75	51.34	57.04	46.17	54.86	47.02	56.57
	(1.05)	(1.22)	(1.17)	(1.29)	(1.12)	(1.27)	(1.06)	(1.50)
Size	-59.49*	-61.99*	-76.49**	-59.64*	-66.99*	-82.71**	-62.90	8.75
	(-1.75)	(-1.90)	(-2.12)	(-1.80)	(-1.91)	(-2.47)	(-0.86)	(0.12)
NetLong × Size	25.86	53.94*	40.52*	37.23	38.92	47.01**	54.30	86.95*
	(1.12)	(1.69)	(1.80)	(1.32)	(1.33)	(2.06)	(1.58)	(1.87)
NetShort × Size	123.84***	90.01**	129.84***	145.95***	122.08***	126.28***	107.07***	84.48*
	(4.13)	(2.22)	(4.21)	(3.72)	(2.90)	(4.25)	(2.67)	(1.65)

Notes: Monthly Fama–MacBeth regressions of next-month excess returns. All regressors are within-month percentile ranks. Coefficients in bps; Newey–West t-statistics with lag 3 in parentheses. Additional control coefficients are reported in Appendix Table 15. *, **, *** denote 10%, 5%, and 1% significance.

Table 15: Anomaly Exposure, Borrowing Fees, Short-Selling Risk, Continued

	Dependent variable: next-month excess return (in bps)							
Factor	Base	+IOR	+IVOL	+ShortInt	+Turnover	+BidAsk	+Amihud	Full
Panel C. Additional controls and interactions								
IOR		21.11						20.85
		(0.73)						(0.58)
NetLong × IOR		-88.79**						-77.84*
		(-2.44)						(-1.87)
NetShort × IOR		83.10*						74.17*
		(1.93)						(1.69)
IVOL			-34.72					8.66
			(-1.04)					(0.22)
NetLong × IVOL			44.93					-9.00
			(1.20)					(-0.21)
NetShort × IVOL			-51.10					-63.50*
			(-1.14)					(-1.71)
ShortInt				-26.10				-30.15
				(-0.77)				(-0.69)
NetLong × ShortInt				-40.60				-17.70
				(-0.88)				(-0.37)
NetShort × ShortInt				30.69				-10.19
				(0.73)				(-0.20)
Turnover					2.13			41.77
					(0.06)			(0.85)
NetLong × Turnover					-14.79			-15.93
					(-0.37)			(-0.33)
NetShort × Turnover					3.69			34.09
					(0.07)			(0.57)
Bid–Ask						-59.49*		-73.59**
						(-1.69)		(-2.11)
NetLong × Bid–Ask						73.45*		86.82**
						(1.85)		(2.32)
NetShort × Bid–Ask						-42.55		14.66
						(-0.84)		(0.29)
Amihud							-1.64	127.93
							(-0.02)	(1.51)
NetLong × Amihud							32.95	-30.44
							(0.73)	(-0.57)
NetShort × Amihud							-28.92	-9.16
							(-0.63)	(-0.16)
Total obs.	420803	345491	420624	374849	420724	420773	420720	340682
Avg. adj. R^2	0.054	0.059	0.059	0.060	0.060	0.060	0.059	0.077

Notes: Continues Table 15. Coefficients are in bps. Newey–West t-statistics with lag 3 are reported in parentheses. *, **, *** denote 10%, 5%, and 1% significance.

only the current cost of borrowing but also the instability of borrow access.

Taken together, the anomaly results support a short-side arbitrage interpretation. Borrowing fees matter, but the strongest return predictability appears where borrow access is fragile and where arbitrage requires short positions.

8 Conclusion

This paper identifies lendable inventory concentration as a state variable for borrow fragility. Borrowing fees capture the spot cost of borrowing shares, but short arbitrage also depends on whether borrow access can be maintained until mispricing corrects. IC captures this durability margin by measuring the concentration of lendable supply across lenders.

The empirical evidence supports this borrow-fragility channel. First, high-IC stocks exhibit greater instability in borrowing conditions after controlling for borrowing fees, shorting demand, lendable supply, and standard firm characteristics. Second, negative earnings news is incorporated more slowly among high-IC stocks, while the response to positive news is much weaker. Because the specification controls for borrowing fees, this result is not merely a high-borrowing-cost effect; it suggests a borrow-fragility component of short-sale constraints that is captured by IC and distinct from the current price of borrowing shares. Third, anomaly return spreads are larger among high-IC stocks, and the High–Low difference is driven primarily by the short leg. These spreads remain economically large after CAPM adjustment, size–liquidity benchmarking, and explicit fee adjustment.

The broader implication is that effective short-sale constraints are dynamic. They depend not only on how expensive shares are to borrow today, but also on whether borrow access can be maintained until overpricing is corrected. The paper therefore links the structure of lendable supply to short-selling risk as a durability margin that limits short-sale arbitrage.

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A Summary Statistics of Lendable Inventory Concentration

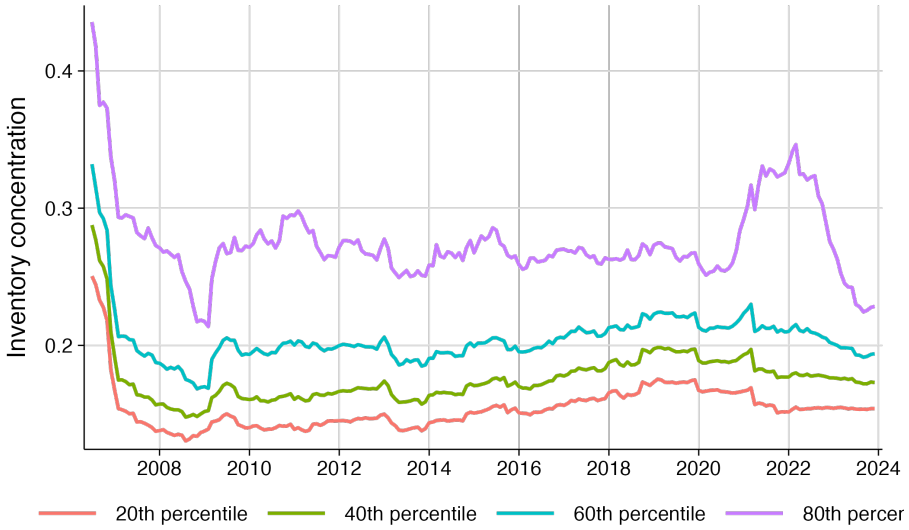


Figure 6: Time-Series Evolution of Lendable Inventory Concentration

Notes: This figure plots the time-series evolution of the cross-sectional distribution of lendable inventory concentration (IC) in the IHS Markit data from 2007 to 2023. IC is first averaged from daily observations to the stock-month level. Higher values indicate that lendable inventory is concentrated among fewer lenders.

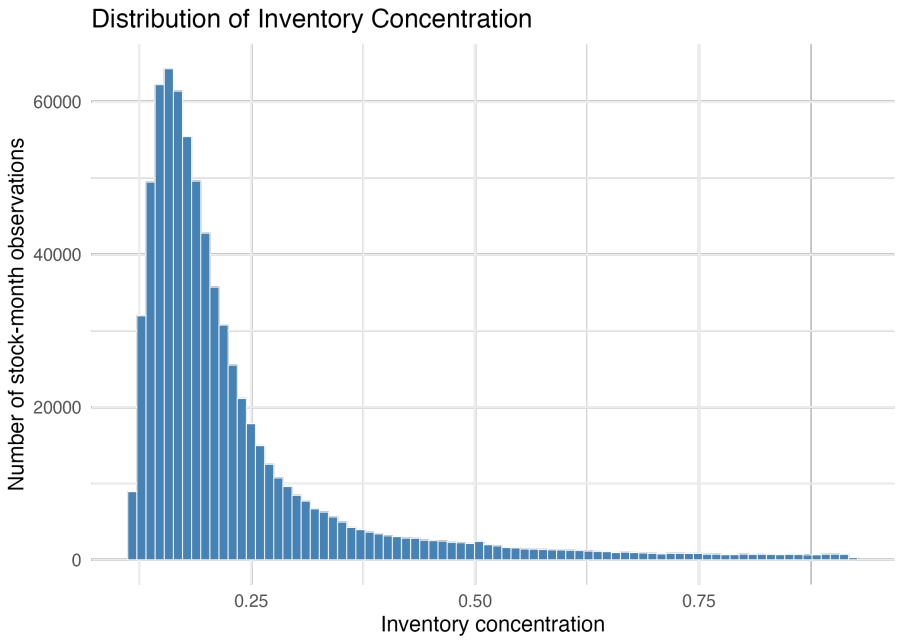


Figure 7: Distribution of Inventory Concentration

Note: This figure plots the distribution of inventory concentration, $IC_{i,t}$, in the stock-month sample. Inventory concentration measures the concentration of lendable inventory across securities lenders. The histogram is trimmed at the 1st and 99th percentiles for readability. The figure shows that inventory concentration varies substantially across stock-month observations.

Table 16: Persistence of Inventory Concentration

Panel A. Autocorrelation of Inventory Concentration

Horizon	Autocorrelation
1 month	0.950
3 months	0.886
6 months	0.817
12 months	0.726

Panel B. Between- and Within-Stock Variance Decomposition

Component	Variance	Share of Total (%)
Total variance	0.0228	100.00
Between-stock variance	0.0150	65.55
Within-stock variance	0.0079	34.45

Notes: Both panels use the stock-month average of inventory concentration (IC). Panel A reports the average within-stock autocorrelation of IC at the indicated horizons, computed as the mean across stocks of each stock's serial correlation at the corresponding lag. Panel B decomposes the total variance of the stock-month IC panel into a between-stock component (the variance of stock-level means) and a within-stock component (the variance of IC around each stock's mean). By construction, the between- and within-stock components sum to the total variance. The high autocorrelation reported in Panel A, together with the predominance of between-stock variation in Panel B, indicates that IC is a persistent characteristic that varies primarily across stocks rather than within stocks over time. Accordingly, the main specifications employ FF49 industry fixed effects rather than stock fixed effects, which would absorb much of the economically relevant cross-sectional variation in IC.

B Specialization in Fund-Stock Securities Lending

Table 17: Specialization in Fund-Stock Securities Lending

Panel A. Extensive margin: position on loan

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent variable	On loan indicator						
Affiliated lending agent							0.0308***
							(0.0010)
Nonaffiliated lending agent							0.0175***
							(0.0004)
Fund FE	Yes	No	Yes	No	No	No	No
Stock FE	No	Yes	Yes	No	No	No	No
Fund-stock FE	No	No	No	Yes	Yes	Yes	Yes
Month FE	No	No	No	Yes	No	No	No
R^2	0.160	0.168	0.292	0.539	0.537	0.835	0.538
Within R^2							0.001
Observations	9,677,087	9,677,087	9,677,087	9,677,087	9,677,087	570,838	9,677,087

Panel B. Intensive margin: loan share

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent variable	Loan share						
Affiliated lending agent							0.0332***
							(0.0041)
Nonaffiliated lending agent							0.0504***
							(0.0023)
Fund FE	Yes	No	Yes	No	No	No	No
Stock FE	No	Yes	Yes	No	No	No	No
Fund-stock FE	No	No	No	Yes	Yes	Yes	Yes
Month FE	No	No	No	Yes	No	No	No
R^2	0.277	0.191	0.376	0.632	0.628	0.866	0.629
Within R^2							0.002
Observations	603,777	603,777	603,777	603,777	603,777	50,965	603,777

Notes: This table reports fixed-effect decompositions of securities-lending outcomes at the fund-stock-position level using N-PORT filings. Panel A uses an indicator equal to one if a fund-stock position is on loan. Panel B uses the share of the position that is on loan. Fund fixed effects are defined by fund series identifier. Stock fixed effects are defined by CUSIP. Fund-stock fixed effects are defined at the fund-stock pair level. Column (6) restricts the sample to observations with either an affiliated or nonaffiliated lending agent. Column (7) includes lending-agent indicators while controlling for fund-stock pair fixed effects; standard errors are clustered by fund-stock pair. Significance levels: ***, **, and * for the 1%, 5%, and 10% levels.

C Additional Evidence on Inventory Concentration, Borrowing Costs, and Short-Selling Risk

This appendix reports additional evidence on the relation between lendable inventory concentration, borrowing costs, and short-selling risk. The first set of tests examines whether inventory concentration is related to the level of borrowing costs. The second set shows that the lendable-quantity disruption results are robust to using a more inclusive 5% disruption threshold. The final set re-estimates the main specifications with stock fixed effects, identifying the IC coefficient only from within-stock changes in inventory concentration.

C.1 Inventory Concentration and Borrowing Costs

Before turning to borrowing-risk outcomes, I first examine whether inventory concentration is related to the level of borrowing costs. The fee-level regression is

$$\text{BorrowFee}_{i,t} = \lambda_{j(i)} + \tau_t + \beta_1 \text{IC}_{i,t-1} + \beta_2 \text{LQS}_{i,t-1} + \Gamma' X_{i,t-1} + \varepsilon_{i,t}, \tag{5}$$

where $\lambda_{j(i)}$ denotes FF49 industry fixed effects and τ_t denotes month fixed effects. The vector $X_{i,t-1}$ includes utilization, log market equity, book-to-market, institutional ownership, prior six-month returns, turnover, bid–ask spread, and lendable quantity. Table 18 reports the results. Inventory concentration is positively related to average borrowing fees. In column (1), which includes IC, LQS, month fixed effects, and FF49 fixed effects, the coefficient on IC is 4.055 and statistically significant. In column (2), the coefficient remains positive and statistically significant after adding the full set of controls. This evidence suggests that stocks with more concentrated lendable inventory face higher borrowing costs.

Table 18: Inventory Concentration and Borrowing Fees

	(1)	(2)
Dep. variable:	BorrowFee	BorrowFee
Controls	No	Yes
IC	4.055***	3.217***
	(0.146)	(0.165)
LQS	−0.354***	−0.285***
	(0.071)	(0.084)
Utilization		0.036***
		(0.001)
Log(ME)		0.000
		(0.013)
BM		−0.000
		(0.000)
IOR		−0.503***
		(0.049)
Ret(−6, −1)		−0.024
		(0.016)
Turnover		0.015
		(0.010)
BidAsk		0.133***
		(0.017)
LQ		−1.021***
		(0.095)
Month FE	Yes	Yes
FF49 FE	Yes	Yes
Observations	719,504	527,361
R^2	0.159	0.351
Within adj. R^2	0.115	0.327

This table reports panel regressions of borrowing fees on lagged inventory concentration and the stable lendable quantity share. Column (1) includes IC, LQS, month fixed effects, and FF49 industry fixed effects. Column (2) additionally controls for utilization, log market equity, book-to-market, institutional ownership, prior six-month returns, turnover, bid–ask spread, and lendable quantity. Standard errors are clustered by stock and month and reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels.

C.2 Lendable Inventory Concentration and Quantity Disruption at 5% level

The main text defines lendable-quantity disruptions using a 10% daily decline threshold. To show that the results are not specific to this threshold, I repeat the disruption tests using a 5% threshold. This lower threshold captures a broader set of supply contractions and therefore provides a more inclusive measure of lendable-supply fragility. Tables 19 and 20 report the results. The evidence is very similar to the baseline 10% threshold results. Inventory concentration positively predicts the number of active-lendable-quantity disruptions, the number of joint ALQ–OLQ disruptions, and the probability that a stock-month experiences at least one joint disruption. The coefficients remain positive and statistically significant after controlling for utilization, borrowing fees, firm size, book-to-market, institutional ownership, prior returns, turnover, bid–ask spreads, and lendable quantity. The intensive-margin results tell the same story. Conditional on experiencing an ALQ disruption, high-IC stocks have larger average ALQ drops. In Table 20, the coefficient on IC is positive and statistically significant both without and with controls. These results reinforce the borrow fragility channel: concentrated lendable inventory predicts not only more frequent disruptions, but also larger supply contractions when disruptions occur.

Table 19: Inventory Concentration and Next-Month Lendable-Quantity Disruptions: 5% Threshold

Dep. var.:	(1) ALQ ct (5%)	(2) ALQ ct (5%)	(3) Joint ct (5%)	(4) Joint ct (5%)	(5) Any joint (5%)	(6) Any joint (5%)
IC	3.369***	2.609***	1.834***	1.576***	0.711***	0.556***
	(0.132)	(0.173)	(0.089)	(0.122)	(0.028)	(0.035)
LQS	−0.621***	−0.480***	−0.240***	−0.228***	−0.120***	−0.096***
	(0.062)	(0.070)	(0.039)	(0.052)	(0.011)	(0.013)
Utilization		0.797***		0.114***		0.143***
		(0.068)		(0.041)		(0.014)
BorrowingFee		−0.444**		−0.228**		−0.216***
		(0.224)		(0.103)		(0.044)
Log(ME)		0.064***		0.033***		0.014***
		(0.012)		(0.008)		(0.002)
BM		−0.000		0.000		−0.000
		(0.000)		(0.000)		(0.000)
IOR		−0.291***		−0.111***		−0.046***
		(0.037)		(0.022)		(0.008)
Ret(−6, −1)		0.034***		0.030***		0.010***
		(0.013)		(0.009)		(0.003)
Turnover		0.048***		0.021***		0.011***
		(0.007)		(0.003)		(0.001)
BidAsk		0.110***		0.033***		0.021***
		(0.012)		(0.007)		(0.002)
LQ		−1.908***		−0.976***		−0.382***
		(0.124)		(0.067)		(0.024)
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
FF49 FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	710,928	517,268	710,928	517,268	710,928	517,268
Within adj. R^2	0.113	0.184	0.085	0.120	0.090	0.129

This table reports panel regressions of next-month lendable-quantity disruptions using the 5% threshold. ALQ ct (5%) counts the number of days in month t on which active lendable quantity falls by more than 5% from the previous trading day. Joint ct (5%) counts the number of days on which both active lendable quantity and quantity on loan fall by more than 5%. Any joint (5%) is an indicator for whether the stock-month has at least one joint ALQ–OLQ disruption greater than 5%. Odd-numbered columns include only IC and LQS as regressors; even-numbered columns additionally control for utilization, borrowing fee, size, book-to-market, institutional ownership, prior six-month returns, turnover, bid–ask spread, and lendable quantity. All specifications include month and FF49 fixed effects. Standard errors are clustered by month and stock. *, **, and *** denote significance at the 10%, 5%, and 1% levels.

Table 20: Inventory Concentration and Next-Month Lendable-Quantity Disruptions: Conditional Size, 5% Threshold

	(1)	(2)
Dep. var.:	ALQ drop size (%)	ALQ drop size (%)
IC	48.333***	33.409***
	(1.489)	(2.190)
LQS	3.811***	3.571***
	(0.856)	(1.129)
Utilization		−34.070***
		(1.649)
BorrowingFee		23.248***
		(3.717)
Log(ME)		1.032***
		(0.217)
BM		0.000
		(0.001)
IOR		−6.829***
		(1.215)
Ret(−6, −1)		0.503**
		(0.222)
Turnover		−0.467***
		(0.084)
BidAsk		−0.024
		(0.217)
LQ		−35.895***
		(4.059)
Month FE	Yes	Yes
FF49 FE	Yes	Yes
Observations	173,506	107,325
Within adj. R^2	0.101	0.193

This table reports panel regressions of next-month ALQ disruption size using the 5% threshold. The dependent variable is the stock-month average absolute percentage drop in ALQ, computed over all days in month t on which ALQ falls by more than 5% from the previous trading day. The sample is restricted to stock-months with at least one such ALQ drop, so the estimates capture the intensive margin conditional on a disruption. Column (1) includes only IC and LQS as regressors; column (2) additionally controls for utilization, borrowing fee, size, book-to-market, institutional ownership, prior six-month returns, turnover, bid–ask spread, and lendable quantity. All specifications include month and FF49 fixed effects. Standard errors are clustered by month and stock. *, **, and *** denote significance at the 10%, 5%, and 1% levels.

C.3 Robustness: Stock Fixed Effects

The main specifications use industry (FF49) and month fixed effects, exploiting the predominantly cross-sectional variation in inventory concentration documented in Table 16: about two-thirds of the variance of IC is between stocks, and its one-month autocorrelation is 0.95. This appendix re-estimates every main result with stock fixed effects, which absorb all time-invariant firm characteristics and identify the IC coefficient from within-stock variation alone. Although this uses only the smaller within-stock component of IC's variation, the relationships are robust throughout. Inventory concentration continues to predict more frequent and more severe lendable-quantity disruptions (Tables 21–24), a higher level of borrowing fees (Table 25), greater fee-volatility and fee-tail risk (Table 26), greater utilization-tail risk, and shorter average loan tenure (Table 27).

As in the main specifications, ordinary utilization volatility behaves differently from the tail measures. Inventory concentration shows no robust relationship with UtilVar: the coefficient is economically small and changes sign across specifications—weakly positive under industry fixed effects and weakly negative under stock fixed effects (-0.334)—in sharp contrast to its consistently positive and significant relationship with utilization-tail risk. This sign instability is itself evidence that concentration does not predict smooth, normal-times variation in utilization, reinforcing the interpretation that concentration matters for tail states—abrupt disruptions, fee spikes, and extreme utilization pressure—rather than for routine fluctuations in lending-market tightness.

The utilization-tail result is the one outcome that is sensitive to the inclusion of stock fixed effects. In the cross-sectional (industry fixed-effects) specifications of the main text, concentration is positively and significantly associated with utilization-tail risk, consistent with the other fragility measures. Under stock fixed effects, the within-stock IC coefficient is negative without controls (-7.588) and positive once the utilization level is held fixed (4.839); because utilization and utilization-tail risk are mechanically close, this sign sensitivity is unsurprising, and I therefore rely on the cross-sectional estimate rather than the within-stock one. This is also consistent with the high persistence of inventory concentration, whose effects are identified primarily from cross-sectional variation. The paper's central findings—the disruption, fee-instability, and loan-tenure results—are robust across both specifications. Taken together, the persistence of these results under stock fixed effects indicates that they are not driven by time-invariant firm characteristics.

Table 21: Inventory Concentration and Next-Month Lendable-Quantity Disruptions (Stock Fixed Effects)

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. var.:	ALQ ct (10%)	ALQ ct (10%)	Joint ct (10%)	Joint ct (10%)	Any joint (10%)	Any joint (10%)
IC	1.370***	1.206***	0.738***	0.630***	0.321***	0.279***
	(0.085)	(0.125)	(0.054)	(0.078)	(0.020)	(0.027)
LQS	−0.349***	−0.217***	−0.148***	−0.082**	−0.065***	−0.033***
	(0.044)	(0.052)	(0.025)	(0.034)	(0.009)	(0.011)
Utilization		0.002***		−0.001***		0.000*
		(0.000)		(0.000)		(0.000)
Borrowing fee		0.085		0.138*		−0.044
		(0.137)		(0.075)		(0.029)
Log(ME)		0.055***		0.024***		0.010***
		(0.009)		(0.006)		(0.002)
BM		0.000*		0.000**		0.000*
		(0.000)		(0.000)		(0.000)
IOR		−0.228***		−0.052***		−0.027***
		(0.031)		(0.016)		(0.007)
Ret(−6, −1)		0.056***		0.030***		0.014***
		(0.016)		(0.009)		(0.004)
Turnover		0.017***		0.003		0.004***
		(0.005)		(0.002)		(0.001)
BidAsk		0.010		−0.001		−0.000
		(0.006)		(0.004)		(0.002)
LQ		−1.201***		−0.618***		−0.257***
		(0.153)		(0.081)		(0.031)
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Stock FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	717,546	521,643	717,546	521,643	717,546	521,643
Within adj. R^2	0.016	0.025	0.012	0.015	0.013	0.017

This table reports panel regressions of next-month lendable-quantity disruptions using the 10% threshold, with stock fixed effects. ALQ ct (10%) counts the number of days in month t on which active lendable quantity falls by more than 10% from the previous trading day. Joint ct (10%) counts the number of days on which both active lendable quantity and quantity on loan fall by more than 10%. Any joint (10%) is an indicator for whether the stock-month has at least one joint ALQ–OLQ disruption greater than 10%. Odd-numbered columns include only IC and LQS as regressors; even-numbered columns additionally control for utilization, borrowing fee, size, book-to-market, institutional ownership, prior six-month returns, turnover, bid–ask spread, and lendable quantity. All specifications include month and stock fixed effects. Standard errors are clustered by stock and month. *, **, and *** denote significance at the 10%, 5%, and 1% levels.

Table 22: Inventory Concentration and Next-Month Lendable-Quantity Disruptions: Conditional Size (Stock Fixed Effects)

Dep. var.:	(1) ALQ drop size (%)	(2) ALQ drop size (%)
IC	31.286***	23.967***
	(1.373)	(2.193)
LQS	0.700	0.668
	(0.845)	(1.230)
Utilization		−0.345***
		(0.017)
Borrowing fee		−13.776***
		(4.673)
Log(ME)		0.377
		(0.242)
BM		−0.001
		(0.001)
IOR		−1.119
		(1.600)
Ret(−6, −1)		0.300
		(0.237)
Turnover		−0.260***
		(0.095)
BidAsk		−0.259
		(0.213)
LQ		−24.555***
		(5.746)
Month FE	Yes	Yes
Stock FE	Yes	Yes
Observations	123,512	73,385
Within adj. R^2	0.027	0.081

This table reports panel regressions of next-month ALQ disruption size using the 10% threshold, with stock fixed effects. The dependent variable is the stock-month average absolute percentage drop in ALQ, computed over all days in month t on which ALQ falls by more than 10% from the previous trading day. The sample is restricted to stock-months with at least one such ALQ drop, so the estimates capture the intensive margin conditional on a disruption. Column (1) includes only IC and LQS as regressors; column (2) additionally controls for utilization, borrowing fee, size, book-to-market, institutional ownership, prior six-month returns, turnover, bid–ask spread, and lendable quantity. All specifications include month and stock fixed effects. Standard errors are clustered by stock and month. *, **, and *** denote significance at the 10%, 5%, and 1% levels.

Table 23: Inventory Concentration and Next-Month Lendable-Quantity Disruptions: 5% Threshold (Stock Fixed Effects)

Dep. var.:	(1) ALQ ct (5%)	(2) ALQ ct (5%)	(3) Joint ct (5%)	(4) Joint ct (5%)	(5) Any joint (5%)	(6) Any joint (5%)
IC	1.465***	1.339***	0.944***	0.821***	0.335***	0.307***
	(0.108)	(0.155)	(0.072)	(0.104)	(0.023)	(0.030)
LQS	−0.453***	−0.285***	−0.200***	−0.105**	−0.082***	−0.047***
	(0.055)	(0.064)	(0.033)	(0.044)	(0.010)	(0.013)
Utilization		0.007***		0.001***		0.001***
		(0.001)		(0.000)		(0.000)
Borrowing fee		0.067		−0.112		−0.148***
		(0.199)		(0.108)		(0.039)
Log(ME)		0.075***		0.036***		0.016***
		(0.012)		(0.007)		(0.002)
BM		0.000*		0.000*		0.000
		(0.000)		(0.000)		(0.000)
IOR		−0.341***		−0.109***		−0.052***
		(0.043)		(0.023)		(0.009)
Ret(−6, −1)		0.073***		0.049***		0.019***
		(0.020)		(0.013)		(0.004)
Turnover		0.045***		0.016***		0.011***
		(0.007)		(0.004)		(0.002)
BidAsk		0.028***		0.010*		0.005***
		(0.009)		(0.005)		(0.002)
LQ		−1.551***		−0.890***		−0.324***
		(0.199)		(0.113)		(0.039)
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Stock FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	717,546	521,643	717,546	521,643	717,546	521,643
Within adj. R^2	0.012	0.030	0.011	0.018	0.009	0.020

This table reports panel regressions of next-month lendable-quantity disruptions using the 5% threshold, with stock fixed effects. ALQ ct (5%) counts the number of days in month t on which active lendable quantity falls by more than 5% from the previous trading day. Joint ct (5%) counts the number of days on which both active lendable quantity and quantity on loan fall by more than 5%. Any joint (5%) is an indicator for whether the stock-month has at least one joint ALQ–OLQ disruption greater than 5%. Odd-numbered columns include only IC and LQS as regressors; even-numbered columns additionally control for utilization, borrowing fee, size, book-to-market, institutional ownership, prior six-month returns, turnover, bid–ask spread, and lendable quantity. All specifications include month and stock fixed effects. Standard errors are clustered by stock and month. *, **, and *** denote significance at the 10%, 5%, and 1% levels.

Table 24: Inventory Concentration and Next-Month Lendable-Quantity Disruptions: Conditional Size, 5% Threshold (Stock Fixed Effects)

Dep. var.:	(1) ALQ drop size (%)	(2) ALQ drop size (%)
IC	33.734***	28.476***
	(1.270)	(2.032)
LQS	0.131	0.893
	(0.790)	(1.200)
Utilization		−0.257***
		(0.013)
Borrowing fee		3.837
		(3.788)
Log(ME)		0.701***
		(0.186)
BM		0.000
		(0.001)
IOR		−4.360***
		(1.301)
Ret(−6, −1)		0.416
		(0.259)
Turnover		−0.171**
		(0.082)
BidAsk		−0.423**
		(0.192)
LQ		−27.494***
		(5.396)
Month FE	Yes	Yes
Stock FE	Yes	Yes
Observations	177,424	109,577
Within adj. R^2	0.029	0.062

This table reports panel regressions of next-month ALQ disruption size using the 5% threshold, with stock fixed effects. The dependent variable is the stock-month average absolute percentage drop in ALQ, computed over all days in month t on which ALQ falls by more than 5% from the previous trading day. The sample is restricted to stock-months with at least one such ALQ drop, so the estimates capture the intensive margin conditional on a disruption. Column (1) includes only IC and LQS as regressors; column (2) additionally controls for utilization, borrowing fee, size, book-to-market, institutional ownership, prior six-month returns, turnover, bid–ask spread, and lendable quantity. All specifications include month and stock fixed effects. Standard errors are clustered by stock and month. *, **, and *** denote significance at the 10%, 5%, and 1% levels.

Table 25: Inventory Concentration and Borrowing Fees: Stock Fixed Effects

	(1)	(2)
Dep. variable	BorrowFee	BorrowFee
IC	1.756***	1.861***
	(0.112)	(0.151)
LQS	−0.112*	−0.149**
	(0.060)	(0.070)
Utilization		0.033***
		(0.001)
Log(ME)		0.031**
		(0.012)
BM		0.000
		(0.000)
IOR		−0.505***
		(0.050)
Ret(−6, −1)		−0.002
		(0.010)
Turnover		0.006
		(0.012)
BidAsk		0.068***
		(0.011)
LQ		−0.688***
		(0.108)
Month FE	Yes	Yes
Stock FE	Yes	Yes
Observations	727,022	532,404
R^2	0.510	0.574
Within adj. R^2	0.014	0.153

Note: This table reports stock-month panel regressions of borrowing fees on lagged inventory concentration and the stable lendable quantity share. Column (1) includes IC, LQS, month fixed effects, and stock fixed effects. Column (2) adds the full set of controls. Standard errors are clustered by stock and month and reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels.

Table 26: Inventory Concentration and Borrowing-Fee Risk: Stock Fixed Effects

	FeeVar		FeeTail	
	(1)	(2)	(3)	(4)
IC	3.278***	3.176***	3.427***	3.609***
	(0.138)	(0.217)	(0.174)	(0.253)
LQS		−0.587***		−0.360***
		(0.104)		(0.118)
Utilization		0.029***		0.044***
		(0.001)		(0.002)
BorrowFee		1.657***		0.260
		(0.450)		(0.549)
Log(ME)		0.107***		0.060***
		(0.021)		(0.019)
BM		0.000		0.000
		(0.000)		(0.000)
IOR		−1.200***		−0.949***
		(0.119)		(0.089)
Ret(−6, −1)		0.079***		0.027*
		(0.022)		(0.016)
Turnover		0.027**		0.005
		(0.011)		(0.016)
BidAsk		0.115***		0.096***
		(0.017)		(0.017)
LQ		−4.209***		−1.426***
		(0.555)		(0.220)
Month FE	Yes	Yes	Yes	Yes
Stock FE	Yes	Yes	Yes	Yes
Observations	576,585	406,735	576,585	406,735
R^2	0.493	0.544	0.482	0.547
Within adj. R^2	0.021	0.103	0.023	0.136

Note: This table reports stock-month panel regressions of borrowing-fee risk on lagged inventory concentration. Columns (1) and (3) include IC, month fixed effects, and stock fixed effects. Columns (2) and (4) add LQS and the full set of controls. Standard errors are clustered by stock and month and reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels.

Table 27: Inventory Concentration, Utilization Pressure, and Loan Tenure: Stock Fixed Effects

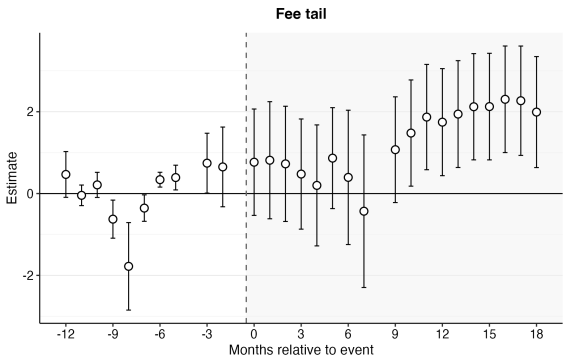
	UtilVar		UtilTail		AT	
	(1)	(2)	(3)	(4)	(5)	(6)
IC	-0.484^{***}	-0.334^{**}	-7.588^{***}	4.839^{***}	-35.069^{***}	-20.486^{***}
	(0.123)	(0.166)	(1.220)	(0.715)	(3.136)	(5.082)
LQS		-0.271^{***}		-2.788^{***}		36.750^{***}
		(0.083)		(0.361)		(3.605)
Utilization		0.041^{***}		0.972^{***}		0.642^{***}
		(0.001)		(0.004)		(0.032)
BorrowFee		3.654^{***}		13.438^{***}		20.028
		(0.409)		(1.365)		(13.266)
Log(ME)		-0.011		-0.022		3.763^{***}
		(0.013)		(0.053)		(0.756)
BM		0.000		0.000		-0.008^{**}
		(0.000)		(0.000)		(0.005)
IOR		-0.028		-1.486^{***}		10.281^{***}
		(0.089)		(0.249)		(3.141)
Ret$(-6,-1)$		0.084^{***}		-0.032		0.616
		(0.021)		(0.078)		(0.559)
Turnover		0.172^{***}		0.527^{***}		-9.300^{***}
		(0.019)		(0.061)		(1.001)
BidAsk		0.057^{***}		0.150^{**}		-0.362
		(0.013)		(0.058)		(0.537)
LQ		-3.273^{***}		-7.693^{***}		40.972^{***}
		(0.466)		(1.125)		(7.775)
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Stock FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	576,585	406,735	576,585	406,735	727,022	524,613
R^2	0.465	0.530	0.548	0.898	0.231	0.249
Within adj. R^2	0.000	0.135	0.001	0.756	0.002	0.025

Note: This table reports stock-month panel regressions of utilization-based fragility and average loan tenure on lagged inventory concentration. Columns (1), (3), and (5) include IC, month fixed effects, and stock fixed effects. Columns (2), (4), and (6) add LQS and the full set of controls. Standard errors are clustered by stock and month and reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels.

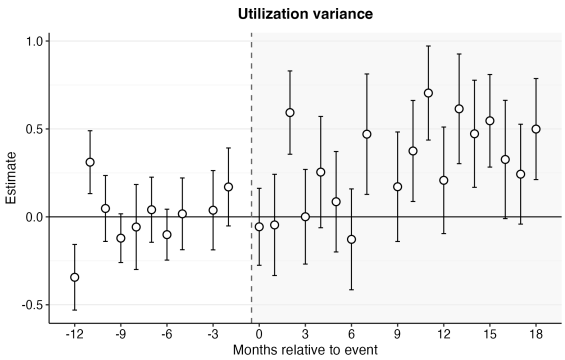
C.4 Additional Event-Study Results for the Janus–Henderson Merger

Figure 8 reports additional event-study estimates for borrow-fragility outcomes around the Janus–Henderson merger. These outcomes complement the main-text evidence by showing whether treated stocks also experience greater fee-tail risk and utilization-based instability after the merger.

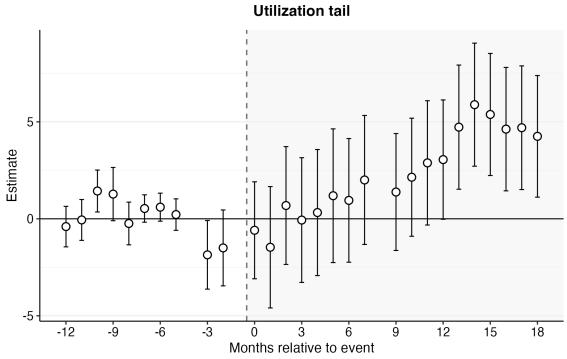
Figure 8: Janus–Henderson Merger: Additional Borrow-Fragility Outcomes



(a) Fee tail



(b) Utilization variance



(c) Utilization tail

Notes: This figure reports additional event-study estimates around the Janus–Henderson merger. Treated stocks are those with large pre-merger ownership by both Janus and Henderson. Control stocks are those with zero average pre-merger ownership by both Janus and Henderson. Panel A reports fee-tail events. Panels B and C report utilization-based borrow-fragility outcomes. The omitted month is May 2017, and June 2017 is the first full post-merger month. The shaded region denotes the post-merger period. Regressions include stock and month fixed effects. Standard errors are two-way clustered by stock and month.

D Additional Earnings-Announcement Results

Table 28: Earnings-Announcement Returns and Post-Announcement Drift by News Sign and Inventory Concentration

Horizon	**Negative News**		**Positive News**	
	High IC	**Low IC**	**High IC**	**Low IC**
$[-1,+1]$	-4.08	-4.11	4.51	4.07
	[-4.26, -3.91]	[-4.25, -3.97]	[4.30, 4.71]	[3.94, 4.20]
$[+2,+5]$	-8.24	-6.82	7.32	6.70
	[-8.54, -7.93]	[-7.00, -6.64]	[6.94, 7.71]	[6.51, 6.90]
$[+2,+10]$	-9.62	-7.01	7.48	6.93
	[-10.04, -9.20]	[-7.24, -6.79]	[7.00, 7.95]	[6.70, 7.16]
$[+2,+15]$	-11.35	-7.29	7.88	7.17
	[-11.87, -10.83]	[-7.56, -7.02]	[7.30, 8.46]	[6.90, 7.45]
$[+2,+20]$	-13.13	-7.65	8.10	7.58
	[-13.75, -12.50]	[-7.95, -7.34]	[7.45, 8.76]	[7.27, 7.89]
$[+2,+30]$	-16.75	-8.19	7.88	7.84
	[-17.59, -15.92]	[-8.56, -7.81]	[7.07, 8.69]	[7.46, 8.22]
$[+2,+40]$	-20.44	-9.12	7.47	8.07
	[-21.45, -19.42]	[-9.57, -8.67]	[6.51, 8.44]	[7.62, 8.52]
$[+2,+50]$	-23.91	-10.02	6.41	7.92
	[-25.09, -22.73]	[-10.55, -9.49]	[5.28, 7.53]	[7.40, 8.44]
$[+2,+60]$	-27.54	-10.91	5.19	7.83
	[-28.86, -26.22]	[-11.52, -10.30]	[3.94, 6.44]	[7.24, 8.43]
$[+2,+90]$	-36.70	-13.48	1.49	7.28
	[-38.36, -35.03]	[-14.33, -12.63]	[-0.15, 3.12]	[6.48, 8.08]
$[+2,+120]$	-43.40	-16.85	-2.60	6.04
	[-45.31, -41.50]	[-17.91, -15.80]	[-4.51, -0.69]	[5.05, 7.02]

Notes: The first row reports mean announcement-window abnormal returns $CAR^{CAPM}_{[-1,+1]}$ in percent. Subsequent rows report mean post-announcement abnormal returns $CAR^{CAPM}_{[+2,+h]}$ relative to the announcement-window return, in percent. Brackets report 95% confidence intervals. Positive-news events are the top 30% of positive announcement-window abnormal returns, and negative-news events are the bottom 30% of negative announcement-window abnormal returns. High IC and Low IC denote the top and bottom quintiles of inventory concentration.

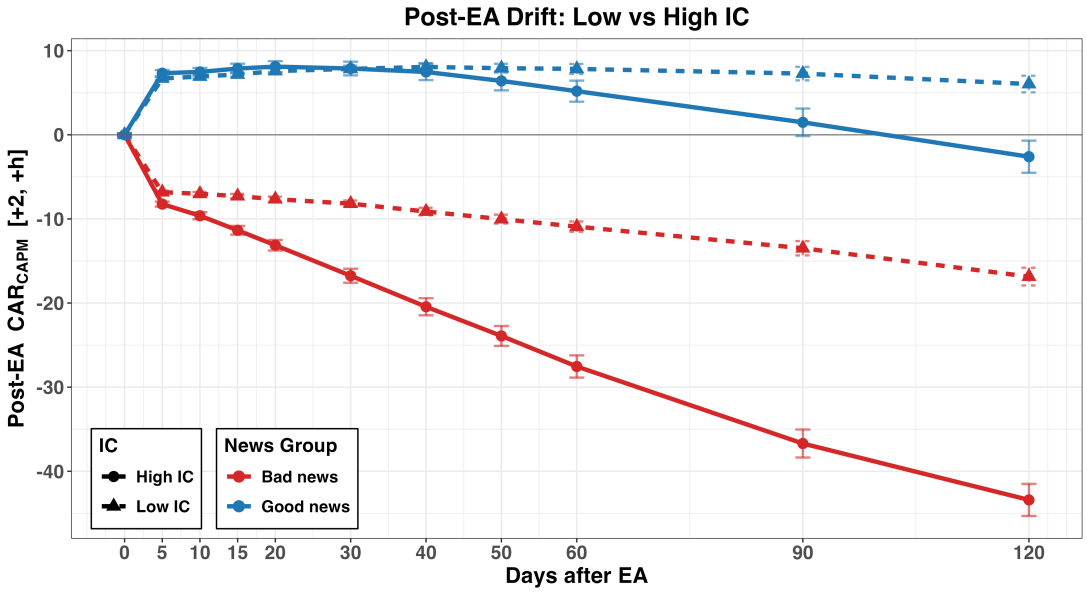


Figure 9: Asymmetric post–earnings-announcement drift by inventory concentration. Positive-news events are defined each month as the top 30% of positive announcement-window $CAR^{CAPM}_{i,t,[-1,+1]}$; negative-news events are defined as the bottom 30% of negative announcement-window $CAR^{CAPM}_{i,t,[-1,+1]}$. High IC and Low IC denote the top and bottom quintiles of lendable inventory concentration.

Table 29: Baseline local-projection estimates of β_h on announcement-window news

News Group	5	10	15	20	30	40	50	60	90	120
Positive	0.038	0.055	0.066	0.092	0.122	0.144	0.136	0.129	0.023	-0.102
	(5.46)	(5.43)	(4.31)	(5.04)	(4.80)	(4.57)	(3.42)	(2.76)	(0.35)	(-1.08)
Negative	0.009	0.018	0.034	0.058	0.085	0.131	0.193	0.270	0.543	1.008
	(0.91)	(1.22)	(1.84)	(2.65)	(2.83)	(3.45)	(4.10)	(4.73)	(5.65)	(6.72)

Notes: This table reports β_h from the baseline local-projection specification:

$$CAR^{CAPM}_{i,t,[+2,+h]} = \eta_t + \beta_h CAR^{CAPM}_{i,t,[-1,+1]} + \varepsilon_{i,t,h}. \tag{A.1}$$

The dependent variable is $CAR^{CAPM}_{i,t,[+2,+h]}$, and the regressor is the announcement-window abnormal return $CAR^{CAPM}_{i,t,[-1,+1]}$. The specification includes calendar-month fixed effects. Estimates are reported separately for positive- and negative-news events. t-statistics are in parentheses. Standard errors are clustered by month and stock.

Table 30: Controlled local-projection estimates of β_h on announcement-window news

News Group	5	10	15	20	30	40	50	60	90	120
Positive	0.031	0.052	0.061	0.089	0.121	0.153	0.166	0.179	0.153	0.157
	(4.42)	(4.99)	(3.95)	(5.10)	(5.14)	(5.33)	(4.47)	(4.21)	(2.58)	(1.90)
Negative	-0.000	-0.004	0.002	0.021	0.023	0.053	0.085	0.118	0.244	0.474
	(-0.05)	(-0.31)	(0.13)	(1.11)	(0.90)	(1.60)	(2.13)	(2.45)	(3.24)	(4.17)

Notes: This table reports β_h from the controlled local-projection specification:

$$CAR^{CAPM}_{i,t,[+2,+h]} = \eta_t + \beta_h CAR^{CAPM}_{i,t,[-1,+1]} + \delta_h' Z_{i,t-1} + \varepsilon_{i,t,h}. \tag{A.2}$$

The dependent variable is $CAR^{CAPM}_{i,t,[+2,+h]}$, and the regressor is the announcement-window abnormal return $CAR^{CAPM}_{i,t,[-1,+1]}$. The specification includes calendar-month fixed effects and controls for lagged size, institutional ownership, idiosyncratic volatility, illiquidity, short interest, and the borrowing fee. Estimates are reported separately for positive- and negative-news events. t-statistics are in parentheses. Standard errors are clustered by stock and month.

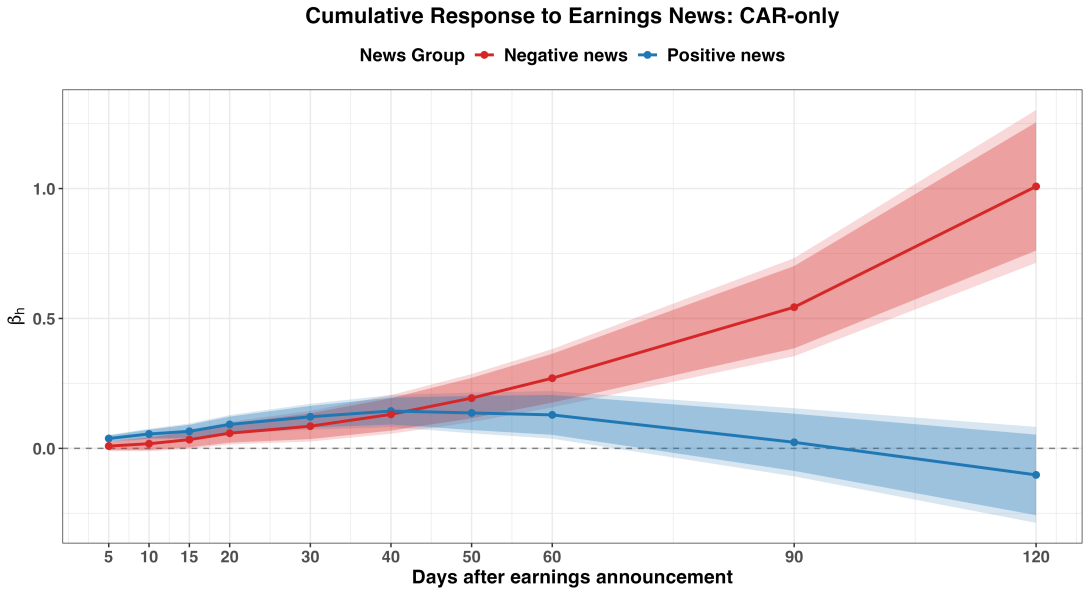


Figure 10: Baseline post-announcement response to announcement-window news. This figure plots β_h, the horizon-h coefficient on $CAR^{CAPM}_{i,t,[-1,+1]}$ from equation (A.1), where the dependent variable is $CAR^{CAPM}_{i,t,[+2,+h]}$. Estimates are reported separately for positive- and negative-news events.

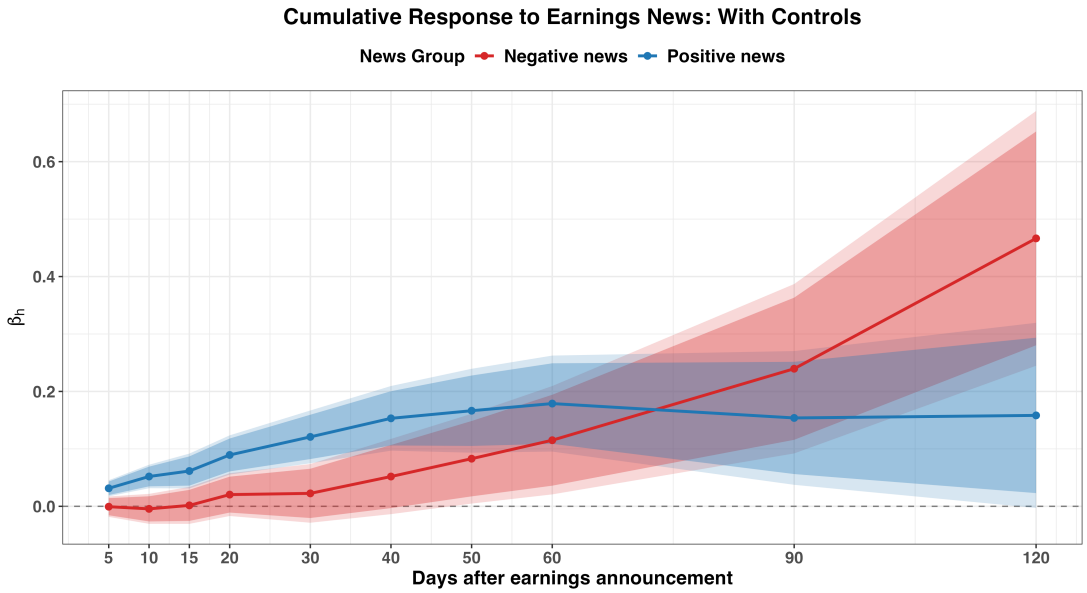


Figure 11: Controlled post-announcement response to announcement-window news. This figure plots β_h, the horizon-h coefficient on $CAR^{CAPM}_{i,t,[-1,+1]}$ from equation (A.2), where the dependent variable is $CAR^{CAPM}_{i,t,[+2,+h]}$. The specification includes calendar-month fixed effects and lagged controls. Estimates are reported separately for positive- and negative-news events.

E Additional Anomaly Portfolio Results

E.1 DGTW-Adjusted Anomaly Portfolio Results

This appendix details the size– and illiquidity-based characteristic adjustment used throughout Section 7 and reports the corresponding adjusted versions of the main anomaly results.

To ensure that cross-IC differences in anomaly payoffs do not simply reflect the size and liquidity composition of high-IC stocks, I construct DGTW-style characteristic-adjusted excess returns following Daniel et al. (1997). I form monthly benchmark portfolios on lagged market capitalization and lagged Amihud illiquidity using a 10×10 split: in each month, I first assign stocks to ten size portfolios using NYSE breakpoints, and then, within each size portfolio, to ten illiquidity portfolios. Let $b(i,t)$ denote the resulting size–illiquidity benchmark portfolio for stock i in month t. The value-weighted benchmark excess return is

$$r^{e,\text{bench}}_{b(i,t),t} = \sum_{j \in b(i,t)} \omega_{j,t-1} \left(r_{j,t} - r_{f,t} \right), \qquad \omega_{j,t-1} = \frac{ME_{j,t-1}}{\sum_{k \in b(i,t)} ME_{k,t-1}},$$

and the characteristic-adjusted excess return is

$$r^{e,\text{DGTW}}_{i,t} = (r_{i,t} - r_{f,t}) - r^{e,\text{bench}}_{b(i,t),t}.$$

These adjusted returns remove the component attributable to a stock's size–illiquidity benchmark, so that the anomaly comparisons across IC groups are not driven by mechanical differences in size or liquidity.

The size– and illiquidity-adjusted results mirror the excess-return results in the main text. Across the gross double sorts (Table 31), the fee-adjusted cluster results (Table 32), and the NetLeg portfolios (Table 33 and Figure 12), high-IC anomaly profitability remains large, concentrated on the short leg, and robust to explicit fee adjustment. The characteristic adjustment therefore confirms that the main-text findings do not reflect differences in the size or liquidity composition of high- and low-IC stocks.

Table 31: DGTW-adjusted anomaly return spreads by inventory concentration

Cluster	**High IC LS Ret.**	**Low IC LS Ret.**	**High–Low LS Ret.**	**Long Contri.**	**Short Contri.**
Value	0.88***	0.21	0.67***	0.14	-0.53***
	(2.94)	(0.99)	(2.69)	(0.95)	(-2.61)
Momentum	0.86***	0.09	0.77***	0.23	-0.54***
	(2.78)	(0.29)	(2.90)	(1.40)	(-2.74)
Profitability	0.71**	0.21	0.50*	0.06	-0.44*
	(2.25)	(1.12)	(1.82)	(0.40)	(-1.93)
Low Risk	0.71**	0.10	0.61**	0.17	-0.44**
	(2.21)	(0.46)	(2.55)	(1.24)	(-2.10)
Short-Term Reversal	0.67***	0.21	0.46**	0.03	-0.43***
	(3.15)	(1.26)	(2.20)	(0.17)	(-2.72)
Quality	0.67**	0.34*	0.32	0.01	-0.32
	(2.51)	(1.86)	(1.14)	(0.04)	(-1.29)
Profit Growth	0.65***	-0.00	0.66***	0.25*	-0.41**
	(3.57)	(-0.04)	(3.48)	(1.67)	(-2.57)
Investment	0.56***	0.15	0.41*	-0.04	-0.45**
	(2.71)	(0.92)	(1.79)	(-0.24)	(-2.55)
Debt Issuance	0.26	0.14	0.12	-0.10	-0.22
	(1.17)	(0.97)	(0.56)	(-0.61)	(-1.37)
Accruals	0.23	0.05	0.18	-0.06	-0.25
	(1.18)	(0.40)	(0.85)	(-0.35)	(-1.44)
Seasonality	0.14	0.22	-0.08	0.28	0.36**
	(0.67)	(1.37)	(-0.34)	(1.56)	(2.15)

Notes: Entries report monthly DGTW-adjusted anomaly returns, with t-statistics in parentheses on the line below. High IC and Low IC are long–short anomaly portfolios formed separately within high- and low-inventory-concentration stocks. High–Low is the difference between the two long–short return spreads. Long and Short decompose this difference into the corresponding long- and short-leg components. Because the short leg is subtracted in a long–short portfolio, negative values in the Short column imply that high-IC short-leg stocks earn lower DGTW-adjusted returns than low-IC short-leg stocks, thereby increasing the High–Low spread. *, **, and *** denote significance at the 10%, 5%, and 1% levels based on $|t|$.

Table 32: Fee-adjusted anomaly returns by inventory concentration (using DGTW-adjusted excess returns).

Cluster	**High IC**		**Low IC**		**High–Low**
	LS Ret.	α_{CAPM}	**LS Ret.**	α_{CAPM}	**LS Ret.**
Momentum	0.77**	1.06***	0.06	0.36	0.71***
	(2.51)	(3.59)	(0.21)	(1.28)	(2.66)
Value	0.71**	0.90***	0.19	0.22	0.52**
	(2.37)	(3.08)	(0.87)	(1.04)	(2.10)
Short-Term Reversal	0.62***	0.76***	0.20	0.23	0.42**
	(2.94)	(3.63)	(1.19)	(1.33)	(2.04)
Profit Growth	0.60***	0.59***	-0.02	0.02	0.62***
	(3.30)	(3.17)	(-0.17)	(0.17)	(3.30)
Low Risk	0.58*	0.99***	0.06	0.41**	0.52**
	(1.81)	(3.57)	(0.32)	(2.03)	(2.15)
Profitability	0.53*	0.73**	0.19	0.33*	0.34
	(1.68)	(2.33)	(0.99)	(1.75)	(1.25)
Quality	0.52**	0.59**	0.32*	0.43**	0.19
	(1.97)	(2.17)	(1.78)	(2.30)	(0.68)
Investment	0.48**	0.53**	0.14	0.16	0.34
	(2.31)	(2.52)	(0.81)	(0.91)	(1.51)
Debt Issuance	0.21	0.26	0.13	0.17	0.09
	(0.89)	(1.17)	(0.87)	(1.17)	(0.38)
Accruals	0.17	0.21	0.03	0.07	0.14
	(0.89)	(1.07)	(0.28)	(0.57)	(0.65)
Seasonality	0.09	0.14	0.21	0.17	-0.12
	(0.43)	(0.69)	(1.30)	(1.03)	(-0.50)

Notes: Entries report monthly DGTW- and fee-adjusted excess returns, with t-statistics in parentheses on the line below. High IC and Low IC denote anomaly portfolios formed separately within high- and low-inventory-concentration stocks. LS Ret. is the fee-adjusted long–short anomaly return after DGTW benchmark adjustment. α_{CAPM} is the corresponding CAPM alpha. The High − Low column reports the difference between high-IC and low-IC fee-adjusted long–short returns. *, **, and *** denote significance at the 10%, 5%, and 1% levels based on $|t|$.

Table 33: NetLeg portfolios: Low-IC vs. High-IC comparison using DGTW-adjusted returns. Returns, α, and borrow fees are in basis points.

Metric	Group	1	2	3	4	5	H–L
r	Low-IC	-18.80	7.20	19.30	14.40	15.30	34.10
		(-0.88)	(0.71)	(2.81)	(2.50)	(1.80)	(1.27)
	High-IC	-90.70	-25.10	20.90	20.10	52.00	143.00
		(-3.09)	(-1.62)	(1.91)	(1.76)	(3.43)	(3.54)
Avg. Fee	Low-IC	5.49	3.81	3.49	3.38	3.33	–
	High-IC	26.70	17.90	14.60	12.90	10.30	–
SR	Low-IC	-0.234	0.199	0.630	0.561	0.431	0.330
	High-IC	-0.786	-0.431	0.453	0.413	0.929	0.956
r^{feeadj}	Low-IC	-13.30	9.87	21.80	16.80	17.60	31.00
		(-0.62)	(0.97)	(3.17)	(2.90)	(2.07)	(1.16)
	High-IC	-64.00	-12.60	31.10	29.10	59.20	123.00
		(-2.19)	(-0.81)	(2.80)	(2.51)	(3.91)	(3.07)
SR^{feeadj}	Low-IC	-0.166	0.273	0.710	0.653	0.497	0.300
	High-IC	-0.556	-0.216	0.672	0.597	1.060	0.827
α_{CAPM}	Low-IC	-22.90	2.01	14.50	8.57	13.10	36.00
		(-1.12)	(0.20)	(1.79)	(1.06)	(1.41)	(1.52)
	High-IC	-55.90	-16.00	31.30	28.50	58.50	114.00
		(-1.79)	(-1.12)	(1.99)	(2.10)	(3.78)	(2.83)
$\alpha_{CAPM}^{\text{feeadj}}$	Low-IC	-17.40	4.73	17.00	10.90	15.40	32.80
		(-0.86)	(0.48)	(2.09)	(1.35)	(1.67)	(1.38)
	High-IC	-29.10	-3.47	41.40	37.60	65.60	94.70
		(-0.94)	(-0.25)	(2.59)	(2.72)	(4.23)	(2.36)
Num. Months	Low-IC	208	208	208	208	208	–
	High-IC	208	208	208	208	208	–
Avg. Num. Stocks	Low-IC	142	138	133	132	153	–
	High-IC	136	118	140	148	126	–

Notes: This table reports NetLeg portfolio returns by inventory-concentration group using DGTW-adjusted returns. Low-IC and High-IC denote portfolios formed within the low- and high-inventory-concentration subsamples, respectively. Columns 1–5 report anomaly-sorted portfolios and H–L reports the high-minus-low spread. Returns, CAPM alphas, and average borrowing fees are in basis points. r denotes returns before borrowing-fee adjustment, while r^{feeadj} subtracts borrowing fees from the short leg and adds discounted lending income to the long leg, as described in Section 7.4. SR denotes the Sharpe ratio. Entries in parentheses are t-statistics. For Avg. Fee, the t-statistic is reported only for the H–L fee difference.

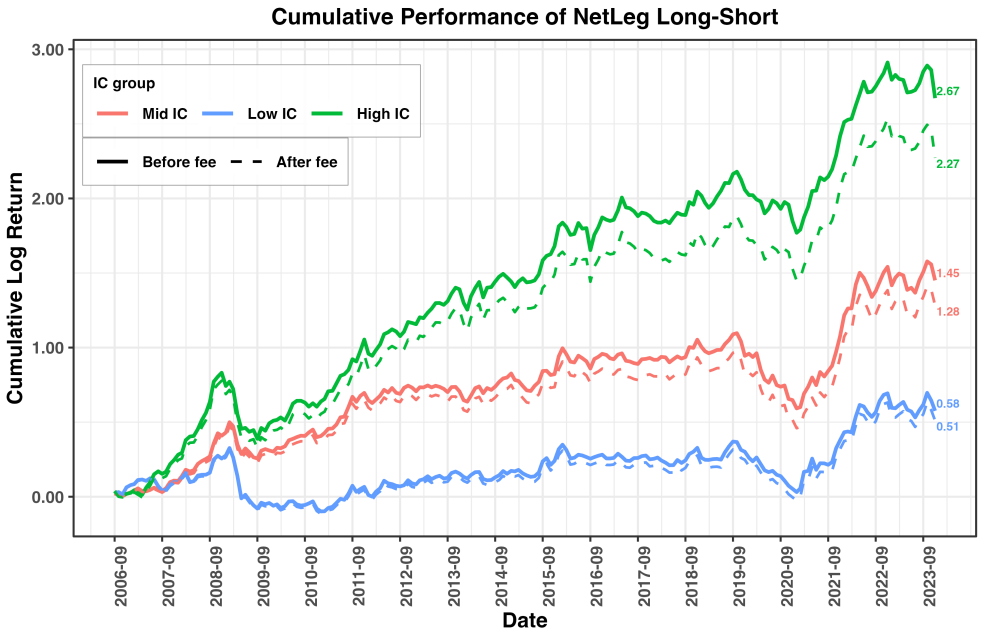


Figure 12: Cumulative log DGTW-adjusted returns of NetLeg portfolios (borrowing-fee adjustment applied to both short and long legs), 2006:08–2023:12. This is the DGTW counterpart to main-text Figure 5.

Table 34: Short-selling risk metrics across NetLeg quintiles for High vs. Low IC

Group	Metric	Q1	Q2	Q3	Q4	Q5
High IC	log(FeeVar)	-2.66	-3.29	-3.44	-3.52	-3.86
	log(UtilVar)	-0.767	0.008	-0.186	0.000	0.243
	FeeTail	4.80	3.59	3.11	2.86	2.23
	UtilTail	75.20	58.50	55.60	51.60	41.60
Low IC	log(FeeVar)	-5.90	-6.30	-6.34	-6.32	-6.29
	log(UtilVar)	0.556	-0.492	-0.950	-1.180	-1.440
	FeeTail	1.12	0.692	0.615	0.581	0.549
	UtilTail	31.50	18.50	14.20	12.30	10.90

Notes: This table reports short-selling risk metrics across NetLeg quintiles separately for High-IC and Low-IC stocks. FeeVar and UtilVar are log variance measures of borrowing fees and utilization. FeeTail denotes fee-tail risk, while UtilTail denotes utilization pressure.

Table 35: Short-Selling Risk Beyond Borrowing Fees: Panel and Fama–MacBeth

	Panel		Fama–MacBeth	
	Base	Full	Base	Full
Fee	-30.49*	-16.93	-27.24*	-5.44
	(-1.73)	(-0.90)	(-1.69)	(-0.33)
SSR	-84.74**	-88.57**	-110.35**	-131.47***
	(-2.07)	(-2.35)	(-2.29)	(-3.45)
Beta		42.83		31.89
		(1.02)		(0.67)
Size		39.62		35.03
		(1.63)		(1.34)
BM		38.18		-2.59
		(0.99)		(-0.07)
Controls	No	Yes	No	Yes
Time FE	Yes	Yes	No	No
FF49 FE	Yes	Yes	No	No
Inference	Double-clustered	Double-clustered	FM (NW)	FM (NW)
R^2	0.241	0.241	0.010	0.052
Obs. / Months	418806	418806	203	203

This table reports regressions of next-month excess returns on the loan fee and short-selling risk (SSR), both as within-month percentile ranks. Full specifications add beta, size, and book-to-market. Panel specifications include time and FF49 industry fixed effects with standard errors double-clustered by firm and month. Fama–MacBeth specifications report average monthly cross-sectional slopes with Newey–West t-statistics (lag 3). For panel regressions R^2 is the within R^2; for Fama–MacBeth it is the average monthly cross-sectional R^2. *, **, *** denote 10%, 5%, 1% significance.