Lendable Inventory Concentration, Short-Selling Risk, and Equity Pricing Anomalies

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Abstract

Equity anomalies remain profitable net of borrowing fees, yet exploiting them requires short positions that are difficult to sustain when short-selling risk is high. This paper shows that a structural source of short-selling risk is the concentration of lendable inventory across institutional lenders. Using IHS Markit securities lending data, I show that concentrated lending supply is associated not only with higher borrowing fees, but also with higher short-selling risk, measured by fee instability, utilization instability, and tail events in lending markets. Around earnings announcements, negative news is incorporated more slowly among high-IC stocks. Across a broad set of equity anomalies, high-concentration stocks earn larger long-short returns, driven primarily by the short leg. Cross-sectional regressions show that short-leg predictability is strongest when short-selling risk is high and is not fully captured by loan fees. The evidence suggests that lendable inventory concentration is a structural source of short-selling risk and persistent mispricing.

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

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1 Introduction

Short-sellers are widely viewed as sophisticated arbitrageurs who contribute to price discovery by trading on negative information. In a frictionless market with abundant and competitive securities lending, public signals of overpricing should be rapidly arbitraged away. Yet many cross-sectional return patterns remain economically large after accounting for borrowing costs, and their long–short spreads are driven disproportionately by the short leg.

A natural interpretation is that short-selling is not frictionless. Exploiting equity anomalies requires arbitrageurs to establish and maintain short positions on the short side: they must borrow shares, pay borrowing fees, post collateral, and remain exposed to changes in borrowing conditions. This paper asks whether concentrated lendable inventory creates short-selling risk that delays bad-news incorporation and sustains after-fee anomaly profits that are difficult to fully exploit.

Rather than treating borrowing fees as the only relevant short-selling friction, I focus on the organization of lendable supply. The key idea is that short-selling constraints depend not only on the price of borrowing, but also on who controls lendable shares and whether lenders are substitutable. When lendable inventory is concentrated among a small set of institutions, short sellers are exposed to discrete supply shocks. A retrenchment by a dominant lender can abruptly tighten borrowing conditions by raising fees, increasing utilization, or reducing available quantity. Anticipating these risks, arbitrageurs reduce short exposure precisely when trading against overpricing is most valuable for price efficiency.

I study this mechanism using detailed IHS Markit securities lending data. The central state variable is *lendable inventory concentration*, measured from the cross-lender distribution of lendable shares. For each stock-month, I construct concentration measures such as the Herfindahl index of lendable inventory across lenders and the inventory share of the largest lenders. I then relate this lender-base structure to three outcomes: short-selling risk, the incorporation of negative information, and the strength of anomaly return spreads.

The analysis proceeds in three steps. First, I show that concentrated lendable inventory is associated with more constrained and unstable shorting conditions. High-concentration stocks not only tend to have higher borrowing fees, but the more important pattern is instability. They exhibit greater fee volatility, greater utilization volatility, and more frequent tail events in lending conditions. These results suggest that inventory concentration captures a dimension of short-sale constraints that is not fully summarized by average fee levels.

Second, I examine whether this lending-market structure matters for price discovery. Earnings announcements provide high-salience information events with a natural distinction between positive and negative news. If concentrated lendable inventory constrains short sellers, the effect should be asymmetric: negative news should be incorporated more slowly when shorting is risky, while the response to positive news should be less affected. Consistent with this prediction, I find that negative news is incorporated more slowly among high-IC stocks. The post-announcement drift following negative news is stronger when lendable inventory is concentrated, whereas the corresponding effect following positive news is weaker.

Third, I study a broad set of equity anomalies. If lending concentration is a structural source of limits to arbitrage, anomaly return spreads should be larger in high-concentration stocks and the effect should be concentrated on the short leg. This is what the data show. Long–short anomaly returns are larger among high-IC stocks, and the difference is driven primarily by stocks that anomaly strategies classify as short candidates. These return patterns remain economically meaningful after accounting for borrowing fees. Cross-sectional regressions further show that short-leg predictability is strongest when short-selling risk is high and is not fully captured by loan fees.

The evidence points to a distinction between borrowing costs and short-selling risk. Borrowing fees measure the price of borrowing conditional on access to shares. Short-selling risk captures the instability of that access. A stock can have a moderate average fee but still be difficult to short if lending conditions are volatile, utilization is unstable, or lendable supply is controlled by a small number of institutions. This distinction helps explain why anomaly returns can remain large net of borrowing fees: the profits are present in measured returns, but they are not necessarily fully exploitable by arbitrageurs facing unstable borrowing conditions.

This paper makes three contributions. First, it introduces lendable inventory concentration as a lender-base state variable that captures the substitutability and fragility of lending supply. Second, it links this lending-market structure to price efficiency by showing that negative information is incorporated more slowly when lender concentration is high. Third, it provides a structural explanation for heterogeneity in anomaly return spreads: short-leg anomaly returns are strongest where borrowing conditions are most fragile, helping reconcile persistent fee-adjusted anomaly profitability with the presence of sophisticated arbitrageurs.

The remainder of the paper is organized as follows. Section 2 reviews the related literature. Section 3 describes the data and the construction of the inventory concentration and short-selling risk measures. Section 4 presents evidence on how inventory concentration relates to borrowing conditions and short-selling risk. Section 5 examines how concentration affects price adjustment around earnings announcements. Section 6 analyzes how lending-market structure conditions anomaly return spreads. Section 7 concludes.

2 Related Literature

This paper relates to three strands of literature: cross-sectional anomalies and limits to arbitrage, short-sale constraints and securities lending markets, and the role of ownership and lender structure in price efficiency.

The first strand studies whether cross-sectional return predictors reflect true mispricing, compensation for risk, or statistical artifacts. A large literature shows that many published 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). Other studies document that predictability persists out of sample, internationally, or after correcting for selective reporting (McLean and Pontiff, 2016; Jacobs and Müller, 2020; Y. Chen and Zimmermann, 2022; Jensen et al., 2023). This debate naturally raises a second question: if return predictability is real, why do sophisticated investors not arbitrage it away?

A prominent answer is limits to arbitrage. Arbitrageurs face funding risk, margin requirements, price impact, and the risk of forced unwinds (Shleifer and Vishny, 1997; Vayanos and Gromb, 2010). These limits are especially relevant for short-side anomalies because correcting overpricing requires short positions. Pessimistic investors must borrow shares, maintain collateral, and remain exposed to changing borrowing conditions (Miller, 1977; Diamond and Verrecchia, 1987). Empirically, 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).

A second strand connects securities lending frictions directly to anomaly profitability. Recent work shows that borrowing costs can substantially reduce, and in some cases eliminate, the net profitability of anomaly-based long–short strategies (Muravyev et al., 2025; Da et al., 2025). This evidence highlights borrowing fees as an economically important implementation cost. Related work shows that institutional investors often do not trade aggressively on anomaly signals, consistent with trading and short-sale constraints limiting arbitrage activity (Lewellen, 2011; Edelen et al., 2016).

At the same time, borrowing fees are not the only relevant short-selling friction. Fees measure the current price of borrowing conditional on access to shares, but they do not fully capture the risk that borrowing conditions change after a position is initiated. Engelberg et al. (2018) formalize this distinction by measuring short-selling risk through variation and uncertainty in lending fees and showing that this risk is priced in the cross-section. Ma (2019) show that hedge funds bearing more short-selling risk earn higher performance, consistent with sophisticated arbitrageurs being the primary holders of this risk. This paper builds on this insight by identifying a structural source of short-selling risk: the concentration of lendable inventory across lenders.

The third related strand studies how ownership and lending-market structure affect short-sale constraints. Nagel (2005) and Porras Prado et al. (2016) show that institutional ownership affects lending supply and short-sale constraints, and that concentrated ownership can be associated with higher borrowing fees and stronger mispricing. More recent work emphasizes that securities lending markets are not perfectly competitive or frictionless. Lending supply can be granular and persistent, with a small number of lenders supplying a large share of available inventory (Dong and Zhu, 2022). Market power and strategic lending behavior can affect both fees and quantities (Chen et al., 2022; Atmaz et al., 2024), while the identity of lenders can shape the stability of lendable supply (Palia and Sokolinski, 2024).

This paper contributes by measuring the cross-lender distribution of lendable inventory directly and showing that its concentration predicts both borrowing costs and borrowing instability. Relative to studies that focus on average borrowing fees, the paper emphasizes that fee levels are an incomplete measure of short-sale constraints. Relative to work on short-selling risk, it identifies lender-base concentration as a concrete source of that risk. Relative to the anomalies literature, it shows that anomaly return spreads are strongest where short-selling risk is high and where lendable inventory is concentrated.

Finally, the paper relates to research on price discovery and information incorporation. Short sellers are important for incorporating negative information into prices, so frictions that constrain short selling should affect the speed with which bad news is impounded. The earnings-announcement evidence in this paper supports that prediction: negative news is incorporated more slowly among high-IC stocks, while the positive-news response is less affected. This asymmetry links the lending-market structure directly to price efficiency and distinguishes the mechanism from symmetric explanations such as general inattention or illiquidity.

Taken together, the literature establishes that anomaly returns are sensitive to short-sale costs, that short-selling entails risk beyond average fees, and that ownership and lending behavior shape the supply of lendable shares. This paper connects these insights by showing that the concentration of lendable inventory across lenders is a structural source of short-selling risk, slower bad-news incorporation, and persistent short-leg anomaly returns.

3 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.

3.1 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 hard-to-borrow stock-months with monthly average borrowing fees above 1%. These filters focus the analysis on the economically relevant region where anomaly strategies are potentially implementable while avoiding extremely distressed or special borrowing environments. I apply the same filters consistently across the lending-condition tests, the earnings-announcement tests, and the anomaly portfolio analyses.

3.2 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. I also retain additional Markit lending variables, such as average loan tenure, when they are used as controls.

Lendable inventory concentration. The central variable in the paper is the concentration of lendable inventory across lenders. Let $s_{i\ell d}$ denote lender ℓ's lendable inventory in stock i on day d, and let

$$S_{id} = \sum_{\ell} s_{i\ell d}$$

denote total lendable inventory in that stock. The lender's share of lendable inventory is

$$w_{i\ell d} = \frac{s_{i\ell d}}{S_{id}}.$$

I measure inventory concentration using the Herfindahl–Hirschman index:

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

Higher values of IC indicate that lendable inventory is concentrated among fewer lenders. I aggregate daily IC to the stock–month level by averaging within each month. This measure captures the substitutability of lendable supply: when IC is high, short sellers depend on a smaller set of lenders and are more exposed to lender-specific supply shocks.

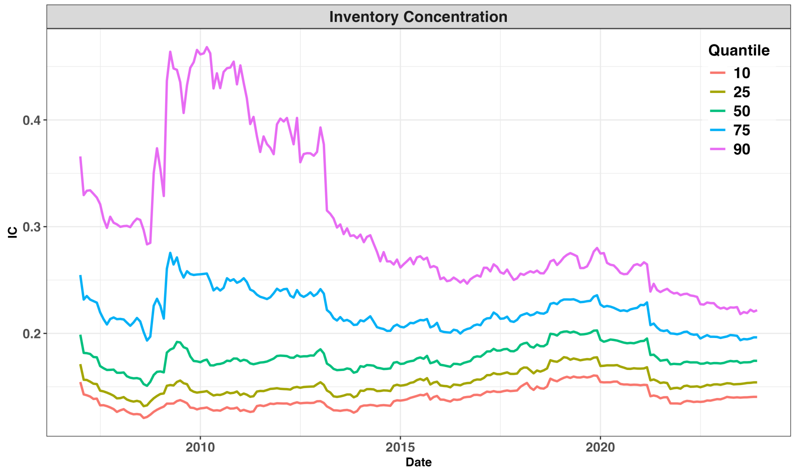

Figure 1: Lendable inventory concentration (IC) in the IHS Markit data, 2007–2023.

Stable-lender supply. I also use Markit's lender classification to construct LQS, defined as the fraction of loan quantity supplied by stable, low-turnover lenders. This variable captures the composition of the lending base and helps distinguish lender concentration from lender type.

3.3 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 fees or utilization are 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 73 trading days.

Fee instability and fee tail risk. Fee instability is the natural logarithm of the variance of daily borrowing fees over the prior 73 trading days:

$$FeeRisk_{it} = \log\left(\mathrm{Var}(Fee_{i,d})\right).$$

Fee tail risk captures extreme fee pressure:

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

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

Utilization instability and utilization tail risk. Utilization instability is the natural logarithm of the variance of daily utilization over the prior 73 trading days:

$$UtilRisk_{it} = \log\left(\mathrm{Var}(Util_{i,d})\right).$$

Utilization tail risk is defined analogously:

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

High values of these measures indicate that the stock is exposed to unstable lending demand or unstable residual lending capacity.

Composite short-selling risk. In the anomaly regressions, I also use a composite short-selling risk measure, denoted SSR_{it}^{rnk}. I first transform the fee-risk, fee-tail, utilization-risk, and utilization-tail variables into within-month percentile ranks. I then average the available non-missing ranked components:

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

where

$$\mathcal{K}_{it} = \{FeeRisk, FeeTail, UtilRisk, UtilTail\}_{it}^{\mathrm{nonmissing}}.$$

If all four components are missing for a stock-month observation, I set SSR_{it}^{rnk} to missing. Higher values of SSR^{rnk} 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.

3.4 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 and corporate finance, including size, book-to-market, momentum, bid–ask spread, institutional ownership, short interest, turnover, and idiosyncratic volatility. I winsorize continuous variables at conventional percentiles to reduce the influence of outliers.

Earnings announcement dates are from Compustat quarterly report dates (RDQ). For each announcement, I compute CAPM-adjusted cumulative abnormal returns around the event and over post-announcement horizons.

3.5 Institutional Holdings

Quarterly institutional holdings are from Thomson Reuters 13F, which covers institutions with more than $100 million in assets under management. For each stock–quarter, I compute institutional ownership and ownership concentration measures.

I also use the institutional classification of Bushee (1998). This classification groups institutions based on historical investment behavior, including portfolio turnover and portfolio concentration. The three main categories are quasi-indexers, transient investors, and dedicated investors. Quasi-indexers have low turnover and diversified portfolios; transient investors have high turnover and diversified portfolios; dedicated investors have low turnover and concentrated portfolios.

Following Appel et al. (2016), I use the permanent Bushee classification in my baseline analysis. This avoids classifying the same institution as passive in some periods and active in others. I construct two quasi-indexer ownership measures. The first, $qixior$, is the fraction of institutional ownership held by quasi-indexers. The second, $qixhhi$, is a Herfindahl index of quasi-indexer holdings. These variables capture the extent to which ownership is concentrated among large, low-turnover institutions that may play an important role in securities lending supply. I use them as ownership-based proxies that complement the direct IHS Markit measure of lendable inventory concentration.

3.6 Equity Pricing Anomalies

To study how lending-market structure conditions anomaly strength, I use the anomaly library of Jensen et al. (2023). The data provide monthly signed anomaly predictors at the stock–month level using standard implementations from the return-predictability literature.

Each month, I form long–short anomaly portfolios by sorting stocks on each anomaly signal and comparing returns across the extreme portfolios. I focus on the subset of anomaly signals that generate statistically positive CAPM alphas in the merged CRSP–Markit sample from 2006 to 2023 after applying the baseline microcap and extreme borrow-cost filters. This restriction ensures that the analysis focuses on anomalies that are economically relevant in the tradable universe studied in this paper.

I evaluate anomaly performance using raw returns, fee-adjusted returns, and risk-adjusted returns from CAPM and multifactor models. I then examine whether anomaly return spreads vary with lendable inventory concentration and whether the effect is concentrated on the short leg.

3.7 Summary Statistics

Table 1 reports summary statistics for the main variables used in the paper. Panel A reports firm characteristics and ownership variables. Panel B reports securities lending variables and short-selling risk measures. The table shows substantial cross-sectional heterogeneity in both the level and the stability of borrowing conditions. This motivates the use of lendable inventory concentration as a key state variable for studying short-sale constraints.

4 Lendable Inventory Concentration and Short-Sale Constraints

This section tests whether a more concentrated lender base is associated with tighter and less stable short-sale constraints. I focus on two outcomes. The first is the *level* of borrowing costs, measured by average borrowing fees. The second is the *risk* of maintaining short positions, measured by instability in fees, instability in

Table 1: Summary statistics

Variable	N	Mean	SD	Median	P25	P75
Panel A: Firm characteristics and ownership						
ME	625,816	8,376.060	43,169.542	1,127.375	298.938	4,097.509
BM	606,154	0.689	1.086	0.521	0.280	0.850
Short Interest	625,971	0.081	3.643	0.029	0.013	0.061
qixior	574,783	0.694	0.157	0.719	0.619	0.796
qixhhi	574,514	0.114	0.113	0.077	0.056	0.124
Panel B: Securities lending and short-selling risk						
IC	625,971	0.206	0.102	0.178	0.152	0.218
LQS	625,971	0.562	0.225	0.610	0.469	0.715
Utilization	625,971	0.117	0.137	0.063	0.020	0.165
BorrowFee	625,971	0.391	0.122	0.375	0.304	0.409
log(FeeVar)	572,941	-5.869	2.072	-6.067	-7.342	-5.029
FeeTail	572,941	0.718	1.557	0.466	0.407	0.608
log(UtilVar)	572,941	0.676	2.150	0.797	-0.719	2.196
UtilTail	572,941	17.390	18.258	10.597	4.035	24.891

utilization, tail realizations of lending conditions, and average loan tenure. The key explanatory variable is inventory concentration, IC, defined as the Herfindahl–Hirschman index of lendable inventory across lenders using IHS Markit lender-level inventory data. As a complementary ownership-based proxy, I also use `qixhhi`, the Herfindahl index of quasi-indexer holdings constructed from 13F filings using the permanent classification of Bushee (1998).

4.1 Economic mechanisms and hypothesis development

Inventory concentration can affect short selling through two related channels.

Mechanism 1: Market power. When lendable inventory is concentrated among a small number of effective lenders, competition on the supply side of the securities lending market is weaker. Large lenders may have greater bargaining power and can charge higher borrowing fees for a given level of shorting demand (Chen et al., 2022). This channel predicts that borrowing fees should be higher when IC is higher.

Prediction (Fees). *Average borrowing fees increase with inventory concentration, conditional on shorting demand and standard stock characteristics.*

Mechanism 2: Lender-base fragility. A concentrated lender base can also make short positions harder to maintain. When lendable supply is provided by only a few dominant institutions, shocks to these institutions can translate into abrupt changes in available supply. A reduction in supply by a dominant lender can raise fees, increase utilization, or reduce available borrowable quantity. This creates instability in borrowing conditions and increases the risk faced by short sellers (Dong and Zhu, 2022). This channel predicts that higher IC should be associated not only with higher average fees, but also with more volatile and more extreme lending conditions.

Prediction (Risk). *Short-selling risk increases with inventory concentration, conditional on shorting demand and standard stock characteristics.*

Link to ownership concentration. Quasi-indexers are large, low-turnover institutions that may represent stable sources of lendable supply. Concentration among quasi-indexers can therefore be informative about the concentration of effective lending supply. However, ownership concentration and lending-supply concentration need not coincide. An institution can own shares without lending them, and the distribution of actual lendable inventory may differ from the distribution of reported ownership. I therefore treat `qixhhi` as an ownership-based proxy that complements, but does not replace, the direct lending-market measure IC.

4.2 Empirical specifications

I estimate stock–month panel regressions with stock and calendar-month fixed effects:

$$Fee_{i,t} = \alpha_i + \tau_t + \beta_1 IC_{i,t} + \beta_2 Demand_{i,t} + \Gamma' X_{i,t} + \varepsilon_{i,t}, \tag{1}$$

$$Risk_{i,t} = \alpha_i + \tau_t + \gamma_1 IC_{i,t} + \gamma_2 Demand_{i,t} + \Gamma' X_{i,t} + u_{i,t}. \tag{2}$$

To evaluate whether direct lending-market concentration contains information beyond ownership concentration, I also estimate specifications that replace IC with `qixhhi`:

$$Fee_{i,t} = \alpha_i + \tau_t + \beta_1 IC_{i,t} + \beta_2 Demand_{i,t} + \Gamma' X_{i,t} + \varepsilon_{i,t}, \tag{3}$$

$$Risk_{i,t} = \alpha_i + \tau_t + \gamma_1 IC_{i,t} + \gamma_2 Demand_{i,t} + \Gamma' X_{i,t} + u_{i,t}. \tag{4}$$

The stock fixed effect α_i absorbs time-invariant firm characteristics, and the month fixed effect τ_t absorbs aggregate changes in lending conditions and market-wide risk. Standard errors are two-way clustered by stock and calendar month.

Dependent variables. The dependent variables are the borrowing-cost and short-selling-risk measures defined in Section 3.3. The fee outcome is the monthly average `BorrowFee`. The risk outcomes are `FeeRisk`, `FeeTail`, `UtilRisk`, `UtilTail`, and average loan tenure `AT`. Higher values of the risk measures indicate more unstable or more extreme borrowing conditions, while lower values of `AT` indicate shorter loan duration and less stable access to borrowed shares.

Shorting demand and controls. I control for short-selling demand using short interest and utilization. The control vector includes standard firm and trading characteristics: market equity, book-to-market, volatility, idiosyncratic volatility, liquidity, turnover, institutional ownership, and lendable supply. I also control for lender composition using `LQS`, the share of loan quantity supplied by stable, low-turnover lenders. When the dependent variable is a short-selling-risk measure, I additionally control for the contemporaneous borrowing fee.

4.3 Results

Lendable inventory concentration and borrowing fees. Table 2 shows that inventory concentration is positively related to average borrowing fees. In column (1), the coefficient on IC is positive and statistically significant, consistent with the market-power channel: when lendable supply is more concentrated, borrowing is more expensive even after absorbing stock and month fixed effects and conditioning on lender composition. Column (2) reports the analogous specification using the ownership-based concentration proxy `qixhhi`. Quasi-indexer concentration is also positively related to fees, while the quasi-indexer ownership share is negatively related to fees. These results suggest that both direct lending-market concentration and ownership-side concentration contain information about borrowing costs.

Lendable inventory concentration and fee risk. Table 3 shows that inventory concentration is strongly associated with fee instability. Higher IC predicts a significant increase in `FeeRisk` and `FeeTail`, indicating both greater variability in borrowing fees and a greater likelihood of extreme fee realizations. The coefficient on `LQS` is negative, consistent with stable lenders dampening fee volatility.

Table 2: Inventory concentration and borrowing fees

	(1)	(2)
Dependent variable:	BorrowFee	BorrowFee
IC	0.052***	
	(0.015)	
LQS	-0.006	
	(0.006)	
qixhhi		0.022**
		(0.010)
qixior		-0.018***
		(0.005)
Month FE	Yes	Yes
Permno FE	Yes	Yes
Observations	481,962	481,835
R^2	0.521	0.521
Within adj. R^2	0.090	0.089

Standard errors are clustered by month and PERMNO.
*, **, and *** denote significance at the 10%, 5%, and 1% levels.

Columns (2) and (4) show that `qixhhi` is also positively related to fee risk, while higher quasi-indexer ownership share is associated with lower fee instability in some specifications. Overall, the evidence supports the lender-base fragility channel: concentrated lendable supply is associated with a less stable borrowing environment.

Table 3: Inventory concentration and fee risk

	(1)	(2)	(3)	(4)
Dependent variable:	log(FeeVar)	log(FeeVar)	FeeTail	FeeTail
IC	1.69***		1.22***	
	(0.240)		(0.152)	
LQS	-0.576***		-0.396***	
	(0.094)		(0.071)	
qixhhi		0.720***		0.591***
		(0.170)		(0.115)
qixior		-0.605***		-0.087
		(0.087)		(0.048)
Month FE	Yes	Yes	Yes	Yes
Permno FE	Yes	Yes	Yes	Yes
Observations	440,202	440,099	440,202	440,099
R^2	0.599	0.598	0.257	0.255
Within adj. R^2	0.252	0.250	0.058	0.056

Standard errors are clustered by month and PERMNO.
*, **, and *** denote significance at the 10%, 5%, and 1% levels.

Lendable inventory concentration and utilization risk. Table 4 reports analogous results for utilization instability and loan tenure. Higher IC predicts higher `UtilRisk` and `UtilTail`, consistent with greater instability in the intensity of borrowing demand and tighter residual lending capacity. Columns (2) and (4) show that `qixhhi` is also positively related to utilization risk, while higher quasi-indexer ownership share is associated with lower utilization instability. In addition, IC is negatively related to average loan tenure, `AT`. Since longer tenure indicates more persistent loan relationships and more stable access to borrowed shares, the negative coefficient on IC suggests that concentrated lending bases are associated with shorter-lived borrowing relationships. This pattern reinforces the interpretation that high-IC stocks face a less stable shorting environment.

Table 4: Inventory concentration and utilization risk

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	log(UtilVar)	log(UtilVar)	UtilTail	UtilTail	AT	AT
IC	1.17***		2.86***		-0.629***	
	(0.136)		(0.733)		(0.123)	
LQS	-0.369***		-1.56***		0.632***	
	(0.068)		(0.356)		(0.069)	
qixhhi		0.583***		4.31***		0.138
		(0.118)		(0.796)		(0.108)
qixior		-0.863***		-2.47***		0.447***
		(0.061)		(0.344)		(0.061)
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Permno FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	267,285	267,218	440,202	440,099	481,962	481,835
R^2	0.468	0.470	0.903	0.903	0.246	0.245
Within adj. R^2	0.193	0.196	0.787	0.788	0.023	0.021

Standard errors are clustered by month and PERMNO.
*, **, and *** denote significance at the 10%, 5%, and 1% levels.

4.4 Summary and implications

Across specifications with stock and month fixed effects, inventory concentration is systematically associated with more costly and less stable shorting conditions. The evidence supports both mechanisms. First, higher IC is associated with higher average borrowing fees, consistent with market power among concentrated lenders. Second, higher IC is associated with greater instability in borrowing conditions: fee risk, fee-tail risk, utilization risk, and utilization-tail risk all increase with inventory concentration, while average loan tenure declines. These findings suggest that IC captures a non-price dimension of short-sale constraints that is not fully summarized by the current borrowing fee.

The results motivate the subsequent analysis. If concentrated lendable inventory raises short-selling risk, then high-IC stocks should incorporate negative information more slowly and display stronger short-leg anomaly returns. The next sections test these predictions directly.

5 Lendable Inventory Concentration and Earning News Incorporation

This section examines whether lending-market structure affects the speed at which earnings news is incorporated into stock prices. A large literature documents post–earnings-announcement drift (PEAD), i.e., the tendency for stock prices to continue to rise (fall) following good (bad) earnings news (Bernard and Thomas, 1989). A common 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. In particular, arbitrage risk has been emphasized as a key friction that magnifies drift (Mendenhall, 2004; Pontiff, 2006). Because short sellers are natural traders on negative information, short-sale constraints should matter disproportionately for *bad* earnings news.

we hypothesize that higher lendable inventory concentration slows the incorporation of negative earnings information into prices. The mechanism follows directly from the results in Section 4. When inventory is concentrated among a few dominant lenders, short selling becomes (i) more expensive (higher average fees) and (ii) riskier (greater fee and utilization volatility and fatter tails). These frictions reduce the willingness or ability of arbitrageurs to establish or maintain short positions in response to bad news, particularly when positions must be carried over multiple days to realize profits. As a result, prices should underreact more to negative earnings news on the announcement date and exhibit larger post-announcement drift in the subsequent days.

This channel yields two testable predictions. First, the post-announcement adjustment to *bad* earnings news should be more delayed when IC is high. Second, the effect should be asymmetric: for *good* news, price correction does not rely on short selling, so the lending channel should play little role, the relation between inventory concentration and drift should be weaker.

5.1 Earnings announcement events and abnormal return measures

we use Compustat quarterly report dates (RDQ) to identify earnings announcements. For each earnings event, we compute CAPM-adjusted cumulative abnormal returns (CARs) in event time. We define the *announcement-window reaction* as $CAR^{CAPM}_{i,t,[-1,+1]}$ and study *post-announcement drift* using cumulative abnormal returns beginning after the immediate reaction window. Specifically, for each horizon h, we compute $CAR^{CAPM}_{i,t,[+2,+h]}$, which captures delayed adjustment beyond the first trading days after earnings announcements.

In each month, we classify earnings announcements into *Good* and *Bad* news based on the sign and magnitude of the announcement-window return. Specifically, among events with *positive* $CAR^{CAPM}[-1,+1]$, we label the top 30% (largest positive CARs) as *Good* news. Among events with *negative* $CAR^{CAPM}[-1,+1]$, we label the bottom 30% (most negative CARs) as *Bad* news. All remaining events are excluded from the Good/Bad subsample analysis. In parallel, we define *High IC* (*Low IC*) stocks each month as those in the top (bottom) quintile of the cross-sectional distribution of average inventory concentration, $IC_{i,t}$.

Figure 2 illustrates how lending-market structure is related to the speed of price adjustment after earnings announcements. Following *bad* news, prices continue to drift downward well beyond the immediate announcement window, and the drift is markedly larger when lendable inventory is more concentrated. Table 5 quantifies this difference: by $h = 60$, cumulative post-announcement $CAR^{CAPM}_{[+2,+h]}$ is **-26.93%** for high-IC stocks versus **-10.91%** for low-IC stocks. The gap widens further at longer horizons, reaching **-42.55%** (high IC) versus **-16.87%** (low IC) by $h = 120$. Importantly, the divergence emerges early and persists: even at $h = 5$, high-IC bad-news events exhibit a more negative drift (**-8.25%** vs. **-6.80%**).

In contrast, the drift after *good* news does not display the same pattern. While good-news events show positive post-announcement CARs, the high–low IC differences are small and do not consistently favor stronger drift in high-IC stocks. For example, at $h = 60$ the cumulative CAR is **5.17%** in high-IC stocks versus **7.81%** in low-IC stocks, and by $h = 120$ the high-IC group even turns negative (**-2.36%**) whereas the low-IC group remains positive (**5.97%**). Overall, the high-IC amplification is therefore concentrated in the bad-news subsample.

These patterns are consistent with a short-sale-friction channel. When inventory concentration is high, short positions are more difficult to scale and maintain, slowing the correction of overpricing after negative information arrives and generating a larger, more persistent PEAD. Because good-news adjustment does not rely on short selling, the corresponding high-vs-low IC differences are muted.

While Figure 2 is informative, it does not condition on other determinants of PEAD (e.g., size, liquidity, volatility, institutional ownership, or contemporaneous shorting demand) that may covary with IC. To quantify the incremental role of lending-market structure, we therefore estimate equation (7), which relates post-announcement abnormal returns to the announcement-window shock and its interaction with IC, while including firm and month fixed effects and a rich set of controls and interaction terms.

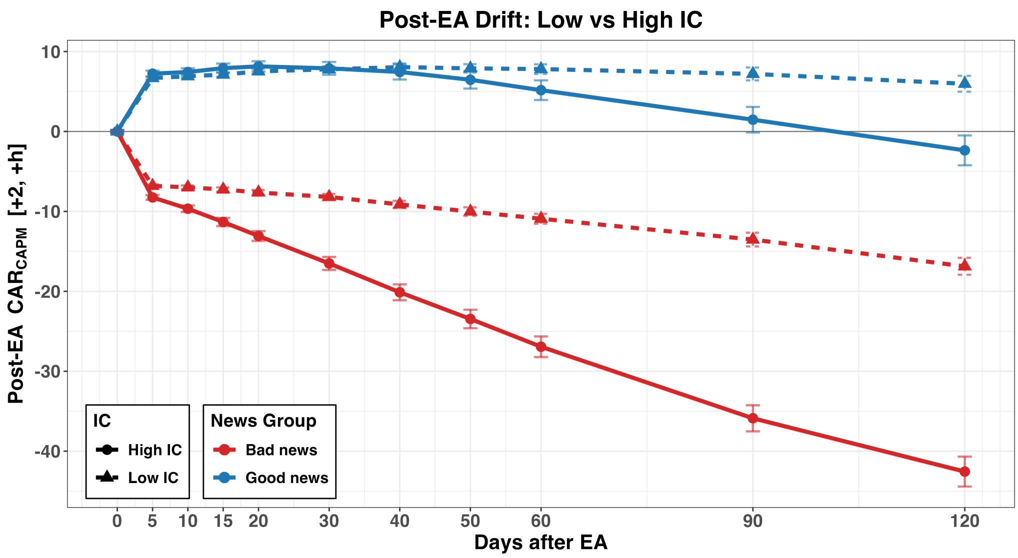

Figure 2: Asymmetric post–earnings-announcement drift by inventory concentration. Good news events are defined each month as the top 30% of *positive* announcement-window $CAR^{CAPM}_{[-1,+1]}$; Bad news events are defined as the bottom 30% of *negative* announcement-window $CAR^{CAPM}_{[-1,+1]}$.

5.2 Empirical specification

we study post-announcement price adjustment using local projections in event time. Let $CAR^{CAPM}_{i,t,[-1,+1]}$ denote the announcement-window abnormal return around the earnings announcement at event date t, and let $CAR^{CAPM}_{i,t,[+2,+h]}$ denote the cumulative post-announcement abnormal return from day $+2$ through horizon h. The baseline

Table 5: PEAD: CAR^{CAPM} from trading day +2 through $+h$ after the earnings announcement, by news × IC group.

Horizen	**Bad**		**Good**	
	High IC	**Low IC**	**High IC**	**Low IC**
$[+2, +5]$	-8.25	-6.80	7.23	6.68
	[-8.55, -7.95]	[-6.99, -6.62]	[6.85, 7.61]	[6.49, 6.88]
$[+2, +10]$	-9.66	-6.99	7.44	6.91
	[-10.07, -9.25]	[-7.21, -6.76]	[6.97, 7.91]	[6.67, 7.14]
$[+2, +15]$	-11.32	-7.26	7.92	7.11
	[-11.84, -10.81]	[-7.53, -6.99]	[7.35, 8.50]	[6.84, 7.39]
$[+2, +20]$	-13.08	-7.63	8.14	7.51
	[-13.69, -12.46]	[-7.94, -7.32]	[7.49, 8.79]	[7.20, 7.83]
$[+2, +30]$	-16.51	-8.19	7.90	7.78
	[-17.32, -15.70]	[-8.57, -7.81]	[7.09, 8.70]	[7.39, 8.16]
$[+2, +40]$	-20.12	-9.13	7.45	8.05
	[-21.11, -19.13]	[-9.58, -8.68]	[6.50, 8.39]	[7.60, 8.51]
$[+2, +50]$	-23.46	-10.02	6.47	7.90
	[-24.61, -22.30]	[-10.55, -9.48]	[5.36, 7.57]	[7.37, 8.42]
$[+2, +60]$	-26.93	-10.91	5.17	7.81
	[-28.22, -25.64]	[-11.53, -10.30]	[3.93, 6.40]	[7.21, 8.41]
$[+2, +90]$	-35.88	-13.52	1.47	7.20
	[-37.52, -34.25]	[-14.38, -12.66]	[-0.13, 3.07]	[6.39, 8.01]
$[+2, +120]$	-42.55	-16.87	-2.36	5.97
	[-44.43, -40.68]	[-17.93, -15.81]	[-4.23, -0.49]	[4.97, 6.96]

Notes: Each cell in the first row reports the mean CAR in percentage. The row immediately below reports the corresponding 95% confidence interval.

local-projection regression at each horizon h is

$$CAR^{CAPM}_{i,t,[+2,+h]} = \beta_h \, CAR^{CAPM}_{i,t,[-1,+1]} + \varepsilon_{i,t,h}, \tag{5}$$

which summarizes average PEAD dynamics through the sequence $\{\beta_h\}_h$.

To benchmark how much of the drift survives once conventional return-predictability and limits-to-arbitrage correlates are accounted for, we also estimate a controlled specification with firm and calendar-month fixed effects and a standard vector of lagged covariates,

$$CAR^{CAPM}_{i,t,[+2,+h]} = \alpha_i + \eta_t + \beta_h \, CAR^{CAPM}_{i,t,[-1,+1]} + \delta_h X_{i,t-1} + \varepsilon_{i,t,h}, \tag{6}$$

where α_i and η_t denote firm and calendar-month fixed effects, respectively. The control vector $X_{i,t-1}$ includes size, market beta, book-to-market, institutional ownership, total volatility and idiosyncratic volatility, illiquidity, turnover, and short interest (all measured at $t-1$).

The main specification introduces inventory concentration ($IC_{i,t-1}$) both directly and through an interaction with the announcement shock, while allowing the shock to load on other friction proxies via interactions:

$$\begin{aligned} CAR^{CAPM}_{i,t,[+2,+h]} = {} & \alpha_i + \eta_t + \beta_h \, CAR^{CAPM}_{i,t,[-1,+1]} + \theta_h \, IC_{i,t-1} \\ & + \gamma_h \left(CAR^{CAPM}_{i,t,[-1,+1]} \times IC_{i,t-1} \right) \\ & + \sum_{Z \in \mathcal{Z}} \psi_{h,Z} \left(CAR^{CAPM}_{i,t,[-1,+1]} \times Z_{i,t-1} \right) + \delta_h \, X_{i,t-1} + \varepsilon_{i,t,h}, \end{aligned} \tag{7}$$

where $\mathcal{Z}$ includes proxies for trading and short-sale frictions (institutional ownership, idiosyncratic volatility, and illiquidity). This structure ensures that any incremental role of inventory concentration is identified off the interaction term, rather than confounding IC with other frictions that also slow incorporation of the same earnings-news shock.

The coefficient of interest is γ_h. It measures whether inventory concentration changes the mapping from announcement-window news $CAR^{CAPM}_{[-1,+1]}$ into subsequent cumulative post-announcement abnormal returns $CAR^{CAPM}_{[+2,+h]}$, holding fixed standard predictors and allowing the shock to interact with other friction proxies.

5.3 Results: asymmetric drift under high inventory concentration

Tables 6 and 7 report the benchmark local-projection estimates of β_h separately for good- and bad-news events. In the CAR-only baseline, β_h is positive and statistically significant at short and intermediate horizons for good news, but becomes negative at long horizons (e.g., $h = 90$ and $h = 120$). For bad news, β_h rises sharply with horizon and is strongly significant at longer horizons, consistent with substantial delayed adjustment following negative information.

Adding fixed effects and the standard control set in equation (6) does not eliminate these patterns. For good news, the estimated β_h remains positive and precisely estimated across all horizons reported in Table 7. For bad news, the short-horizon response is weak and even slightly negative, while longer-horizon coefficients turn positive, indicating that the post-announcement dynamics differ markedly by news sign even after conditioning on conventional PEAD correlates.

Table 8 reports the key interaction coefficients γ_h from the full specification in equation (7). The asymmetry is stark. Following *good* news, the interaction estimates are small and statistically indistinguishable from zero across horizons, indicating little systematic amplification of drift by inventory concentration on the upside. In contrast, following *bad* news, γ_h is economically large and statistically significant at essentially all horizons shown, and it increases with horizon. For example, the interaction is already sizable at $h = 5$ and grows monotonically through $h = 120$, where $\widehat{\gamma}_{120} = 5.933$ with a t-statistic of 3.22. This pattern implies that the same negative earnings-news shock generates substantially larger cumulative drift when lendable inventory is concentrated among a few dominant lenders.

Overall, the regression evidence mirrors the idea that inventory concentration matters primarily when short selling is most relevant: negative-information events. The results are difficult to reconcile with purely symmetric trading-friction mechanisms and instead support a short-sale-constraint channel in which concentrated lending supply makes the shorting environment more fragile and riskier, slowing the incorporation of bad news.

These patterns are consistent with the interpretation that inventory concentration increases both the cost and riskiness of shorting, discouraging short sellers from immediately and fully trading on bad earnings news. The resulting underreaction on impact is followed by delayed adjustment, generating larger PEAD precisely in stocks where lending supply is most concentrated.

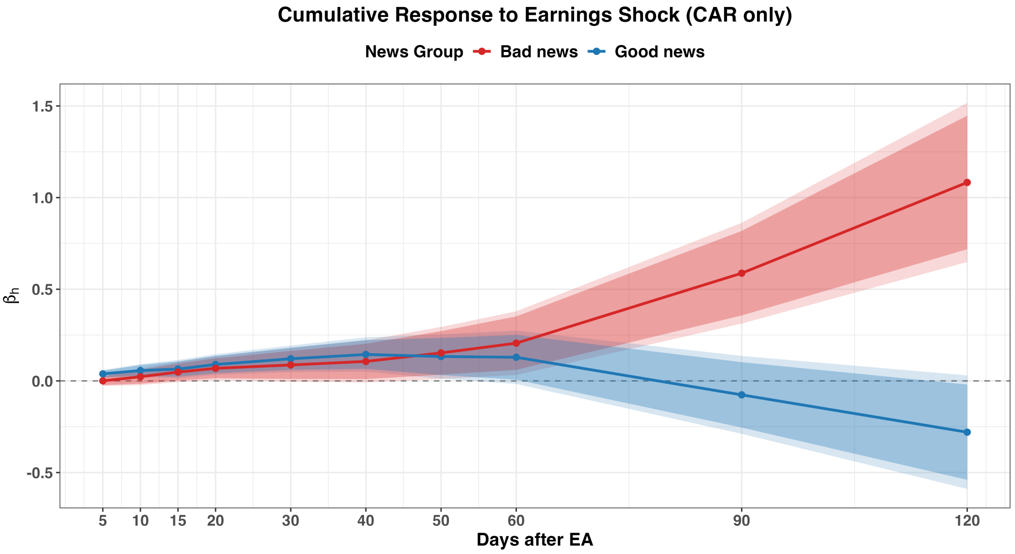

Figure 3: **Post-announcement response (β_h) to announcement-window news.** This figure plots β_h, the horizon-h coefficient on $CAR^{CAPM}_{i,t,[-1,+1]}$ from equation (5), where the dependent variable is $CAR^{CAPM}_{i,t,[+2,+h]}$. Thus, β_h captures the unconditional post-announcement sensitivity of cumulative abnormal returns to announcement-window news.

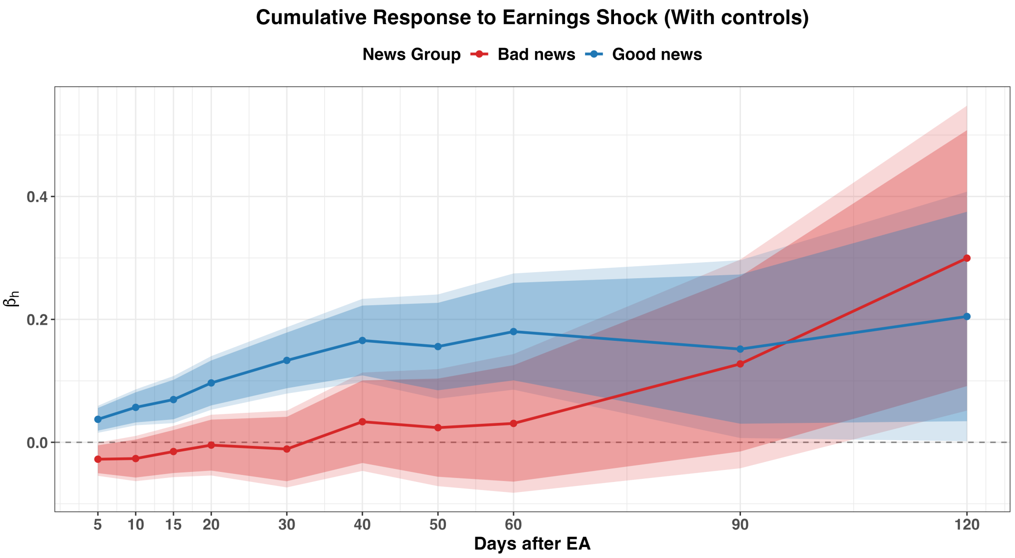

Figure 4: Post-announcement impulse (β_h) to announcement-window news: good- vs. bad-news events. This figure plots β_h, the horizon-h coefficient on $CAR^{CAPM}_{i,t,[-1,+1]}$ from equation (6), where the dependent variable is $CAR^{CAPM}_{i,t,[+2,+h]}$. Thus, β_h measures the post-announcement sensitivity of cumulative abnormal returns to announcement-window news. Estimates are reported separately for good- and bad-news events.

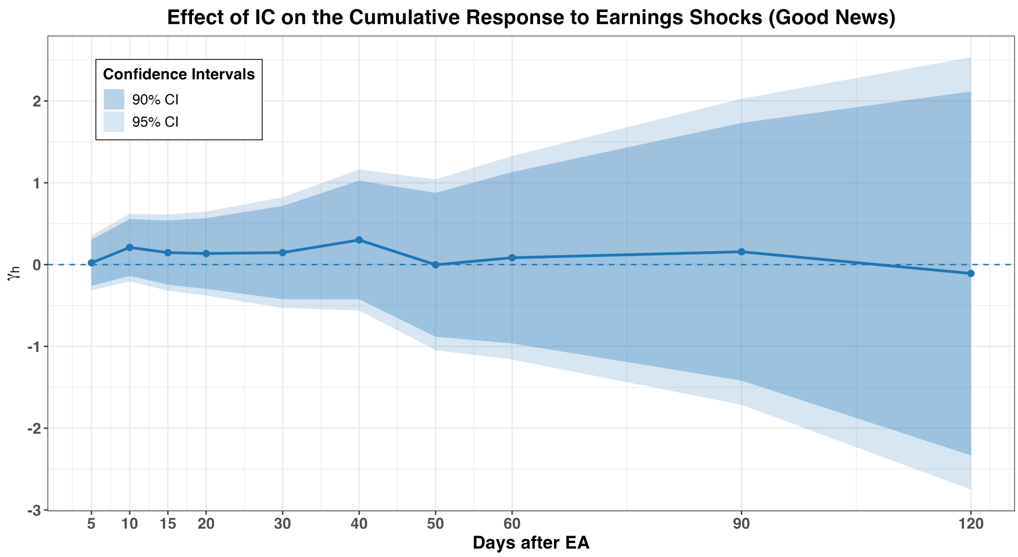

Figure 5: Post-announcement response to announcement-window news: good-news subsample. The figure reports γ_h from equation (7), i.e., the coefficient on $CAR^{CAPM}_{i,t,[-1,+1]} \times IC_{i,t-1}$ in a regression of $CAR^{CAPM}_{i,t,[+2,+h]}$ on announcement-window news, $IC_{i,t-1}$, and controls. γ_h captures how the post-announcement response to announcement-window news varies with $IC_{i,t-1}$.

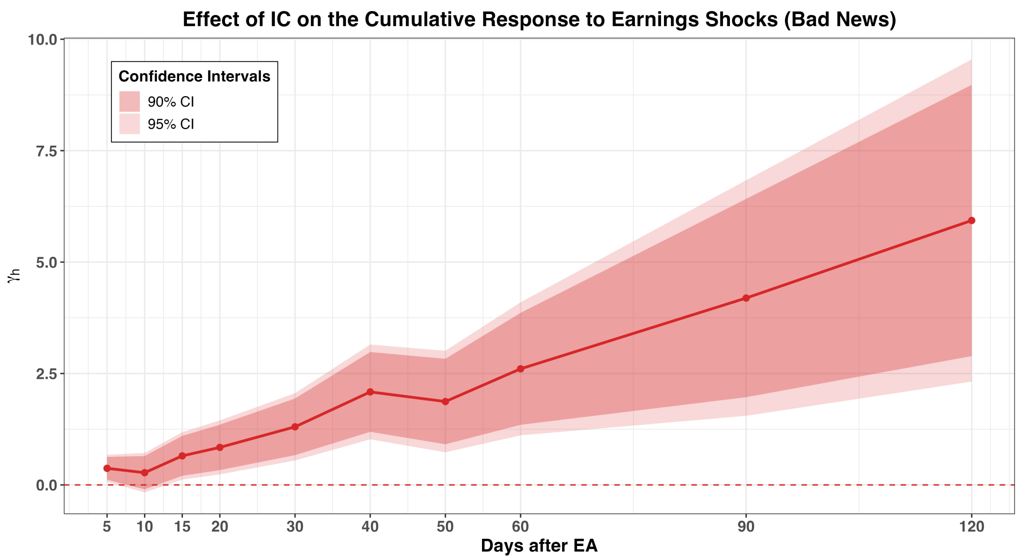

Figure 6: Post-announcement response to announcement-window news: bad-news subsample. The figure reports γ_h from equation (7), i.e., the coefficient on $CAR^{CAPM}_{i,t,[-1,+1]} \times IC_{i,t-1}$ in a regression of $CAR^{CAPM}_{i,t,[+2,+h]}$ on announcement-window news, $IC_{i,t-1}$, and controls. γ_h captures how the post-announcement response to announcement-window news varies with $IC_{i,t-1}$.

Table 6: Baseline local-projection estimates of β_h on announcement-window news. The dependent variable is post-announcement cumulative abnormal returns $CAR^{CAPM}_{i,t,[+2,+h]}$, and the regressor is the announcement-window shock $CAR^{CAPM}_{i,t,[-1,+1]}$ as in equation (5). Estimates are reported separately for good- and bad-news events. Entries show the coefficient with the t-statistic in parentheses.

News Group	5	10	15	20	30	40	50	60	90	120
Good	0.038	0.056	0.065	0.090	0.121	0.144	0.133	0.129	-0.076	-0.280
	(3.62)	(3.16)	(2.57)	(3.14)	(3.27)	(3.03)	(2.16)	(1.74)	(-0.70)	(-1.77)
Bad	0.000	0.022	0.048	0.069	0.087	0.106	0.153	0.206	0.588	1.083
	(0.02)	(0.97)	(1.73)	(2.09)	(1.87)	(1.82)	(2.11)	(2.32)	(4.19)	(4.89)

Table 7: Controlled local-projection estimates of β_h on announcement-window news. The dependent variable is $CAR^{CAPM}_{i,t,[+2,+h]}$. The specification follows equation (6) and includes firm and calendar-month fixed effects and lagged controls $X_{i,t-1}$, but excludes the inventory-concentration interaction. Estimates are reported separately for good- and bad-news events. Entries show the coefficient with the t-statistic in parentheses.

News Group	5	10	15	20	30	40	50	60	90	120
Good	0.037	0.057	0.070	0.097	0.133	0.166	0.156	0.180	0.152	0.205
	(3.34)	(3.82)	(3.56)	(4.34)	(4.84)	(4.80)	(3.60)	(3.74)	(2.06)	(1.98)
Bad	-0.028	-0.026	-0.015	-0.005	-0.011	0.033	0.024	0.031	0.128	0.300
	(-2.00)	(-1.41)	(-0.71)	(-0.18)	(-0.34)	(0.82)	(0.49)	(0.53)	(1.47)	(2.37)

Table 8: Inventory-concentration effect on post-announcement drift: local-projection interaction estimates. The table reports γ_h, the coefficient on $CAR^{CAPM}_{i,t,[-1,+1]} \times IC_{i,t-1}$ from the full specification in equation (7), where the dependent variable is $CAR^{CAPM}_{i,t,[+2,+h]}$. Estimates are reported separately for good- and bad-news events. Entries show the coefficient with the t-statistic in parentheses.

News Group	5	10	15	20	30	40	50	60	90	120
Good	0.021	0.210	0.147	0.135	0.147	0.301	-0.002	0.084	0.157	-0.108
	(0.12)	(1.00)	(0.62)	(0.52)	(0.42)	(0.69)	(0.00)	(0.13)	(0.16)	(-0.08)
Bad	0.372	0.275	0.652	0.842	1.303	2.087	1.871	2.605	4.193	5.933
	(2.40)	(1.21)	(2.40)	(2.73)	(3.39)	(3.85)	(3.22)	(3.42)	(3.11)	(3.22)

5.4 Summary

Earnings announcements offer a clean setting to test information incorporation. We find that securities lending market structure significantly affects price discovery: post-announcement drift is substantially amplified following bad earnings news when lendable inventory is concentrated among few dominant lenders. This is shown by the large, positive, and horizon-increasing interaction coefficient γ_h in Table 8 for bad news, contrasting with insignificant estimates for good news.

This stark asymmetry supports a short-sale-constraint mechanism—concentrated supply makes shorting more fragile, slowing negative news incorporation—rather than a symmetric friction or attention-based story. It directly motivates the next section, which examines whether the same lending-market structure amplifies cross-sectional anomalies.

6 Lendable Inventory Concentration and Equity Pricing Anomalies

This section tests whether lending-market structure organizes the strength of cross-sectional return predictability. The central hypothesis is that anomalies are stronger when short-sale constraints are tighter and more fragile. Because inventory concentration raises both borrow fees and short-selling risk (Section 4) and slows the incorporation of negative earnings information (Section 5), it should also amplify the profitability and persistence of anomaly-based long–short strategies, particularly through the short leg.

6.1 Data inputs and anomaly universe

we use the monthly signed anomaly signals from Jensen et al. (2023) and focus on 149 anomalies with a complete history (209 months) in the merged CRSP–Markit universe from July 2006 to December 2023, after applying the baseline microcap and hard-to-borrow screens. This leaves 149 anomalies. For each anomaly, we sort stocks each month into equal-weighted signal quintiles and compute the long–short spread (high minus low), using the signal sign conventions from the library.

Because lendable inventory concentration (IC) is strongly correlated with firm size and liquidity, we got benchmark-adjust returns to purge the mechanical influence of these characteristics. Following the characteristic-based benchmarking approach of Daniel et al. (1997) (DGTW), we form monthly value-weighted benchmark portfolios based on size and liquidity and subtract the matched benchmark return from each stock's return. Concretely, in each month t we sort stocks using characteristics measured at $t-1$ into 5×5 portfolios: first into NYSE-based size quintiles using lagged market capitalization, and then into liquidity quintiles within each size bin using lagged illiquidity (e.g., Amihud or bid–ask-based measures). Let $b(i,t)$ denote stock i's assigned size–liquidity bin in month t and let $r^{\text{bench}}_{b(i,t),t}$ be the corresponding value-weighted benchmark return (using lagged market cap weights).

The DGTW-style characteristic-adjusted return is

$$r_{i,t}^{\text{DGTW}} = r_{i,t} - r_{b(i,t),t}^{\text{bench}},$$

(and analogously for excess returns net of risk-free interest rate). This adjustment ensures that any differences in anomaly payoffs across IC groups are not simply reflecting systematic tilts toward small or illiquid stocks.

6.2 Double-sorts on inventory concentration and anomaly signals

The main portfolio construction is a monthly double sort designed to isolate how anomaly strength varies across lending-market states. In month t, we 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, we 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. We also require at least 20 stocks in both the long and short legs within each IC group-month.

6.3 Cluster-level evidence: anomalies are stronger when lendable inventory is more concentrated

To summarize patterns across signals, we follow Jensen et al. (2023) and group the 149 anomalies into economically interpretable clusters (e.g., momentum, value,

Table 9: 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 $r_t^q = r_{5q,t} - r_{1q,t}$.

investment, profitability, accruals). At the cluster level, we average the anomaly-specific High–Low IC return differences across all characteristics in the cluster.

Table 10 reports cluster-average High–Low IC differentials using raw excess returns. The pattern is broad-based: in most clusters, anomaly spreads are larger in High-IC stocks than in Low-IC stocks. The magnitudes are economically meaningful. For example, the High–Low IC differential is 0.77% per month for momentum (t = 19.60) and 0.59% for value (t = 9.99). Investment and profitability also exhibit sizeable amplification (0.42% and 0.46% per month, respectively, both highly significant). One exception is the low-leverage cluster: its High–Low IC difference is negative, meaning the anomaly is weaker (or reverses) in High-IC stocks relative to Low-IC stocks. This suggests that leverage-related anomalies' returns respond differently to lending-market conditions than the other anomaly clusters.

The CAPM-adjusted results point to a similar conclusion. The second column of Table 10 reports High–Low IC differences in CAPM alpha; these alphas are typically close to the corresponding return differentials (e.g., momentum: 0.68%; value: 0.55%; low risk: 0.67%). This indicates that the amplification is not mechanically driven by differential market exposure across IC groups.

Decomposing the High–Low IC differential into long- and short-leg contributions reveals where the difference comes from. The third column ("HC L – LC L") is generally small, while the fourth column ("HC S – LC S") is significantly large and negative in most clusters. For momentum, the long-leg contribution is 0.13% per month whereas the short-leg contribution is –0.64%. For value, the long-leg contribution is essentially zero (0.01%) and the short-leg contribution is –0.59%. This asymmetric decomposition suggests that inventory concentration primarily attenuates the profitability of short positions: when lendable inventory is more concentrated, stocks in the short leg appear to remain more overpriced , consistent with tighter short-sale constraints and weaker arbitrage on the short side.

Because IC is correlated with firm size and liquidity, Table 11 repeats the same analysis using DGTW-style characteristic-adjusted excess returns based on size×liquidity benchmark portfolios. The qualitative pattern is unchanged: High–Low IC differentials remain positive and economically large for the main clusters, and the difference continues to load primarily on the short leg. This robustness indicates that the cluster-level evidence reflects lending-market conditions rather than a mechanical size or liquidity tilt.

Table 10: Cluster-level High–Low IC anomaly return differentials (raw excess returns).

Cluster	**HC–LC**	**HC–LC $\alpha_{\mathbf{CAPM}}$**	**HC L – LC L**	**HC S – LC S**
Momentum	0.77***	0.68***	0.13***	-0.64***
	(19.60)	(7.22)	(3.20)	(-13.39)
Value	0.59***	0.55***	0.01	-0.59***
	(9.99)	(9.25)	(0.21)	(-10.32)
Profitability	0.46***	0.60***	-0.07	-0.52***
	(7.74)	(9.85)	(-1.43)	(-12.96)
Size	0.43**	0.18***	0.00	-0.43***
	(2.42)	(7.41)	(0.01)	(-9.92)
Investment	0.42***	0.37***	-0.10***	-0.53***
	(7.52)	(10.09)	(-3.15)	(-13.86)
Low Risk	0.38***	0.67***	-0.05	-0.43***
	(5.73)	(10.09)	(-1.36)	(-8.24)
Quality	0.33***	0.58***	-0.09***	-0.42***
	(5.38)	(9.48)	(-2.87)	(-7.22)
Short-Term Reversal	0.28**	0.18	-0.13***	-0.40***
	(2.28)	(1.44)	(-4.85)	(-4.15)
Accruals	0.25***	0.12***	-0.18*	-0.43***
	(2.76)	(4.58)	(-1.88)	(-7.53)
Profit Growth	0.19**	0.16***	-0.15**	-0.34***
	(2.16)	(3.87)	(-2.23)	(-5.36)
Debt Issuance	0.11*	0.21***	-0.18***	-0.30***
	(1.91)	(3.89)	(-7.06)	(-8.20)
Seasonality	0.09	0.17***	0.05	-0.03
	(1.17)	(4.58)	(0.76)	(-0.65)
Low Leverage	-0.27***	0.13***	-0.31***	-0.04
	(-2.63)	(7.46)	(-2.61)	(-0.58)

Notes: Entries report estimates with t-statistics in parentheses on the line below. *, **, and *** denote significance at the 10%, 5%, and 1% levels based on $|t|$.

Table 11: Cluster-level High–Low IC anomaly return differentials (DGTW-adjusted excess returns).

Cluster	**HC–LC**	**HC–LC $\alpha_{\mathbf{CAPM}}$**	**HC L – LC L**	**HC S – LC S**
Momentum	0.72***	0.67***	0.21***	-0.51***
	(18.69)	(7.59)	(4.66)	(-11.57)
Value	0.62***	0.42***	0.13***	-0.49***
	(10.79)	(8.52)	(3.34)	(-9.10)
Investment	0.46***	0.33***	0.03	-0.43***
	(7.86)	(9.85)	(0.84)	(-10.97)
Profitability	0.45***	0.47***	0.04	-0.41***
	(8.23)	(8.00)	(0.98)	(-11.34)
Low Risk	0.40***	0.63***	0.08**	-0.32***
	(5.28)	(10.96)	(2.01)	(-5.74)
Quality	0.32***	0.50***	0.02	-0.30***
	(5.27)	(9.77)	(0.57)	(-5.29)
Short-Term Reversal	0.31**	0.19	-0.00	-0.31***
	(2.50)	(1.21)	(-0.01)	(-3.10)
Accruals	0.29***	0.12***	-0.06	-0.35***
	(3.14)	(6.67)	(-0.71)	(-5.47)
Size	0.27	0.28***	-0.01	-0.28***
	(1.52)	(6.53)	(-0.08)	(-6.19)
Profit Growth	0.18**	0.15***	-0.05	-0.23***
	(2.00)	(4.22)	(-0.73)	(-3.41)
Debt Issuance	0.14**	0.22***	-0.06**	-0.21***
	(2.24)	(3.80)	(-2.12)	(-5.70)
Seasonality	0.04	0.12***	0.12*	0.07
	(0.70)	(3.78)	(1.78)	(1.46)
Low Leverage	-0.26***	0.14***	-0.22***	0.04
	(-2.65)	(3.43)	(-2.63)	(0.69)

Notes: Entries report estimates with t-statistics in parentheses on the line below. *, **, and *** denote significance at the 10%, 5%, and 1% levels based on $|t|$.

6.4 Fee-adjusted implementations

Borrow fees are a first-order implementation cost for short-selling-based strategies. To assess net profitability, we construct *fee-adjusted* anomaly returns using Markit indicative borrow fees. Let $r_{i,t+1}$ denote stock i's next-month excess return and let $f_{i,t+1}$ denote the average *buy-side* borrow fee over the same month (converted to monthly units). For a short position, the fee is a direct carrying cost, so the fee-adjusted short-leg return is

$$r_{i,t+1}^{\text{short,net}} \approx -r_{i,t+1} - f_{i,t+1}.$$

For a long position, lending income is earned only on the fraction of shares actually lent and net of intermediary spreads. In the baseline adjustment, we therefore credit $0.7 \times f_{i,t+1}$ to the long leg:

$$r_{i,t+1}^{\text{long,net}} \approx r_{i,t+1} + 0.7\, f_{i,t+1}.$$

Fee-adjusted long–short returns are formed by differencing the fee-adjusted long and short legs, and fee-adjusted CAPM alphas are obtained by regressing the resulting portfolio excess returns on the market excess return.

A useful benchmark implication is that if borrowing costs are the sole source of abnormal performance, then net-of-fee CAPM alphas should vanish once we condition on fees. Under this null, expected abnormal returns for high-fee shorts are exactly offset by the borrowing cost,

$$E[\alpha + f \mid f] \approx 0 \qquad \Leftrightarrow \qquad E[\alpha \mid f] \approx -f,$$

so strategies that systematically short high-fee stocks should not earn positive fee-adjusted alphas.

Tables 12 and 13 provide two complementary views of net implementable performance. Table 12 reports fee-adjusted excess returns, while Table 13 additionally benchmarks returns using DGTW size×liquidity characteristic portfolios. Across both tables, the High–Low IC differences remain economically large for several clusters. In Table 12, the High–Low IC differential is 0.71% per month for momentum ($t = 19.90$), 0.46% for value ($t = 8.54$), and 0.36% for investment ($t = 6.67$); low risk (0.31%, $t = 5.21$) and profitability (0.30%, $t = 5.24$) are also sizable. The corresponding High–Low differences in CAPM alpha remain positive and large (momentum 0.63%, $t = 7.19$; value 0.46%, $t = 8.28$; investment 0.33%, $t = 9.43$; low risk 0.62%, $t = 10.46$; profitability 0.51%, $t = 8.27$), indicating that the net High–Low IC effects are not driven simply by market exposure.

Because the fee adjustment credits $0.7 \times f_{i,t+1}$ to the long leg, the long leg mechanically contributes positively to net anomaly profits. The key question is therefore whether the short side still exhibits meaningful cross-IC differences after accounting for the borrowing cost that arbitrageurs must pay to maintain short positions. The leg decomposition in the tables shows that these differences remain economically large and statistically significant. In Table 12, the short-leg High–Low differences ("HC S – LC S") remain large and statistically significant for the major clusters: –0.49% per month for momentum ($t = -11.73$), –0.39% for value ($t = -7.49$), –0.38% for investment ($t = -10.62$), –0.30% for profitability ($t = -8.01$), and –0.29% for accruals ($t = -4.85$). By comparison, the long-leg High–Low differences are smaller (e.g., momentum 0.22%, value 0.07%, low risk 0.03). Thus, even with fee adjustment—which mechanically boosts the long leg through the $0.7 \times f_{i,t+1}$ credit—the net High–Low IC spread remains closely associated with economically large and statistically significant differences on the short side.

Table 13 shows that this conclusion is robust to additionally removing size–liquidity-related return components via DGTW benchmarking. The High–Low IC differentials remain economically meaningful for the leading clusters (momentum 0.66%, $t = 18.44$; value 0.49%, $t = 9.33$; investment 0.41%, $t = 7.06$; low risk 0.32%, $t = 4.76$; profitability 0.30%, $t = 5.54$). Importantly, the short-leg differences continue to be large: –0.37% for momentum ($t = -9.56$), –0.29% for value ($t = -5.99$), –0.29% for investment ($t = -7.70$), and –0.20% for size ($t = -6.22$). In contrast, the long-leg contributions are again smaller and often positive (e.g., momentum 0.29%, value 0.19%, investment 0.12%, low risk 0.16%).

Overall, once borrowing costs are incorporated—and even after additionally controlling for size and liquidity via DGTW benchmarks—inventory concentration continues to predict larger anomaly profits. A key feature of the results is that the short-leg High–Low IC differences remain economically large and statistically significant, indicating that short-side performance continues to contribute materially to the net anomaly return even after accounting for the fees required to short.

Table 12: Cluster-level High–Low IC anomaly return differentials (fee-adjusted excess returns).

Cluster	**HC–LC**	**HC–LC $\alpha_{\mathbf{CAPM}}$**	**HC L – LC L**	**HC S – LC S**
Momentum	0.71***	0.63***	0.22***	-0.49***
	(19.90)	(7.19)	(5.72)	(-11.73)
Value	0.46***	0.46***	0.07*	-0.39***
	(8.54)	(8.28)	(1.73)	(-7.49)
Investment	0.36***	0.33***	-0.01	-0.38***
	(6.67)	(9.43)	(-0.46)	(-10.62)
Low Risk	0.31***	0.62***	0.03	-0.27***
	(5.21)	(10.46)	(0.97)	(-5.96)
Size	0.31*	0.18***	0.01	-0.30***
	(1.93)	(3.48)	(0.09)	(-9.24)
Profitability	0.30***	0.51***	-0.00	-0.30***
	(5.24)	(8.27)	(-0.02)	(-8.01)
Short-Term Reversal	0.25	0.23	-0.02	-0.27
	(1.12)	(1.26)	(-0.46)	(-1.56)
Quality	0.22***	0.50***	-0.02	-0.24***
	(4.11)	(9.22)	(-0.58)	(-4.61)
Profit Growth	0.17*	0.15***	-0.08	-0.24***
	(1.65)	(3.73)	(-1.07)	(-4.30)
Accruals	0.20***	0.09***	-0.09	-0.29***
	(2.64)	(4.51)	(-1.14)	(-4.85)
Debt Issuance	0.08	0.19***	-0.09***	-0.17***
	(1.33)	(3.37)	(-3.04)	(-4.91)
Seasonality	0.00	0.17***	0.09	0.08
	(0.06)	(4.93)	(1.28)	(1.63)
Low Leverage	-0.28**	0.12***	-0.19	0.09
	(-2.20)	(3.97)	(-1.58)	(1.61)

Notes: Entries report estimates with t-statistics in parentheses on the line below. *, **, and *** denote significance at the 10%, 5%, and 1% levels based on $|t|$.

Table 13: Cluster-level High–Low IC anomaly return differentials (DGTW- and fee-adjusted excess returns).

Cluster	**HC–LC**	**HC–LC $\alpha_{\mathbf{CAPM}}$**	**HC L – LC L**	**HC S – LC S**
Momentum	0.66***	0.62***	0.29***	-0.37***
	(18.44)	(7.57)	(6.99)	(-9.56)
Value	0.49***	0.34***	0.19***	-0.29***
	(9.33)	(7.29)	(4.88)	(-5.99)
Investment	0.41***	0.30***	0.12***	-0.29***
	(7.06)	(9.02)	(3.53)	(-7.70)
Low Risk	0.32***	0.58***	0.16***	-0.16***
	(4.76)	(11.13)	(4.50)	(-3.31)
Profitability	0.30***	0.37***	0.11**	-0.19***
	(5.54)	(6.31)	(2.47)	(-5.64)
Size	0.29*	0.33***	0.10	-0.20***
	(1.71)	(9.25)	(0.69)	(-6.22)
Short-Term Reversal	0.26*	0.15	0.09**	-0.17*
	(1.96)	(0.96)	(2.52)	(-1.67)
Accruals	0.23***	0.09***	0.03	-0.20***
	(3.05)	(6.15)	(0.44)	(-3.10)
Quality	0.21***	0.43***	0.09***	-0.12**
	(3.91)	(9.41)	(2.99)	(-2.39)
Profit Growth	0.14	0.12***	0.04	-0.10
	(1.53)	(3.55)	(0.67)	(-1.52)
Debt Issuance	0.11*	0.20***	0.03	-0.07**
	(1.71)	(3.31)	(1.04)	(-2.22)
Seasonality	0.01	0.11***	0.19***	0.18***
	(0.23)	(3.59)	(3.10)	(3.55)
Low Leverage	-0.25**	0.14***	-0.09	0.15***
	(-2.16)	(3.14)	(-1.08)	(2.61)

Notes: Entries report estimates with t-statistics in parentheses on the line below. *, **, and *** denote significance at the 10%, 5%, and 1% levels based on $|t|$.

6.5 A summary mispricing measure: NetLeg portfolios

To aggregate information across many anomaly signals, we construct a NetLeg measure following Engelberg et al. (2018). Using the 149 anomaly signals, we 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. NetLeg is defined as:

$$\text{NetLeg}_{i,t} = \#\text{LongLeg}_{i,t} - \#\text{ShortLeg}_{i,t}.$$

Stocks with higher NetLeg are more frequently classified as "undervalued" by anomaly signals, whereas stocks with lower NetLeg are more frequently classified as "overvalued."

Each month, we 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. We then repeat the same construction within Low-, Mid-, and High-IC subsamples to test whether anomaly-driven mispricing is stronger when lendable inventory is more concentrated (and, consequently, short-sale constraints are more binding and price discovery is slower). To ensure the results are not mechanically driven by size or liquidity, we rerun all tests using DGTW-adjusted excess returns. Finally, because the assumption that arbitrageurs can effectively "earn" borrowing fees on the long leg is not always realistic, we also construct an alternative version of NetLeg returns that charges borrowing fees only to the short leg, leaving the long leg unadjusted.

Figure 7 plots cumulative log excess returns of the NetLeg strategy across IC groups, with solid lines showing gross (before-fee) performance and dashed lines showing fee-adjusted performance. A clear monotonic pattern emerges: returns are highest for High-IC stocks, intermediate in the full sample, and lowest for Low-IC stocks. This ranking aligns with the cluster-level intuition that mispricing is most pronounced when lendable inventory is more concentrated, short-sale constraints are tighter, and the incorporation of news into prices is slower.

By the end of 2023–12, the High-IC portfolio accumulates 2.573 in log excess returns before fees and 2.207 after fees, well above the full-sample portfolio (1.448 before, 1.255 after) and the Low-IC portfolio (0.516 before, 0.456 after). Thus, relative to the broader universe, the NetLeg strategy identifies substantially stronger and more persistent mispricing in the High-IC segment.

Borrowing fees lower the level of cumulative performance but do not alter the central conclusion. The fee wedge (solid minus dashed) is largest for High IC (≈ 0.366

log points), smaller for the full sample (≈ 0.193), and smallest for Low IC (≈ 0.060). This cross-group pattern is consistent with stronger (but costlier) implementation in High-IC stocks—potentially reflecting higher borrowing costs and related trading frictions—yet fee-adjusted performance remains clearly positive and economically meaningful in that group. DGTW adjustment and fee adjustments applied only to the short legs do not change the conclusion qualitatively(see Figures 8, 9, and 10).

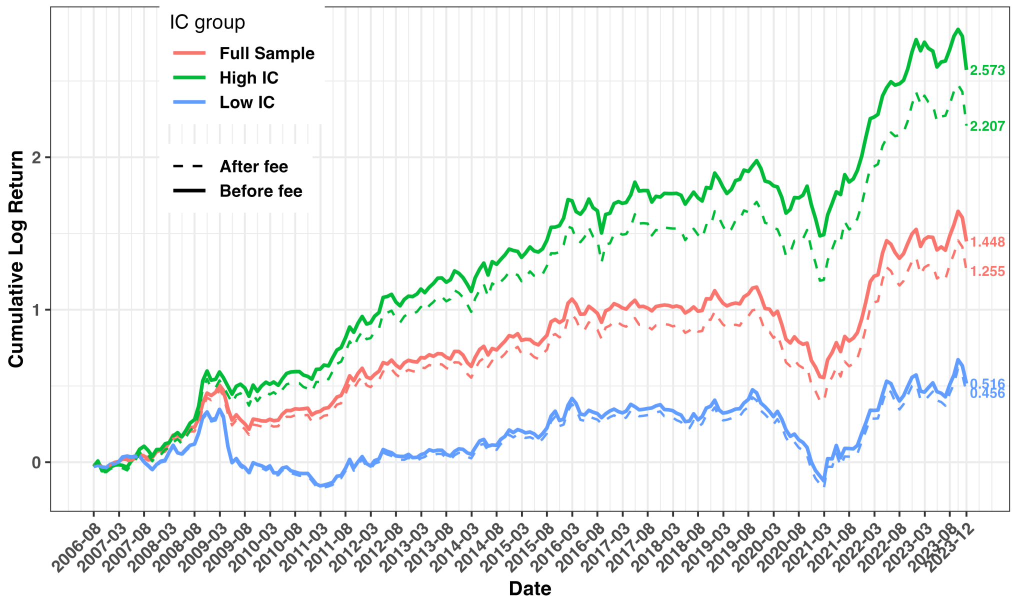

Figure 7: Cumulative log excess returns of NetLeg portfolios (borrowing-fee adjustment is applied to the both short and long legs), 2006–08 to 2023–12.

Table 14 reports portfolio-level statistics for NetLeg quintile sorts in Low- and High-IC subsamples. The state dependence is pronounced. In the High-IC subsample, average monthly excess returns rise steeply from -5.06 bps in the lowest NetLeg quintile to 133.40 bps in the highest quintile, delivering a high-minus-low spread of **138.46** bps per month ($t = 3.52$). This monotonic pattern is also evident in risk-adjusted performance: the CAPM high–low alpha equals **115.04** bps ($t = 3.17$). Consistent with stronger short-sale frictions in High IC stocks, borrowing costs are materially larger in hig-IC groups—average fees are 25.97 bps in quintile 1 versus 11.80 bps in quintile 5, implying a fee spread of -14.17 bps ($t = -22.04$). Even after subtracting fees on both legs, the High-IC long–short remains economically and statistically large: fee-adjusted H–L returns are **120.75** bps ($t = 3.08$) and the fee-adjusted CAPM alpha is **97.50** bps ($t = 2.69$). Sharpe ratios reinforce the economic magnitude: SR increases from -0.02 (Q1) to 0.99 (Q5), and the high–low Sharpe is 0.88 (fee-adjusted: 0.77).

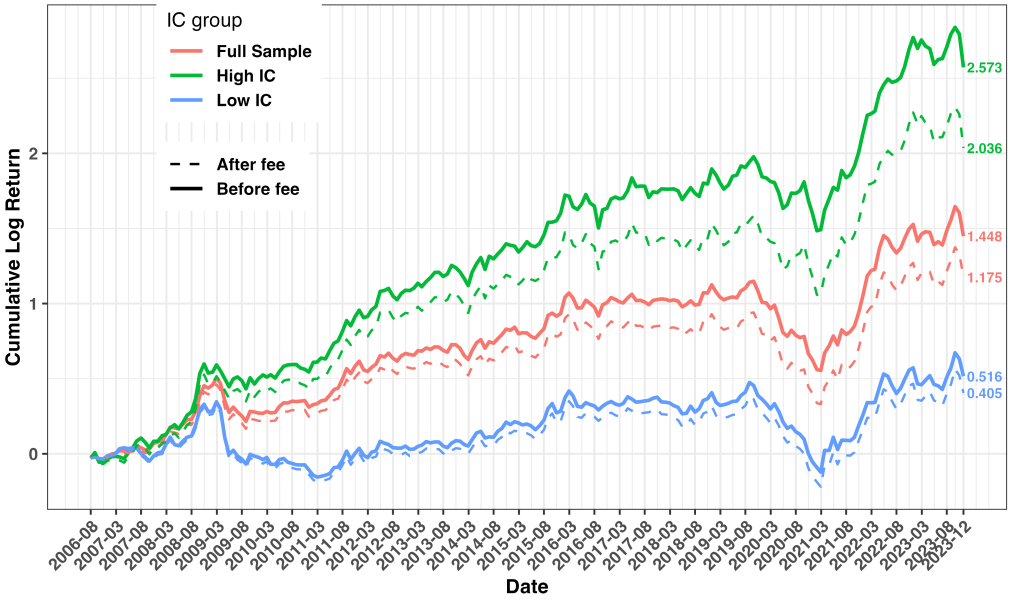

Figure 8: Cumulative log excess returns of NetLeg portfolios (borrowing-fee adjustment is applied to the short leg only), 2006–08 to 2023–12.

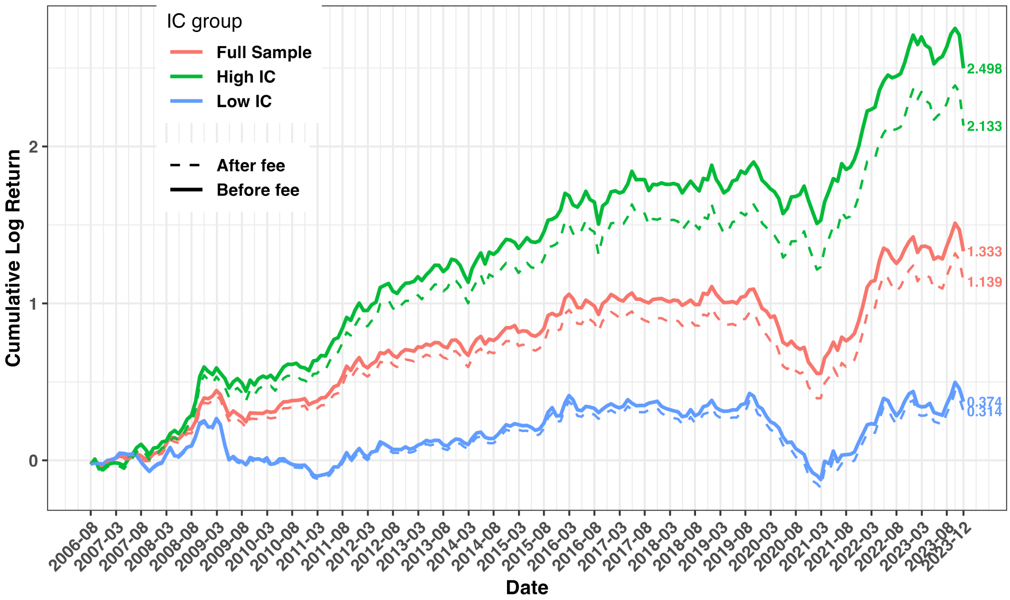

Figure 9: Cumulative log DGTW-adjusted returns of NetLeg portfolios (borrowing-fee adjustment is applied to the both short and long legs), 2006-08–2023-12.

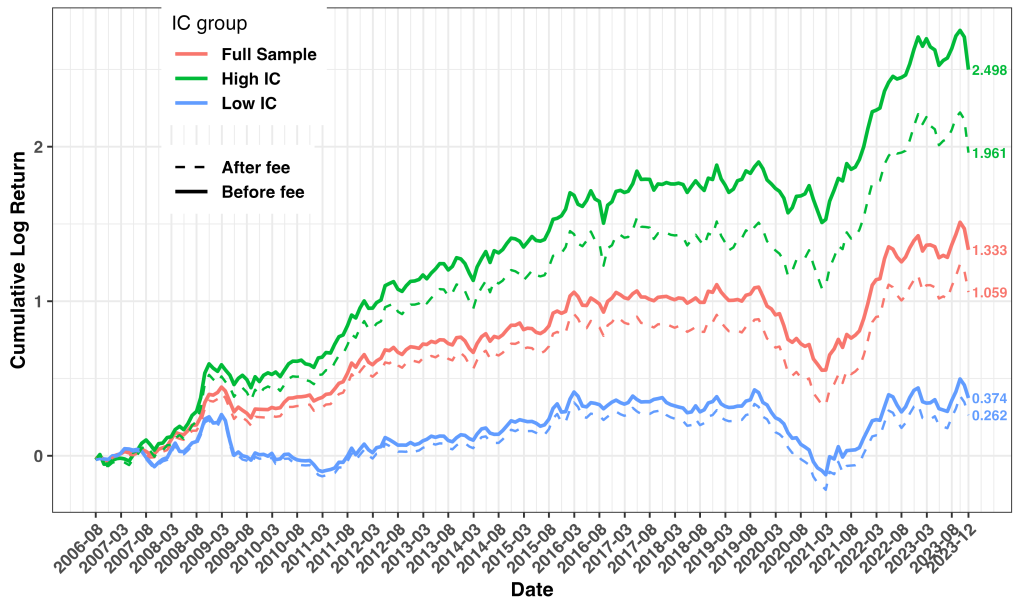

Figure 10: Cumulative log DGTW-adjusted returns of NetLeg portfolios(borrowing-fee adjustment is applied to the short leg only), 2006-08–2023-12.

In contrast, the Low-IC subsample exhibits only a mild cross-quintile gradient. Returns increase from 59.73 bps (Q1) to 93.58 bps (Q5), and the high–low spread is small and statistically weak at **33.85** bps ($t = 1.03$). CAPM alphas are similarly muted, with an H–L alpha of 35.81 bps ($t = 1.23$). Borrow fees are also an order of magnitude lower in Low IC stocks (about 3–5 bps across quintiles), and fee adjustment barely changes the inference: the fee-adjusted H–L return is **30.97** bps ($t = 0.95$) and the fee-adjusted CAPM H–L alpha is 32.99 bps ($t = 1.14$). Notably, Low-IC Sharpe ratios are higher in levels (reflecting positive returns across all quintiles), but the incremental Sharpe from the long–short spread remains modest (H–L $SR = 0.27$, fee-adjusted $SR = 0.25$), underscoring that NetLeg sorting adds limited incremental pricing power when the lendable inventory is less concentrated.

Overall, the results suggest a simple interpretation: the NetLeg signal is most informative exactly when lendable inventory is concentrated (High IC). In that state, short-selling is more constrained and prices incorporate information more slowly, so mispricing can be larger and more persistent even though it is harder to arbitrage away. Consistent with this mechanism, the High-IC segment exhibits a high–low spread that is both economically larger and statistically more precisely estimated, while the much higher borrow-fee differentials indicate that these returns arise precisely where short-selling frictions are most severe. Table 18 reinforces this interpretation by showing that the *short side* of the NetLeg sort (Q1) is also where borrowing conditions are most fragile: in High IC stocks, fee and utilization risk decline sharply from Q1 to Q5 (e.g., log(UtilVar) falls from 3.019 to 0.479 and FeeTail falls from 4.924 to 3.031), and the dispersion in borrowing risk is materially larger than in Low IC stocks (e.g., the Q1–Q5 spread in log(FeeVar) is 0.752 in High IC versus 0.377 in Low IC; FeeTail differs by 1.894 versus 0.421). Taken together, the evidence links anomaly amplification in High IC stocks to a lending environment that is both more expensive on average and more unstable precisely for the stocks that the strategy needs to short.

Table 14: NetLeg portfolios: Low-IC vs. High-IC comparison (fee-adjusted on both legs). Returns, α, and borrow fees in basis points.

Metric	Group	1	2	3	4	5	H–L
r	Low-IC	59.73	87.05	89.93	92.63	93.58	33.85
		(1.05)	(1.92)	(2.35)	(2.59)	(2.81)	(1.03)
	High-IC	-5.06	33.75	69.56	91.04	133.40	138.46
		(-0.08)	(0.62)	(1.58)	(2.12)	(3.35)	(3.52)
Avg. Fee	Low-IC	5.34	3.86	3.51	3.42	3.53	-1.81
		–	–	–	–	–	(-9.06)
	High-IC	25.97	17.13	14.28	13.22	11.80	-14.17
		–	–	–	–	–	(-22.04)
SR	Low-IC	0.271	0.473	0.557	0.598	0.667	0.274
	High-IC	-0.021	0.181	0.460	0.663	0.994	0.883
r^{feeadj}	Low-IC	65.07	89.75	92.39	95.02	96.05	30.97
		(1.14)	(1.98)	(2.42)	(2.66)	(2.89)	(0.95)
	High-IC	20.91	45.74	79.56	100.29	141.66	120.75
		(0.32)	(0.84)	(1.82)	(2.34)	(3.56)	(3.08)
SR^{feeadj}	Low-IC	0.295	0.487	0.573	0.613	0.684	0.251
	High-IC	0.086	0.246	0.526	0.731	1.056	0.771
α_{CAPM}	Low-IC	-26.48	2.41	10.52	11.29	9.32	35.81
		(-1.00)	(0.15)	(0.82)	(1.11)	(0.85)	(1.23)
	High-IC	-27.62	-1.62	29.27	41.85	87.41	115.04
		(-0.66)	(-0.05)	(0.91)	(1.36)	(4.05)	(3.17)
$\alpha^{\text{feeadj}}_{CAPM}$	Low-IC	-21.16	5.11	12.99	13.70	11.83	32.99
		(-0.81)	(0.32)	(1.01)	(1.35)	(1.07)	(1.14)
	High-IC	-1.89	10.23	39.10	50.97	95.61	97.50
		(-0.05)	(0.33)	(1.21)	(1.65)	(4.42)	(2.69)

Table 15: NetLeg portfolios: Low-IC vs. High-IC comparison (fee-adjusted on the short leg only). Returns, α, and borrow fees in basis points.

Metric	Group	1	2	3	4	5	H–L
r	Low-IC	59.73	87.05	89.93	92.63	93.58	33.85
		(1.05)	(1.92)	(2.35)	(2.59)	(2.81)	(1.03)
	High-IC	-5.06	33.75	69.56	91.04	133.40	138.46
		(-0.08)	(0.62)	(1.58)	(2.12)	(3.35)	(3.52)
Avg. Fee	Low-IC	5.34	3.86	3.51	3.42	3.53	-1.81
		–	–	–	–	–	(-9.06)
	High-IC	25.97	17.13	14.28	13.22	11.80	-14.17
		–	–	–	–	–	(-22.05)
SR	Low-IC	0.271	0.473	0.557	0.598	0.667	0.274
	High-IC	-0.021	0.181	0.460	0.663	0.994	0.883
r^{feeadj}	Low-IC	65.07	87.05	89.93	92.63	93.58	28.51
		(1.14)	(1.92)	(2.35)	(2.59)	(2.81)	(0.87)
	High-IC	20.91	33.75	69.56	91.04	133.40	112.50
		(0.32)	(0.62)	(1.58)	(2.12)	(3.35)	(2.87)
SR^{feeadj}	Low-IC	0.295	0.473	0.557	0.598	0.667	0.231
	High-IC	0.086	0.181	0.460	0.663	0.994	0.718
α_{CAPM}	Low-IC	-26.48	2.41	10.52	11.29	9.32	35.81
		(-1.00)	(0.15)	(0.82)	(1.11)	(0.85)	(1.23)
	High-IC	-27.62	-1.62	29.27	41.85	87.41	115.04
		(-0.66)	(-0.05)	(0.91)	(1.36)	(4.05)	(3.17)
$\alpha_{CAPM}^{\text{feeadj}}$	Low-IC	-21.16	2.41	10.52	11.29	9.32	30.48
		(-0.81)	(0.15)	(0.82)	(1.11)	(0.85)	(1.05)
	High-IC	-1.89	-1.62	29.27	41.85	87.41	89.30
		(-0.05)	(-0.05)	(0.91)	(1.36)	(4.05)	(2.47)

Table 16: NetLeg portfolios: Low-IC vs. High-IC comparison (DGTW-adjusted; fee-adjusted on both legs). Returns, α, and borrow fees in basis points.

Metric	Group	1	2	3	4	5	H–L
r	Low-IC	-11.89	10.67	7.59	13.06	12.37	24.26
		(-0.52)	(1.16)	(1.17)	(1.80)	(1.52)	(0.87)
	High-IC	-67.91	-34.41	0.87	20.84	65.05	132.96
		(-2.67)	(-1.97)	(0.07)	(1.28)	(4.11)	(3.59)
Avg. Fee	Low-IC	5.34	3.86	3.51	3.42	3.53	-1.81
		–	–	–	–	–	(-9.06)
	High-IC	25.97	17.13	14.28	13.22	11.80	-14.17
		–	–	–	–	–	(-22.05)
SR	Low-IC	-0.147	0.260	0.256	0.423	0.352	0.235
	High-IC	-0.643	-0.596	0.015	0.308	1.087	0.910
r^{feeadj}	Low-IC	-6.55	13.37	10.05	15.45	14.83	21.39
		(-0.29)	(1.46)	(1.54)	(2.12)	(1.83)	(0.77)
	High-IC	-41.95	-22.42	10.87	30.10	73.31	115.26
		(-1.65)	(-1.28)	(0.82)	(1.83)	(4.60)	(3.12)
SR^{feeadj}	Low-IC	-0.081	0.326	0.340	0.501	0.423	0.207
	High-IC	-0.397	-0.389	0.187	0.444	1.224	0.790
α_{CAPM}	Low-IC	-18.18	5.29	9.40	13.57	8.58	26.75
		(-0.90)	(0.49)	(1.06)	(1.53)	(0.79)	(1.05)
	High-IC	-32.61	-10.77	20.45	25.78	70.15	102.76
		(-1.15)	(-0.70)	(0.99)	(1.16)	(5.23)	(2.93)
$\alpha_{CAPM}^{\text{feeadj}}$	Low-IC	-12.85	7.99	11.87	15.98	11.08	23.93
		(-0.64)	(0.74)	(1.34)	(1.81)	(1.02)	(0.94)
	High-IC	-6.87	1.07	30.28	34.90	78.35	85.23
		(-0.24)	(0.07)	(1.45)	(1.55)	(5.79)	(2.43)

Table 17: NetLeg portfolios: Low-IC vs. High-IC comparison (DGTW-adjusted; fee-adjusted on the short leg only). Returns, α, and borrow fees in basis points.

Metric	Group	1	2	3	4	5	H–L
r	Low-IC	-11.89	10.67	7.59	13.06	12.37	24.26
		(-0.52)	(1.16)	(1.17)	(1.80)	(1.52)	(0.87)
	High-IC	-67.91	-34.41	0.87	20.84	65.05	132.96
		(-2.67)	(-1.97)	(0.07)	(1.28)	(4.11)	(3.59)
Avg. Fee	Low-IC	5.34	3.86	3.51	3.42	3.53	-1.81
		–	–	–	–	–	(-9.06)
	High-IC	25.97	17.13	14.28	13.22	11.80	-14.17
		–	–	–	–	–	(-22.05)
SR	Low-IC	-0.147	0.260	0.256	0.423	0.352	0.235
	High-IC	-0.643	-0.596	0.015	0.308	1.087	0.910
r^{feeadj}	Low-IC	-6.55	10.67	7.59	13.06	12.37	18.92
		(-0.29)	(1.16)	(1.17)	(1.80)	(1.52)	(0.68)
	High-IC	-41.95	-34.41	0.87	20.84	65.05	107.00
		(-1.65)	(-1.97)	(0.07)	(1.28)	(4.11)	(2.90)
SR^{feeadj}	Low-IC	-0.081	0.260	0.256	0.423	0.352	0.183
	High-IC	-0.397	-0.596	0.015	0.308	1.087	0.733
α_{CAPM}	Low-IC	-18.18	5.29	9.40	13.57	8.58	26.75
		(-0.90)	(0.49)	(1.06)	(1.53)	(0.79)	(1.05)
	High-IC	-32.61	-10.77	20.45	25.78	70.15	102.76
		(-1.15)	(-0.70)	(0.99)	(1.16)	(5.23)	(2.93)
$\alpha_{CAPM}^{\text{feeadj}}$	Low-IC	-12.85	5.29	9.40	13.57	8.58	21.43
		(-0.64)	(0.49)	(1.06)	(1.53)	(0.79)	(0.85)
	High-IC	-6.87	-10.77	20.45	25.78	70.15	77.03
		(-0.24)	(-0.70)	(0.99)	(1.16)	(5.23)	(2.20)

Table 18: Short-selling risk across NetLeg quintiles for High vs. Low IC

Group	Metric	Q1	Q2	Q3	Q4	Q5	Q5–Q1
High IC	log(FeeVar)	-2.011	-2.666	-2.745	-2.780	-2.762	-0.752
	log(UtilVar)	3.019	2.135	1.496	1.005	0.479	-2.540
	FeeTail	4.924	3.755	3.525	3.428	3.031	-1.894
	UtilTail	46.005	32.062	24.609	19.694	15.105	-30.900
Low IC	log(FeeVar)	-5.831	-6.194	-6.244	-6.269	-6.208	-0.377
	log(UtilVar)	1.661	0.627	0.219	0.067	0.039	-1.622
	FeeTail	1.035	0.702	0.618	0.589	0.614	-0.421
	UtilTail	30.438	18.410	14.709	13.539	13.332	-17.106

6.6 Equity Mispricing, Borrowing Fees, and Short-Selling Risk

The portfolio results above show that anomaly-based strategies earn larger returns among stocks facing more severe securities-lending frictions. The evidence is especially pronounced on the short side, where arbitrageurs must borrow shares in order to trade against overpricing. This section examines the mechanism in a unified cross-sectional framework. The goal is to distinguish between two related but economically different dimensions of short-sale constraints: the *price* of borrowing, measured by loan fees, and the *risk* or fragility of maintaining a short position, measured by short-selling risk.

This distinction is central to the paper's argument. If lending frictions were fully summarized by the borrowing fee, then loan fees should absorb the predictive content of lending-market tightness. In contrast, if concentrated or fragile lending markets create quantity constraints, recall risk, or unstable access to shares, then short-selling risk should retain explanatory power even after controlling for fees. In this case, the fee is not a sufficient statistic for the effective constraint faced by arbitrageurs.

Percentile-rank standardization. All stock-level regressors are standardized using within-month percentile ranks. For any characteristic $X_{i,t}$ observed in month t, define

$$X_{i,t}^{\text{rnk}} = \text{PercentRank}_t(X_{i,t}) \in [0, 1].$$

Values near zero correspond to the bottom of the monthly cross-sectional distribution, values near one correspond to the top, and a one-unit change corresponds to moving from the bottom to the top of the distribution. This transformation makes coefficients comparable across characteristics and reduces the influence of extreme observations.

The main lending variables are the ranked borrowing fee, $Fee_{i,t}^{\text{rnk}}$, and ranked short-selling risk, $SSR_{i,t}^{\text{rnk}}$. The latter captures the realized fragility of the lending environment faced by short sellers. In the baseline specification, next-month returns are regressed on these two variables. In the full specification, I additionally control for market beta, size, and book-to-market, each measured as within-month percentile ranks.

Short-selling risk. I use the composite short-selling risk measure SSR_{it}^{rnk} defined in Section 3.3. 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_{it}^{rnk} captures the risk that borrowing conditions deteriorate after a short position is initiated.

Panel and Fama–MacBeth specifications. I estimate two complementary regression designs. The first is a panel specification with month fixed effects:

$$r_{i,t+1}^{e} = \alpha_t + \beta_1 Fee_{i,t}^{\text{rnk}} + \beta_2 SSR_{i,t}^{\text{rnk}} + \Gamma' X_{i,t} + \varepsilon_{i,t+1},$$

where $X_{i,t}$ includes beta, size, and book-to-market in the full specification. Standard errors are double-clustered by firm and month.

The second design is a monthly Fama–MacBeth regression:

$$r_{i,t+1}^{e} = \alpha_t + \beta_{1,t} Fee_{i,t}^{\text{rnk}} + \beta_{2,t} SSR_{i,t}^{\text{rnk}} + \Gamma_t' X_{i,t} + \varepsilon_{i,t+1}.$$

I report the time-series averages of the monthly cross-sectional slopes together with Fama–MacBeth t-statistics. The panel specification asks whether the relation is visible in the pooled stock-month panel after absorbing aggregate time variation. The Fama–MacBeth specification asks whether the relation appears consistently in the monthly cross-section.

Results. Table 19 reports the results. Across both panel and Fama–MacBeth specifications, the coefficient on SSR is negative, economically large, and statistically significant. In the panel regressions, the SSR coefficient is -97.29 basis points in the baseline specification ($t = -2.22$) and -103.28 basis points in the full specification ($t = -2.70$). In the Fama–MacBeth regressions, the corresponding estimates are -113.36 basis points ($t = -2.44$) and -132.78 basis points ($t = -3.66$). Thus, short-selling risk robustly predicts lower subsequent returns.

The borrowing fee is less robust. The fee coefficient is negative and statistically significant in the baseline specifications, but it becomes smaller and insignificant after adding beta, size, and book-to-market controls. In the panel specification, the fee coefficient moves from -34.54 basis points ($t = -1.99$) to -19.38 basis points ($t = -1.02$). In the Fama–MacBeth specification, it moves from -27.42 basis points ($t = -1.75$) to -6.88 basis points ($t = -0.45$). This pattern indicates that the observed borrowing fee contains information, but does not fully summarize the relevant short-sale constraint.

The evidence is therefore consistent with a quantity-based interpretation of lending frictions. Fees measure the posted price of borrowing conditional on obtaining access to shares. Short-selling risk captures an additional dimension of implementation difficulty: the instability of borrow access, the risk that positions cannot be maintained, and the possibility that arbitrageurs cannot scale their trades when the lending market is fragile. The strong and stable coefficient on SSR suggests that this non-price dimension of short-sale constraints is central for understanding the persistence of anomaly-related mispricing.

Table 19: Borrowing Fees, Short-Selling Risk, and Next-Month Returns

	Panel		Fama–MacBeth	
	Base	Full	Base	Full
Fee	-34.54**	-19.38	-27.42*	-6.88
	(-1.99)	(-1.02)	(-1.75)	(-0.45)
SSR	-97.29**	-103.28***	-113.36**	-132.78***
	(-2.22)	(-2.70)	(-2.44)	(-3.66)
Beta		42.60		33.99
		(0.85)		(0.78)
Size		36.75		33.52
		(1.37)		(1.18)
BM		26.67		-5.55
		(0.66)		(-0.15)
Controls	No	Yes	No	Yes
Month FE	Yes	Yes	No	No
Inference	Firm-month DC	Firm-month DC	FM	FM
R^2	0.241	0.242	0.012	0.053
Stock $\times$ month Obs.	420,600	420,600		
Months			203	203

Notes: This table reports regressions of next-month excess returns on borrowing fees and short-selling risk. All explanatory variables are measured as within-month percentile ranks. SSR is a composite rank-based measure of short-selling risk, constructed as the average of the ranked fee-volatility, fee-tail-risk, utilization-volatility, and utilization-tail-risk components, using available non-missing components. The base specifications include fee and SSR. The full specifications additionally control for market beta, size, and book-to-market. Panel regressions include month fixed effects and use standard errors double-clustered by firm and month. Fama–MacBeth specifications report average monthly cross-sectional slopes with time-series t-statistics. For panel regressions, the reported R^2 is the within R^2; for Fama–MacBeth regressions, it is the average monthly cross-sectional R^2. Coefficients are reported in basis points, and t-statistics are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

6.7 Anomaly Short-Leg Exposure and Lending-Market Fragility

The previous subsection shows that short-selling risk contains return-predictive information beyond borrowing fees. I now ask whether this lending-market fragility is connected specifically to anomaly arbitrage. If the mechanism is a limit to arbitrage, then lending frictions should matter most for stocks that anomaly strategies want to short. This subsection tests that prediction by interacting lending frictions with the long- and short-leg components of the anomaly signal.

NetLeg, NetLong, and NetShort. The anomaly signal is summarized by three variables. $NetLeg_{i,t}$ measures a stock's net exposure to the anomaly portfolios. $NetLong_{i,t}$ measures how intensively the stock appears on the long side of the anomaly strategies, while $NetShort_{i,t}$ measures how intensively it appears on the short side. Each variable is converted into a within-month percentile rank.

This decomposition is important because a generic relation between lending frictions and returns would not, by itself, imply a short-sale constraint mechanism. The mechanism requires an asymmetry: lending-market frictions should matter more for stocks that arbitrageurs want to short than for stocks that they want to buy. The interaction terms therefore allow the pricing effect of borrowing fees and short-selling risk to differ between long-leg and short-leg anomaly exposure.

Fama–MacBeth specification. In each month, I estimate regressions of the form

$$\begin{aligned} r^e_{i,t+1} = &\alpha_t + \beta_t NetLeg_{i,t} + \theta_t SSR_{i,t} + \phi^L_t \left(NetLong_{i,t} \times SSR_{i,t}\right) + \phi^S_t \left(NetShort_{i,t} \times SSR_{i,t}\right) \\ &+ \lambda_t Fee_{i,t} + \psi^L_t \left(NetLong_{i,t} \times Fee_{i,t}\right) + \psi^S_t \left(NetShort_{i,t} \times Fee_{i,t}\right) + \Gamma'_t X_{i,t} + \varepsilon_{i,t+1}. \end{aligned}$$

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, and bid–ask spreads, each together with its long- and short-leg interactions. The full specification includes all listed controls.

Results. Table 20 reports the Fama–MacBeth estimates across alternative control specifications. The standalone $NetLeg$ coefficient is not robust across specifications. It is positive in most columns, but statistically insignificant except when institutional ownership controls are added. This indicates that anomaly exposure does not generate a uniform unconditional return premium in this cross-sectional setting once lending frictions and control interactions are included.

The main evidence appears in the interaction terms. The interaction between short-leg anomaly exposure and short-selling risk, $NetShort \times SSR$, is negative and statistically significant across all specifications. The coefficient is -148.22 basis points in the baseline specification ($t = -1.78$) and remains large in the full specification at -149.81 basis points ($t = -2.21$). The estimates are similar or stronger when individual controls are added: -175.89 with institutional ownership controls, -180.28 with short interest controls, -157.98 with turnover controls, and -135.41 with bid–ask spread controls. Thus, stocks that are more heavily represented on anomaly short legs earn especially low subsequent returns when short-selling risk is high.

The fee interactions show a similar short-side pattern. The coefficient on $NetShort \times Fee$ is negative and statistically significant in every specification. It equals -132.56 basis points in the baseline specification ($t = -2.91$) and remains significant in the full specification at -90.74 basis points ($t = -2.18$). By contrast, the long-leg interactions with both SSR and Fee are small and statistically insignificant. This asymmetry is central: lending frictions matter primarily where arbitrage requires shorting overpriced stocks.

The control interactions further support this interpretation. Size-related interactions are important, especially on the short side, which is consistent with implementation constraints being more relevant among smaller or less scalable stocks. However, the short-leg lending interactions remain economically large and statistically significant even after accounting for size, institutional ownership, short interest, turnover, and bid–ask spreads. The results therefore suggest that the lending-market channel is not merely a restatement of conventional trading frictions.

Overall, Table 20 connects lending-market fragility directly to anomaly arbitrage. Borrowing fees and short-selling risk both amplify the short-leg return gradient, while the corresponding long-leg effects are weak. This pattern is consistent with a short-sale constraint mechanism: anomaly-related overpricing is most pronounced where arbitrageurs would need to short aggressively, but where doing so is costly, risky, or difficult to scale.

6.8 Summary

The evidence in this section supports a quantity-based interpretation of short-sale constraints. Across specifications, the return-predictive component of lending fric-

Table 20: Anomaly Exposure, Borrowing Fees, Short-Selling Risk, and Next-Month Returns

	Dependent variable: next-month excess return						
Factor	Base	+Size	+IOR	+ShortInt	+Turnover	+BidAsk	Full
Panel A. Anomaly exposure and lending-market frictions							
NetLeg	25.60	25.60	77.69*	38.87	25.43	-18.04	33.56
	(0.62)	(0.62)	(1.66)	(0.93)	(0.62)	(-0.49)	(0.80)
SSR	-4.79	-4.79	15.97	36.91	1.05	22.63	45.74
	(-0.13)	(-0.13)	(0.34)	(0.73)	(0.03)	(0.56)	(0.79)
NetLong × SSR	42.47	42.47	25.48	40.43	41.44	-8.14	-2.06
	(0.83)	(0.83)	(0.45)	(0.68)	(0.92)	(-0.17)	(-0.03)
NetShort × SSR	-148.22*	-148.22*	-175.89**	-180.28**	-157.98**	-135.41**	-149.81**
	(-1.78)	(-1.78)	(-2.15)	(-2.36)	(-2.47)	(-1.97)	(-2.21)
Fee	51.27*	51.27*	31.41	35.03	42.57	42.81	32.42
	(1.65)	(1.65)	(0.91)	(1.03)	(1.37)	(1.46)	(1.02)
NetLong × Fee	2.48	2.48	4.75	11.14	7.57	8.19	8.36
	(0.07)	(0.07)	(0.11)	(0.26)	(0.22)	(0.23)	(0.18)
NetShort × Fee	-132.56***	-132.56***	-86.62*	-125.53**	-115.48***	-116.44***	-90.74**
	(-2.91)	(-2.91)	(-1.96)	(-2.56)	(-2.79)	(-2.66)	(-2.18)
Panel B. Baseline controls and interactions							
β_{mkt}	58.40	58.40	62.36	65.79*	53.98	63.96*	63.84*
	(1.44)	(1.44)	(1.63)	(1.73)	(1.47)	(1.65)	(1.93)
Size	-46.34	-46.34	-47.56	-48.22	-63.39*	-70.61**	-82.79**
	(-1.23)	(-1.23)	(-1.36)	(-1.36)	(-1.72)	(-1.97)	(-2.37)
NetLong × Size	27.35	27.35	50.22*	42.45	46.03	51.67**	91.24***
	(1.13)	(1.13)	(1.66)	(1.63)	(1.60)	(2.37)	(2.80)
NetShort × Size	112.68***	112.68***	78.81**	130.33***	114.27***	111.45***	84.84*
	(3.74)	(3.74)	(1.98)	(3.31)	(2.60)	(3.66)	(1.78)
Panel C. Additional controls and interactions							
IOR			22.51				24.52
			(0.84)				(0.80)
NetLong × IOR			-82.40**				-82.62**
			(-2.52)				(-2.29)
NetShort × IOR			81.83**				74.45*
			(1.97)				(1.68)
ShortInt				-10.58			-4.80
				(-0.35)			(-0.13)
NetLong × ShortInt				-46.94			-38.75
				(-0.97)			(-0.82)
NetShort × ShortInt				21.77			-26.81
				(0.50)			(-0.59)
Turnover					27.15		13.51
					(0.80)		(0.29)
NetLong × Turnover					-24.00		17.68
					(-0.57)		(0.42)
NetShort × Turnover					-11.25		20.40
					(-0.21)		(0.35)
Bid–Ask						-41.96	-26.71
						(-1.28)	(-0.78)
NetLong × Bid–Ask						59.98	41.31
						(1.59)	(1.03)
NetShort × Bid–Ask						-61.14	-52.96
						(-1.23)	(-1.33)

Notes: This table reports monthly Fama–MacBeth regressions of next-month excess returns. All regressors are within-month percentile ranks. *NetLeg* measures net anomaly exposure; *NetLong* and *NetShort* measure long- and short-leg anomaly intensity. *SSR* is the average of ranked fee-volatility, fee-tail-risk, utilization-volatility, and utilization-tail-risk components, using available non-missing components. *Fee* denotes the loan fee. The base specification includes *NetLeg*, *SSR*, *Fee*, size, market beta, and the corresponding *NetLong* and *NetShort* interactions for *SSR*, *Fee*, and size. Other columns add the indicated control and its *NetLong* and *NetShort* interactions; the full specification includes all controls. Coefficients are in basis points, with t-statistics in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels.

tions is not fully captured by the borrowing fee. Short-selling risk is a stronger and more robust predictor of next-month returns, suggesting that the relevant constraint is not only the posted price of borrowing but also the instability of maintaining and scaling short positions.

The first set of regressions shows that SSR remains negative and statistically significant in both panel and Fama–MacBeth specifications after controlling for beta, size, and book-to-market. By contrast, the borrowing fee loses significance once these controls are included. This result is consistent with the idea that fees measure the price of borrowing conditional on access, while SSR captures the fragility of access itself.

The second set of regressions connects this lending-market friction directly to anomaly arbitrage. The standalone $NetLeg$ coefficient is not robust, indicating that anomaly exposure does not generate a uniform unconditional return premium once lending frictions and controls are included. Instead, the predictive relation operates through the short side. Both $NetShort \times SSR$ and $NetShort \times Fee$ are negative and statistically significant across most specifications, while the corresponding long-leg interactions are weak and insignificant.

Taken together, the results suggest that securities-lending frictions amplify anomaly-related mispricing precisely where arbitrage requires short selling. Borrowing fees matter, but they are not sufficient. The stronger evidence comes from measures that capture the riskiness and instability of shorting. This is consistent with the paper's central mechanism: anomaly short-leg profits are largest where short-sale arbitrage is hardest to implement and scale.

7 Conclusion

This paper studies how the structure of securities lending markets shapes short-selling risk, price discovery, and cross-sectional return predictability. The central object is lendable inventory concentration, IC: the extent to which a stock's lendable supply is concentrated among a small number of institutional lenders. I show that IC is not merely a descriptive feature of the lending market. It is systematically related to the riskiness of short selling and to the persistence of return patterns that depend on short-side arbitrage.

The analysis delivers three main findings. First, concentrated lendable inventory is associated with more costly and more unstable shorting conditions. High-IC stocks have higher borrowing fees, more volatile fees, more volatile utilization, and more frequent tail events in lending conditions. These patterns show that borrowing fees do not fully summarize the relevant short-sale friction. The fee measures the current price of borrowing, whereas short-selling risk captures the instability of borrowing conditions after a short position is initiated.

Second, lendable inventory concentration is related to slower price discovery following negative information. Around earnings announcements, negative news is incorporated more slowly among high-IC stocks. Bad-news announcements generate stronger post-announcement drift when lendable inventory is concentrated, while the corresponding response to good news is weaker. This asymmetry is consistent with a short-sale-constraint mechanism: the effect appears precisely when informed trading requires short selling.

Third, the same lending-market structure helps organize anomaly return spreads. Across a broad set of equity anomalies, high-IC stocks earn larger long–short returns, and the difference is driven primarily by the short leg. These patterns remain economically meaningful after accounting for borrowing fees. Cross-sectional regressions reinforce this conclusion. Short-selling risk predicts lower subsequent returns even after controlling for fees, beta, size, and book-to-market. Moreover, anomaly short-leg exposure predicts especially low subsequent returns when short-selling risk is high, and this relation is not fully captured by loan fees.

Taken together, the evidence suggests that securities lending market structure is an important source of limits to arbitrage. The relevant friction is not only the average borrowing fee, but also the instability of the borrowing environment. When lendable inventory is concentrated among a small number of lenders, short sellers face greater risk that fees, utilization, or other lending conditions deteriorate. This risk weakens the arbitrage response to overpricing and helps explain why short-side return predictability remains persistent.

The paper contributes to the literature on short-sale constraints and market efficiency by shifting attention from borrowing fees alone to the organization of lendable supply. A stock can be only moderately expensive to borrow on average while still being risky to short because lending conditions are unstable. This distinction helps reconcile two empirical facts: short-sale costs are observable and economically important, yet after-fee anomaly returns remain concentrated on the short side. The results show that lendable inventory concentration is a structural source of short-selling risk and a useful state variable for understanding when mispricing is most persistent.

Several extensions remain promising. One direction is to exploit more sharply identified shocks to lender composition, such as exits or large portfolio reallocations by dominant lenders, to isolate exogenous changes in lendable inventory concentration. A second direction is to distinguish among lender types. Quasi-indexers, active institutions, mutual funds, ETFs, custodians, and pension funds may differ in lending behavior, fee sensitivity, and the stability of their lending supply. Understanding which lenders stabilize or destabilize borrowing conditions would further clarify the mechanism. Finally, extending the analysis to international equity markets or other asset classes could show whether lending-market structure is a general determinant of price efficiency beyond U.S. equities.

Overall, the findings show that who lends the shares matters for asset prices. Lendable inventory concentration raises short-selling risk, high short-selling risk slows the incorporation of bad news, and this same risk helps sustain short-leg anomaly returns that are not fully explained by borrowing fees.

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A Additional Results

Table 21: NetLeg portfolios within low-IC groups: returns and selected factor alphas (fee-adjusted on both legs). Returns, α, and borrow fees are expressed in basis points.

Metric	1	2	3	4	5	High–Low
r	59.730	87.050	89.930	92.630	93.580	33.850
	(1.047)	(1.917)	(2.354)	(2.588)	(2.811)	(1.030)
SR	0.271	0.473	0.557	0.598	0.667	0.274
Fee	5.340	3.860	3.510	3.420	3.530	-1.810
	–	–	–	–	–	(-9.061)
r^{feeadj}	65.070	89.750	92.390	95.020	96.050	30.970
	(1.142)	(1.977)	(2.419)	(2.656)	(2.886)	(0.945)
SR^{feeadj}	0.295	0.487	0.573	0.613	0.684	0.251
α_{CAPM}	-26.480	2.410	10.520	11.290	9.320	35.810
	(-1.005)	(0.148)	(0.819)	(1.108)	(0.845)	(1.231)
$\alpha_{CAPM}^{\text{feeadj}}$	-21.160	5.110	12.990	13.700	11.830	32.990
	(-0.807)	(0.316)	(1.013)	(1.347)	(1.072)	(1.138)
$\alpha_{FF5+Mom}$	-20.430	6.510	8.450	8.650	3.600	24.030
	(-1.236)	(0.689)	(0.957)	(0.906)	(0.317)	(1.107)
$\alpha_{FF5+Mom}^{\text{feeadj}}$	-15.080	9.200	10.910	11.050	6.100	21.180
	(-0.921)	(0.981)	(1.239)	(1.159)	(0.538)	(0.981)
N Months	209	209	209	209	209	209
Avg. #Stocks	146	126	132	138	140	–
log(FeeVar)	-5.831	-6.194	-6.244	-6.269	-6.208	-0.377
log(UtilVar)	1.661	0.627	0.219	0.067	0.039	-1.622
FeeTail	1.035	0.702	0.618	0.589	0.614	-0.421
UtilTail	30.438	18.410	14.709	13.539	13.332	-17.106

Table 22: NetLeg portfolios within high-IC groups: returns and selected factor alphas (fee-adjusted on both legs). Returns, α, and borrow fees are expressed in basis points.

Metric	1	2	3	4	5	High–Low
r	-5.060	33.750	69.560	91.040	133.400	138.460
	(-0.077)	(0.616)	(1.583)	(2.120)	(3.346)	(3.518)
SR	-0.021	0.181	0.460	0.663	0.994	0.883
Fee	25.970	17.130	14.280	13.220	11.800	-14.170
	–	–	–	–	–	(-22.045)
r^{feeadj}	20.910	45.740	79.560	100.290	141.660	120.750
	(0.320)	(0.837)	(1.816)	(2.342)	(3.558)	(3.085)
SR^{feeadj}	0.086	0.246	0.526	0.731	1.056	0.771
α_{CAPM}	-27.620	-1.620	29.270	41.850	87.410	115.040
	(-0.662)	(-0.053)	(0.913)	(1.361)	(4.046)	(3.171)
$\alpha^{\text{feeadj}}_{CAPM}$	-1.890	10.230	39.100	50.970	95.610	97.500
	(-0.045)	(0.334)	(1.214)	(1.650)	(4.416)	(2.693)
$\alpha_{FF5+Mom}$	-6.890	5.060	38.440	49.340	88.290	95.180
	(-0.279)	(0.285)	(1.793)	(2.461)	(6.064)	(3.385)
$\alpha^{\text{feeadj}}_{FF5+Mom}$	19.140	17.020	48.370	58.600	96.600	77.460
	(0.771)	(0.955)	(2.242)	(2.908)	(6.636)	(2.749)
N Months	209	209	209	209	209	209
Avg. #Stocks	146	126	132	138	140	–
log(FeeVar)	-2.011	-2.666	-2.745	-2.780	-2.762	-0.752
log(UtilVar)	3.019	2.135	1.496	1.005	0.479	-2.540
FeeTail	4.924	3.755	3.525	3.428	3.031	-1.894
UtilTail	46.005	32.062	24.609	19.694	15.105	-30.900

Table 23: NetLeg portfolios within low-IC groups: returns and selected factor alphas (fee-adjusted on the short leg only). Returns, α, and borrow fees are expressed in basis points.

Metric	1	2	3	4	5	High–Low
r	59.730	87.050	89.930	92.630	93.580	33.850

Continued on next page

Table 23 continued

Metric	1	2	3	4	5	High–Low
	(1.047)	(1.917)	(2.354)	(2.588)	(2.811)	(1.030)
SR	0.271	0.473	0.557	0.598	0.667	0.274
Fee	5.340	3.860	3.510	3.420	3.530	-1.810
	–	–	–	–	–	(-9.061)
r^{feeadj}	65.070	87.050	89.930	92.630	93.580	28.510
	(1.142)	(1.917)	(2.354)	(2.588)	(2.811)	(0.869)
SR^{feeadj}	0.295	0.473	0.557	0.598	0.667	0.231
α_{CAPM}	-26.480	2.410	10.520	11.290	9.320	35.810
	(-1.005)	(0.148)	(0.819)	(1.108)	(0.845)	(1.231)
$\alpha_{CAPM}^{\text{feeadj}}$	-21.160	2.410	10.520	11.290	9.320	30.480
	(-0.807)	(0.148)	(0.819)	(1.108)	(0.845)	(1.052)
$\alpha_{FF5+Mom}$	-20.430	6.510	8.450	8.650	3.600	24.030
	(-1.236)	(0.689)	(0.957)	(0.906)	(0.317)	(1.107)
$\alpha_{FF5+Mom}^{\text{feeadj}}$	-15.080	6.510	8.450	8.650	3.600	18.680
	(-0.921)	(0.689)	(0.957)	(0.906)	(0.317)	(0.866)
N Months	209	209	209	209	209	209
Avg. #Stocks	146	126	132	138	140	–
log(FeeVar)	-2.011	-2.666	-2.745	-2.780	-2.762	-0.752
log(UtilVar)	3.019	2.135	1.496	1.005	0.479	-2.540
FeeTail	4.924	3.755	3.525	3.428	3.031	-1.894
UtilTail	46.005	32.062	24.609	19.694	15.105	-30.900

Table 24: NetLeg portfolios within high-IC groups: returns and selected factor alphas (fee-adjusted on the short leg only). Returns, α, and borrow fees are expressed in basis points.

Metric	1	2	3	4	5	High–Low
r	-5.060	33.750	69.560	91.040	133.400	138.460
	(-0.077)	(0.616)	(1.583)	(2.120)	(3.346)	(3.518)
SR	-0.021	0.181	0.460	0.663	0.994	0.883
Fee	25.970	17.130	14.280	13.220	11.800	-14.170

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Table 24 continued

Metric	1	2	3	4	5	High–Low
	–	–	–	–	–	(-22.045)
r^{feeadj}	20.910	33.750	69.560	91.040	133.400	112.500
	(0.320)	(0.616)	(1.583)	(2.120)	(3.346)	(2.874)
SR^{feeadj}	0.086	0.181	0.460	0.663	0.994	0.718
α_{CAPM}	-27.620	-1.620	29.270	41.850	87.410	115.040
	(-0.662)	(-0.053)	(0.913)	(1.361)	(4.046)	(3.171)
$\alpha^{\text{feeadj}}_{CAPM}$	-1.890	-1.620	29.270	41.850	87.410	89.300
	(-0.045)	(-0.053)	(0.913)	(1.361)	(4.046)	(2.469)
$\alpha_{FF5+Mom}$	-6.890	5.060	38.440	49.340	88.290	95.180
	(-0.279)	(0.285)	(1.793)	(2.461)	(6.064)	(3.385)
$\alpha^{\text{feeadj}}_{FF5+Mom}$	19.140	5.060	38.440	49.340	88.290	69.150
	(0.771)	(0.285)	(1.793)	(2.461)	(6.064)	(2.452)
N Months	209	209	209	209	209	209
Avg. #Stocks	146	126	132	138	140	–
log(FeeVar)	-2.011	-2.666	-2.745	-2.780	-2.762	-0.752
log(UtilVar)	3.019	2.135	1.496	1.005	0.479	-2.540
FeeTail	4.924	3.755	3.525	3.428	3.031	-1.894
UtilTail	46.005	32.062	24.609	19.694	15.105	-30.900

Table 25: NetLeg portfolios within low-IC groups: DGTW-adjusted returns and selected factor alphas (fee-adjusted on both legs). Returns, α, and borrow fees are expressed in basis points.

Metric	1	2	3	4	5	High–Low
r	-11.890	10.670	7.590	13.060	12.370	24.260
	(-0.517)	(1.161)	(1.166)	(1.795)	(1.523)	(0.872)
SR	-0.147	0.260	0.256	0.423	0.352	0.235
Fee	5.340	3.860	3.510	3.420	3.530	-1.810
	–	–	–	–	–	(-9.061)
r^{feeadj}	-6.550	13.370	10.050	15.450	14.830	21.390
	(-0.285)	(1.460)	(1.541)	(2.121)	(1.827)	(0.770)

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Table 25 continued

Metric	1	2	3	4	5	High–Low
SR^{feeadj}	-0.081	0.326	0.340	0.501	0.423	0.207
α_{CAPM}	-18.180	5.290	9.400	13.570	8.580	26.750
	(-0.899)	(0.488)	(1.062)	(1.533)	(0.789)	(1.052)
$\alpha_{CAPM}^{\text{feeadj}}$	-12.850	7.990	11.870	15.980	11.080	23.930
	(-0.639)	(0.741)	(1.341)	(1.806)	(1.020)	(0.944)
$\alpha_{FF5+Mom}$	-13.370	8.350	6.210	9.430	1.370	14.740
	(-0.834)	(0.852)	(0.760)	(1.137)	(0.117)	(0.695)
$\alpha_{FF5+Mom}^{\text{feeadj}}$	-8.020	11.040	8.670	11.830	3.880	11.890
	(-0.505)	(1.133)	(1.063)	(1.427)	(0.331)	(0.563)
N Months	209	209	209	209	209	209
Avg. #Stocks	146	126	132	138	140	–
log(FeeVar)	-2.011	-2.666	-2.745	-2.780	-2.762	-0.752
log(UtilVar)	3.019	2.135	1.496	1.005	0.479	-2.540
FeeTail	4.924	3.755	3.525	3.428	3.031	-1.894
UtilTail	46.005	32.062	24.609	19.694	15.105	-30.900

Table 26: NetLeg portfolios within high-IC groups: DGTW-adjusted returns and selected factor alphas (fee-adjusted on both legs). Returns, α, and borrow fees are expressed in basis points.

Metric	1	2	3	4	5	High–Low
r	-67.910	-34.410	0.870	20.840	65.050	132.960
	(-2.667)	(-1.967)	(0.067)	(1.277)	(4.112)	(3.585)
SR	-0.643	-0.596	0.015	0.308	1.087	0.910
Fee	25.970	17.130	14.280	13.220	11.800	-14.170
	–	–	–	–	–	(-22.045)
r^{feeadj}	-41.950	-22.420	10.870	30.100	73.310	115.260
	(-1.647)	(-1.283)	(0.823)	(1.828)	(4.600)	(3.124)
SR^{feeadj}	-0.397	-0.389	0.187	0.444	1.224	0.790
α_{CAPM}	-32.610	-10.770	20.450	25.780	70.150	102.760
	(-1.154)	(-0.695)	(0.990)	(1.163)	(5.227)	(2.928)

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Table 26 continued

Metric	1	2	3	4	5	High–Low
$\alpha_{CAPM}^{\text{feeadj}}$	-6.870	1.070	30.280	34.900	78.350	85.230
	(-0.242)	(0.069)	(1.448)	(1.554)	(5.791)	(2.433)
$\alpha_{FF5+Mom}$	-18.200	-9.230	24.440	28.430	64.690	82.890
	(-0.877)	(-0.610)	(1.263)	(1.609)	(4.870)	(2.944)
$\alpha_{FF5+Mom}^{\text{feeadj}}$	7.830	2.730	34.370	37.680	73.000	65.170
	(0.373)	(0.179)	(1.763)	(2.113)	(5.468)	(2.311)
N Months	209	209	209	209	209	209
Avg. #Stocks	146	126	132	138	140	–
log(FeeVar)	-2.011	-2.666	-2.745	-2.780	-2.762	-0.752
log(UtilVar)	3.019	2.135	1.496	1.005	0.479	-2.540
FeeTail	4.924	3.755	3.525	3.428	3.031	-1.894
UtilTail	46.005	32.062	24.609	19.694	15.105	-30.900

Table 27: NetLeg portfolios within low-IC groups: DGTW-adjusted returns and selected factor alphas (fee-adjusted on the short leg only). Returns, α, and borrow fees are expressed in basis points.

Metric	1	2	3	4	5	High–Low
r	-11.890	10.670	7.590	13.060	12.370	24.260
	(-0.517)	(1.161)	(1.166)	(1.795)	(1.523)	(0.872)
SR	-0.147	0.260	0.256	0.423	0.352	0.235
Fee	5.340	3.860	3.510	3.420	3.530	-1.810
	–	–	–	–	–	(-9.061)
r^{feeadj}	-6.550	10.670	7.590	13.060	12.370	18.920
	(-0.285)	(1.161)	(1.166)	(1.795)	(1.523)	(0.682)
SR^{feeadj}	-0.081	0.260	0.256	0.423	0.352	0.183
α_{CAPM}	-18.180	5.290	9.400	13.570	8.580	26.750
	(-0.899)	(0.488)	(1.062)	(1.533)	(0.789)	(1.052)
$\alpha_{CAPM}^{\text{feeadj}}$	-12.850	5.290	9.400	13.570	8.580	21.430
	(-0.639)	(0.488)	(1.062)	(1.533)	(0.789)	(0.846)
$\alpha_{FF5+Mom}$	-13.370	8.350	6.210	9.430	1.370	14.740

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Table 27 continued

Metric	1	2	3	4	5	High–Low
	(-0.834)	(0.852)	(0.760)	(1.137)	(0.117)	(0.695)
$\alpha^{\text{feeadj}}_{FF5+Mom}$	-8.020	8.350	6.210	9.430	1.370	9.390
	(-0.505)	(0.852)	(0.760)	(1.137)	(0.117)	(0.445)
N Months	209	209	209	209	209	209
Avg. #Stocks	146	126	132	138	140	–
log(FeeVar)	-2.011	-2.666	-2.745	-2.780	-2.762	-0.752
log(UtilVar)	3.019	2.135	1.496	1.005	0.479	-2.540
FeeTail	4.924	3.755	3.525	3.428	3.031	-1.894
UtilTail	46.005	32.062	24.609	19.694	15.105	-30.900

Table 28: NetLeg portfolios within high-IC groups: DGTW-adjusted returns and selected factor alphas (fee-adjusted on the short leg only). Returns, α, and borrow fees are expressed in basis points.

Metric	1	2	3	4	5	High–Low
r	-67.910	-34.410	0.870	20.840	65.050	132.960
	(-2.667)	(-1.967)	(0.067)	(1.277)	(4.112)	(3.585)
SR	-0.643	-0.596	0.015	0.308	1.087	0.910
Fee	25.970	17.130	14.280	13.220	11.800	-14.170
	–	–	–	–	–	(-22.045)
r^{feeadj}	-41.950	-34.410	0.870	20.840	65.050	107.000
	(-1.647)	(-1.967)	(0.067)	(1.277)	(4.112)	(2.899)
SR^{feeadj}	-0.397	-0.596	0.015	0.308	1.087	0.733
α_{CAPM}	-32.610	-10.770	20.450	25.780	70.150	102.760
	(-1.154)	(-0.695)	(0.990)	(1.163)	(5.227)	(2.928)
$\alpha^{\text{feeadj}}_{CAPM}$	-6.870	-10.770	20.450	25.780	70.150	77.030
	(-0.242)	(-0.695)	(0.990)	(1.163)	(5.227)	(2.199)
$\alpha_{FF5+Mom}$	-18.200	-9.230	24.440	28.430	64.690	82.890
	(-0.877)	(-0.610)	(1.263)	(1.609)	(4.870)	(2.944)
$\alpha^{\text{feeadj}}_{FF5+Mom}$	7.830	-9.230	24.440	28.430	64.690	56.860
	(0.373)	(-0.610)	(1.263)	(1.609)	(4.870)	(2.012)

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Table 28 continued

Metric	1	2	3	4	5	High–Low
N Months	209	209	209	209	209	209
Avg. #Stocks	146	126	132	138	140	–
log(FeeVar)	-2.011	-2.666	-2.745	-2.780	-2.762	-0.752
log(UtilVar)	3.019	2.135	1.496	1.005	0.479	-2.540
FeeTail	4.924	3.755	3.525	3.428	3.031	-1.894
UtilTail	46.005	32.062	24.609	19.694	15.105	-30.900