

Lendable Inventory Concentration, Short-Selling Risk, and Mispricing

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Abstract

Short-sellers are often described as sophisticated investors who help correct overvaluation and speed up the incorporation of bad news into prices. In a frictionless market with abundant and competitive lending supply, their activity should quickly eliminate cross-sectional return predictability, especially in strategies that bet against “overpriced” stocks. Yet many anomaly strategies that rely on short positions remain highly profitable and persistent. This paper argues that a key reason is the *structure* of the equity lending market. Using detailed securities lending and institutional holdings data, I show that the concentration of lender base across institutional lenders—*inventory concentration*—is a first-order determinant of short-selling risk, the speed of information incorporation, and the profitability of anomaly strategies. Stocks with highly concentrated lending bases exhibit more volatile lending fees and utilization, slower and less complete reaction to negative information, and substantially stronger anomaly profits on the short leg. The results support a simple mechanism: higher inventory concentration increases short-selling risk, which slows and worsens the incorporation of bad information into prices and ultimately leads to larger anomaly profits. This mechanism links the micro-organization of the lending market—who owns and lends the shares—to the macro-level efficiency of equity prices.

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1 Introduction

Short-sellers are widely viewed as sophisticated investors who play a central role in price discovery. By betting against overvalued firms and negative information, they are supposed to accelerate the incorporation of bad news into prices and limit the buildup of mispricing. In a frictionless market with abundant and competitive lending supply, any tradeable signal that points to overpricing ought to be quickly arbitrated away.

In reality, short-selling is risky and constrained, and many cross-sectional return anomalies—especially those that involve betting against “overpriced” stocks—remain highly profitable. This tension motivates my central question: **How does the structure of the equity lending market—in particular, the concentration of lendable inventory across lenders—shape short-selling risk, the speed of information incorporation into prices, and the profitability of asset pricing anomalies?** Rather than treating short-selling costs as an exogenous friction, I focus on the *organization* of the lending market—who owns and lends the shares—and examine how this structure conditions the effectiveness of informed short-sellers in enforcing price efficiency.

The limits-to-arbitrage literature emphasizes that arbitrageurs are constrained by funding risk, margin requirements, and the risk of forced unwinds (Shleifer and Vishny, 1997; Vayanos and Gromb, 2010). Short-selling is especially exposed to such limits: pessimistic investors must borrow shares, post collateral, and bear the risk that lending conditions deteriorate (Miller, 1977; Diamond and Verrecchia, 1987). Empirically, high borrowing fees, tight lending supply, and regulatory restrictions are associated with overpricing and high subsequent returns (e.g., Jones and Lamont, 2002; Hong and Stein, 2003; Cohen et al., 2007). Using detailed lending data, Engelberg et al. (2018) show that *short-selling risk*—time variation and uncertainty in loan fees and recalls—is priced in the cross-section: stocks with higher exposure to this risk earn higher average returns.

Recent work connects securities lending markets more directly to anomalies. ?

show that once one accounts for short-sale costs implied by securities lending fees, the abnormal returns of many anomaly-based long–short portfolios largely disappear. [Da et al. \(2025\)](#) link short-selling profitability and lending fees to a broad cross-section of asset pricing anomalies, emphasizing that short-sale costs are a key economic limit to exploiting mispricing. From the perspective of intermediaries, [Ma \(2019\)](#) document that hedge funds that take on more short-selling risk earn higher performance, while mutual funds do not, suggesting that this risk is borne primarily by sophisticated arbitrageurs.

Most existing work, however, effectively treats lending supply as *competitive and diffuse*. Fees or rebate rates are the primary prices that adjust, and the underlying stock of lendable shares is modeled as smooth and elastic. In reality, the supply of lendable shares is highly granular and concentrated. In many stocks, a small number of large institutions—such as index funds, custodians, or pension funds—own and lend most of the shares ([Porras Prado et al., 2016](#)). These institutions differ in their willingness to lend, in their internal risk management, and in their exposure to funding and redemption shocks. When one or two dominant lenders reduce their lending supply or exit, the total capacity available to short-sellers can collapse, even if the “average” lender is unchanged.

From the perspective of a short-seller, this means that the decision to establish a position is not only about expected return versus *static* fee and risk, but also about exposure to *lending shocks*. A stock with a diffuse, competitive lending base offers relatively stable access: if one lender withdraws, others can substitute, and fees adjust smoothly. A stock where 60–80% of lendable inventory is controlled by one or two institutions is fundamentally different: if these institutions change their lending behavior, the position may suddenly become extremely costly or impossible to maintain. This “fragility” of lending supply is a form of short-selling risk that is distinct from average fee levels or utilization, and it is inherently tied to *inventory concentration* and lender market power ([Atmaz et al., 2024](#)).

Despite its importance, this channel has received relatively little direct empirical attention. [Porras Prado et al. \(2016\)](#) show that when shares are held by few in-

stitutions, stocks have higher borrow fees and exhibit stronger mispricing. **This is the central focus of my analysis: using richer, more granular short-selling data to examine how securities lending market structure—especially inventory concentration—shapes short-selling fees and risks, the incorporation of information into prices, and ultimately the strength of equity pricing anomalies.**

Using detailed securities lending data with lender-level loan and inventory information at the stock-day level (IHS Markit), complemented by institutional holdings and standard return and accounting databases, I study how the concentration of lendable inventory across lenders shapes short-selling risk, information incorporation, and the strength of equity pricing anomalies.

Lendable Inventory concentration and short-sale constraints. For each stock (at the stock-month frequency), I measure inventory concentration from the stock-level distribution of lendable shares, using a Herfindahl index and top-lender inventory shares. I then relate these concentration measures to both the *level* and the *instability* of borrowing conditions, including average short-selling fees, the variance of lending fees, the level and volatility of utilization, and measures of extreme fee and utilization changes. I find that higher inventory concentration is associated with *higher short-selling fees* and *higher short-selling risk*: high-concentration stocks have higher average fees, more volatile fees, and less stable borrowing conditions than low-concentration stocks, even after controlling for short interest, size, liquidity, and other firm characteristics.

Lendable Inventory concentration and information incorporation. To assess price discovery, I focus on earnings announcements as clean, high-salience information events. Specifically, I compute CAPM-adjusted cumulative abnormal returns (CARs) in short event windows around earnings news (e.g., $(-1, +1)$) as well as longer post-announcement windows to capture delayed adjustment. I then compare the immediate earnings-response and subsequent post-earnings drift across inventory concentration groups and across short-selling risk measures. I find that

when inventory is dispersed (low concentration / low risk), negative earnings news is incorporated relatively quickly, with a sharper immediate price reaction and limited post-earnings drift, consistent with effective arbitrage (cf. [Brogaard et al., 2022](#)). In contrast, when inventory concentration is high, short-selling is riskier, the market response to negative earnings news is weaker on impact and followed by larger post-earnings drift, indicating slower and less complete incorporation of bad news.

Implications for equity pricing anomalies. For a broad set of cross-sectional anomalies (accruals, investment, profitability, and related standard signals), I form standard long-short portfolios and allow anomaly returns to vary with inventory concentration by interacting mispricing signals with concentration groups (and continuous concentration measures) in portfolio sorts and panel/Fama-MacBeth regressions. I find that anomaly profits are significantly larger and more persistent among high-concentration stocks. The same mispricing signal that produces modest, short-lived abnormal returns in low-concentration stocks yields large and persistent abnormal returns when lendable inventory is concentrated, even after controlling for short interest, fee levels, and a rich set of firm and market characteristics.

This paper makes three main contributions. First, it introduces and documents a new dimension of *short-selling risk* tied to the structure of the lending market. While prior work emphasizes borrowing costs, utilization, and regulatory constraints (e.g., [Engelberg et al., 2018](#); [Muravyev et al., 2025](#); [Da et al., 2025](#)), I show that the concentration and fragility of the lending base itself is a powerful predictor of short-selling risk. Inventory concentration summarizes the exposure of short-sellers to discrete lending shocks driven by the behavior of a few dominant institutions.

Second, the paper shows that lending market structure has tangible consequences for *information incorporation and price efficiency*. The evidence that negative-information signals are followed by weaker immediate price adjustments and stronger drift in high-concentration stocks connects micro-level features of the lending market to macro-level outcomes in price discovery (cf. [Brogaard et al., 2022](#)). This provides a new perspective on why some stocks exhibit slow or incomplete reaction to public

news and why post-event drifts are stronger in some segments of the market than in others.

Third, the paper offers a structural explanation for the heterogeneity and persistence of *anomaly profits*. Rather than viewing anomalies as uniform patterns driven solely by fundamental risk or behavioral biases, I show that their profitability is systematically amplified in stocks with certain lending market characteristics. Anomalies that require shorting to exploit (overvaluation-type signals) are especially concentrated in high-inventory-concentration stocks, where short-sale constraints are more binding. This helps reconcile the coexistence of sophisticated short-sellers and large anomaly profits: anomalies survive not because informed traders fail to recognize them, but because the lending market structure makes the relevant trades risky and fragile.

The rest of the paper is organized as follows. Section 2 discusses the related literature in more detail. Section 3 describes the data and the construction of inventory concentration and short-selling risk measures. Section ?? documents the relationship between inventory concentration and short-selling risk. Section 5 analyzes how concentration and short-risk affect the speed and completeness of information incorporation around events. Section 6 studies the interaction between lending structure and anomaly profitability. Section 7 concludes.

2 Related Literature

Whether cross-sectional equity pricing anomalies reflect true mispricing, compensation for risk, or statistical artifacts remains actively debated. A large body of work argues that many published predictors are fragile once one accounts for data-snooping, microcap influence, and declining post-publication performance (e.g., [Harvey et al., 2016](#); [Linnainmaa and Roberts, 2018](#); [Green et al., 2017](#); [Hou et al., 2020](#)). Other studies reach more supportive conclusions, documenting that predictability persists out of sample, internationally, or after correcting for selective reporting (e.g., [McLean and Pontiff, 2016](#); [Jacobs and Müller, 2020](#); [Y. Chen and Zimmer-](#)

mann, 2022; Jensen et al., 2023). This debate naturally shifts attention from the *existence* of anomaly signals to their *economic meaning*: even if predictability is statistically present, can sophisticated investors profitably arbitrage it away, and if not, what frictions determine where anomalies are strongest?

A prominent explanation is that limits to arbitrage render anomaly trading unattractive for the marginal investor. Much of the discussion has focused on execution costs (bid-ask spreads, price impact) and whether these costs are large enough to wipe out abnormal returns (e.g., Novy-Marx and Velikov, 2016; Frazzini et al., 2012). A complementary, and often decisive, friction is the cost of establishing and maintaining short positions. Recent evidence links anomaly profitability to securities lending fees and short-selling profitability, with some studies concluding that borrowing costs largely eliminate the net profitability of many long-short anomaly strategies in modern samples (e.g., Muravyev et al., 2025; Da et al., 2025). This line of work also helps rationalize why many sophisticated institutions do not aggressively tilt their portfolios to exploit known anomaly signals (e.g., Lewellen, 2011; Edelen et al., 2016).

At the same time, the literature has not converged on a single conclusion about the extent to which short-sale costs fully eliminate anomaly profits. Differences in sample periods, the set of anomalies examined, and—critically—the measurement of borrowing costs can generate divergent results. Borrower-paid fees may exceed lender-received fees due to intermediary markups (e.g., D’avolio, 2002), and some approaches rely on coarse or time-invariant mappings (e.g., ordinal cost categories mapped to average fees) that may miss stock-specific and time-varying lending conditions. More broadly, even when average fee *levels* are observed, they need not capture the *risk* of shorting: the ability to maintain a position can be impaired by fee spikes, utilization jumps, or sudden supply withdrawals.

This distinction motivates a second strand of research emphasizing that short-selling is risky beyond borrowing-cost levels. Engelberg et al. (2018) formalize and measure short-selling risk through uncertainty in fees and recalls, and show that this risk is priced as a limit to arbitrage distinct from average fees. Related work

highlights that lending markets have meaningful structure: a small and persistent set of lenders can supply a large share of lendable inventory, so exits and limited replacement capacity can abruptly tighten constraints (e.g., [Dong and Zhu, 2022](#)). Theoretical and empirical studies further stress that lending markets can exhibit oligopolistic features, with concentrated supply and intermediation affecting both fees and quantities (e.g., [Chen et al., 2022](#)), and that the identity of lenders (such as passive funds) can alter the risk profile of borrowing even when fee levels are high (e.g., [Palia and Sokolinski, 2024](#)).

A closely related strand links institutional ownership structure to limits to arbitrage by showing that *who holds shares* matters for whether shares are made available for lending. [Nagel \(2005\)](#) and [Porrás Prado et al. \(2016\)](#) show that when institutional ownership is concentrated among a few large investors and tilted toward non-lending institutions, the effective lendable float is smaller, short-sale constraints are more binding, and mispricing is stronger. These findings imply that aggregate institutional ownership and short interest can be incomplete proxies for effective lending supply and the tightness of short-selling constraints.

Finally, a broader literature on price efficiency and information incorporation emphasizes that frictions affecting informed trading should shape the speed and completeness with which negative information is reflected in prices. In this setting, short-sellers play a central role in impounding bad news, suggesting that variation in short-sale constraints should translate into predictable heterogeneity in post-event adjustment patterns and return predictability.

Existing work has established (i) that anomaly profitability is sensitive to short-sale *cost* levels, (ii) that short-selling entails additional *risk* (fee uncertainty/recalls), and (iii) that ownership and lending behavior shape the supply of lendable shares. What we know much less about is how the *distribution* of lendable inventory across lenders—and, in particular, the *concentration* of that inventory—maps jointly into borrowing costs, short-selling risk, and the extent to which mispricing is corrected.

This paper fills that gap by introducing *inventory concentration* as a lender-

base state variable measured directly from IHS Markit stock-level inventory data. Relative to the literature that focuses on average fees, I show that concentration predicts not only *higher fees* but also *greater instability* in borrowing conditions (fee and utilization volatility, extreme changes), i.e., higher short-selling risk conditional on fee levels and other standard proxies. Relative to the literature on short-selling risk, I identify a concrete and measurable source of that risk: a concentrated lending base is intrinsically more fragile, so shocks to key lenders translate into sharper effective constraint tightening.

Relative to the anomalies and price-discovery literature, I show that this lending-market structure matters for the *incorporation of bad news*: negative information is impounded more slowly when inventory is concentrated, and anomaly returns are correspondingly stronger and more persistent. Taken together, the results imply that fee levels alone cannot fully account for anomaly profitability or alphas: pricing errors are systematically larger precisely where short-selling risk is higher due to concentrated lenders. More broadly, the findings position securities lending market structure as a structural, endogenous source of limits to arbitrage and a key dimension for anomaly-based tests of market efficiency.

In short, the paper connects the anomalies debate and limits-to-arbitrage mechanisms through a single organizing object—the concentration of lendable inventory across lenders—that is distinct from, yet complementary to, borrowing-cost levels and traditional ownership-based proxies.

3 Data and Variable Construction

This section describes the data sources, sample construction, and variable definitions. I combine information from five sources: (i) quarterly institutional holdings from Thomson Reuters 13F (1980–2023), (ii) stock returns and market equity from CRSP, (iii) accounting fundamentals from Compustat (merged to CRSP), (iv) monthly anomaly signals from Jensen, Kelly, and Pedersen (2023), and (v) daily securities lending data from IHS Markit Securities Finance (July 2006–December

2023). The unit of analysis is stock-month unless otherwise stated.

3.1 Sample construction and filters

I begin with the intersection of CRSP common stocks and IHS Markit coverage. I restrict the sample to U.S. common stocks (CRSP share codes 10 and 11) and merge the lending data to CRSP using standard identifiers. Following the anomalies and implementation-cost literature, I apply two baseline filters throughout. First, I exclude microcaps, defined as stocks with market equity below \$50 million and price below \$1 (both lagged). Second, to focus on the economically relevant region where anomalies are potentially tradable and to avoid extreme borrowing environments, I exclude hard-to-borrow observations, defined as stock-months with monthly average borrow fees exceeding 1% (annualized). These filters are applied consistently across all analyses.

3.2 Securities lending data (IHS Markit, 2006.07–2023.12)

IHS Markit provides daily stock-level information on securities borrowing and lending activity. I use the following core daily variables: borrow fees, the quantity on loan, and lending supply. I compute daily utilization as the ratio of the value (or quantity) on loan to total lendable value, and aggregate daily variables to the stock-month level by averaging within each month.

BorrowFee. BorrowFee is IHS Markit’s *Indicative Fee*, interpreted as the expected borrow cost (annualized) faced by a representative hedge fund.

Utilization and lending supply/demand. Utilization is defined as the value of assets on loan divided by total lendable value. I also retain additional Markit lending variables when used as controls, including the average tenure of loans.

Lendable Inventory concentration (IC). A central variable in the paper is the *concentration of lendable inventory across lenders*. Using the stock-day inventory

distribution from IHS Markit, I compute concentration measures for each stock and period (monthly). Let $s_{i\ell t}$ denote lender ℓ 's lendable inventory in stock i at date t , and let $S_{it} = \sum_{\ell} s_{i\ell t}$ denote total lendable inventory across lenders. IHS Markit defines lender shares as $w_{i\ell t} = s_{i\ell t}/S_{it}$.

Herfindahl–Hirschman index (HHI). My primary measure of inventory concentration is the Herfindahl index:

$$IC_{it} = \sum_{\ell} w_{i\ell t}^2.$$

Higher values indicate that lendable inventory is concentrated among fewer lenders.

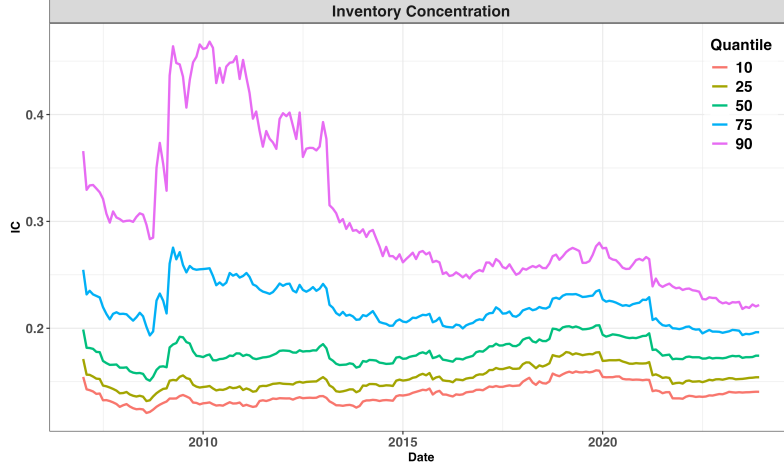


Figure 1: Lendable inventory concentration (IC) in the IHS Markit data, 2007–2023.

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

3.3 Short-selling risk measures

To capture instability in borrowing conditions—distinct from the level of borrow fees—I construct risk measures using daily lending data. 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 risk and fee tail. Fee risk is the natural logarithm of the variance of daily borrow fees over the past 73 trading days:

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

FeeTail summarizes the upper tail of fees using a mean-plus-multiple-of-volatility metric:

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

Recall risk and utilization tail. Recall risk is the natural logarithm of the variance of daily utilization over the past 73 trading days:

$$RecallRisk_{it} = \log(\text{Var}(Util_{i,d})).$$

UtilTail is defined analogously:

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

Average tenure (AT). AT is the average duration of outstanding loans (from Markit), aggregated to the stock-month level.

3.4 Returns, accounting variables, and institutional ownership

Returns, firm characteristics and earning news date. Stock returns, market capitalization, prices, and share codes are from CRSP. Accounting variables used to construct firm characteristics and control variables are from Compustat merged to CRSP using standard links. Unless otherwise stated, controls follow standard definitions in the asset pricing and corporate finance literatures (e.g., size, book-to-

market, momentum, bid-ask spread, idiosyncratic volatility). I winsorize continuous variables at conventional percentiles to limit the influence of outliers.

To assess price discovery, I study stock returns around *earnings announcements*, which provide clean and high-salience information events. Earnings announcement dates are taken from Compustat quarterly report dates (RDQ). For each event, I compute CAPM-adjusted cumulative abnormal returns (CARs) over short windows such as $(-1, +1)$ trading days, as well as longer post-announcement windows to capture delayed adjustment (post-earnings-announcement drift). I then examine how both the immediate earnings response and subsequent drift vary with inventory concentration and short-selling risk, with particular emphasis on negative earnings news where short-sale constraints are most likely to bind.

Institutional holdings (Thomson Reuters 13F). Quarterly institutional holdings are obtained from the Thomson Reuters 13F database, which covers institutions with assets under management above \$100 million. For each stock-quarter, I compute institutional ownership shares and measures of ownership concentration. I use [Bushee \(1998\)](#)’s classification of institutions. [Bushee \(1998\)](#) uses the principle factor analysis and cluster analysis based on institutions’ historical investment behaviors (such as portfolio concentration and portfolio turnover) to distinguish passive and active investors. Specifically, there are three categories: quasi-indexers, with low turnover and high diversification; transient investors, with high turnover and high diversification; and dedicated investors, with low turnover and low diversification. [Bushee \(1998\)](#)’s classification has two versions, one is “permanent” and the other is “time-varying.” Following [Appel et al. \(2016\)](#), we use the permanent classification in our baseline results to avoid an institutional investor being classified as an active investor at some points but a passive investor at others. In particular, I construct two quasi-indexer ownership measures: (i) **qix_ior**, the fraction of institutional holdings accounted for by quasi-indexers, and (ii) **qixhhi**, a Herfindahl index capturing the concentration of quasi-indexer holdings. These variables capture the extent to which ownership is concentrated among large, low-turnover institutions that may

play a central role in securities lending supply, which can be seen as a proxy for lendable inventory concentration.

3.5 Equity pricing anomalies

To study how lending-market structure organizes anomaly strength, I examine a broad set of cross-sectional anomaly signals. I rely on the anomaly library of [Jensen et al. \(2023\)](#), which provides monthly signed predictors at the stock-month level constructed using standard implementations in the return-predictability literature. Each month, I form long-short anomaly portfolios by sorting stocks based on the signal and evaluating the return spread between the extreme quintiles. To ensure that the analysis focuses on anomalies that are economically relevant in my tradable universe, I restrict attention to the subset of signals that exhibit a statistically significant CAPM alpha at 10% level within the merged CRSP–Markit sample over 2006–2023 (after applying the baseline microcap and hard-to-borrow filters). I evaluate anomaly performance using both raw and risk-adjusted returns (CAPM and multifactor models) and examine how anomaly alphas vary with inventory concentration.

3.6 Summary statistics

Table 1 reports summary statistics for the main variables used in the paper, including inventory concentration measures, borrow fee levels, borrowing-condition instability, and standard firm characteristics. The table highlights substantial cross-sectional heterogeneity in both the level and the stability of borrowing conditions, motivating the use of inventory concentration as a key organizing characteristic of the securities lending market.

Table 1: Summary statistics

Variable	N	Mean	SD	Median	P25	P75
<i>Panel A: Firm characteristics and ownership</i>						
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
qix_ior	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
<i>Panel B: Securities lending and short-selling risk</i>						
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

4 Lendable Inventory Concentration and Short-Sale Constraints

This section develops the hypothesis that a more concentrated lender base tightens short-sale constraints. I focus on two outcomes: the *level* of borrowing costs (borrow fees) and the *risk* of maintaining short positions (instability in fees and utilization, and related measures). The key explanatory variable is *inventory concentration* (*IC*), defined as the Herfindahl–Hirschman index (HHI) of lendable inventory across lenders measured from IHS Markit. As a complementary, ownership-based proxy for concentration among large, low-turnover institutions, I also use `qixhhi`, the Herfindahl index of quasi-indexer holdings constructed from 13F filings using [Bushee \(1998\)](#)’s permanent classification.

4.1 Economic mechanisms and hypothesis development

Inventory concentration can affect short selling through two complementary channels.

Mechanism 1: Market power. When lendable inventory is concentrated among a small number of effective lenders, competition on the supply side of securities lending is weaker. Large lenders can exert market power and charge higher borrowing fees for a given level of shorting demand (Chen et al., 2022). This channel yields a clear prediction:

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

Mechanism 2: Lender-base fragility. A concentrated lender base is also mechanically more fragile: if lending supply is provided by a few dominant institutions, shocks to these institutions translate into sharper fluctuations in available supply. This increases the likelihood of fee spikes, utilization jumps, and effective scarcity of borrowable shares, thereby raising the risk of maintaining short positions (Dong and Zhu, 2022). This channel yields a second prediction:

Prediction (Risk). *Short-selling risk—captured by volatility and tail realizations of borrow fees and utilization—increases with inventory concentration, conditional on shorting demand and standard stock characteristics.*

Link to ownership concentration. Because quasi-indexers are large, low-turnover institutions that often represent stable balance-sheet lenders, concentration among quasi-indexers can be informative about the concentration of effective lending supply. However, ownership concentration and lending-supply concentration need not coincide. I therefore treat `qixhhi` as an ownership-based proxy that complements (but does not substitute for) the direct lending-market measure *IC*.

4.2 Empirical specifications

I estimate panel regressions at the stock-month level with stock and calendar-month fixed effects:

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

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

To evaluate whether lending-market concentration contains incremental information beyond ownership concentration, I also estimate parallel specifications that replace $IC_{i,t}$ with `qixhhi` and specifications that include both measures:

$$Fee_{i,t} = \alpha_i + \tau_t + \beta_1 IC_{i,t} + \beta_2 \text{qixhhi}_{i,t} + \beta_3 Demand_{i,t} + \Gamma' X_{i,t} + \varepsilon_{i,t}, \quad (3)$$

$$Risk_{i,t} = \alpha_i + \tau_t + \gamma_1 IC_{i,t} + \gamma_2 \text{qixhhi}_{i,t} + \gamma_3 Demand_{i,t} + \Gamma' X_{i,t} + u_{i,t}. \quad (4)$$

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 (PERMNO) and calendar month.

Dependent variables. The fee outcome is the monthly average `BorrowFee` (annualized IHS Markit indicative fee). The risk outcomes capture instability and tail risk in borrowing conditions: `FeeRisk` = $\log(\text{Var}(\text{daily fees}))$, `FeeTail`, `RecallRisk` = $\log(\text{Var}(\text{daily utilization}))$, `UtilTail`, and `AT` (average loan tenure).

Shorting demand and controls. $Demand_{i,t}$ proxies for shorting demand (e.g., short interest and utilization). The vector $X_{i,t}$ includes standard firm and market controls used in the short-selling literature: market equity (`ME`), book-to-market (`BM`), volatility and idiosyncratic volatility (`VOL`, `IVOL`), liquidity/illiquidity measures, turnover, institutional ownership, and lendable supply. I also control for lender composition using `LQS`, the share of loan quantity supplied by stable (low-turnover) funds.

4.3 Results

Lendable inventory concentration and borrow fees. Table 2 shows that inventory concentration is positively related to average borrow fees. In column (1), the coefficient on *IC* is positive and statistically significant, consistent with the market-power mechanism: when lending supply is concentrated, borrowing is more expensive even after absorbing stock and month fixed effects and conditioning on lender composition (*LQS*). Column (2) reports the analogous specification using the ownership-based concentration proxy *qixhhi* (and quasi-indexer share), showing that quasi-indexer concentration is also positively related to fees. Taken together, the results suggest that both direct lending-market concentration and ownership-side concentration among quasi-indexers are informative about borrowing costs.

Table 2: Inventory concentration and borrow fees

	(1)	(2)
Dependent variable:	BorrowFee	BorrowFee
IC	0.052*** (0.015)	
LQS	-0.006 (0.006)	
qixhhi		0.022** (0.010)
qix_ior		-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 clustered by month and PERMNO.

*, **, *** denote 10%, 5%, 1% significance.

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

(2) and (4) show that the ownership-based proxy `qixhhi` is also positively related to fee risk, while higher quasi-indexer share is associated with lower fee volatility in some specifications. Overall, these patterns align with the lender-base fragility mechanism: concentrated supply is associated with a more fragile borrowing environment.

Table 3: Inventory concentration and fee risk

	(1)	(2)	(3)	(4)
Dependent variable:	log(FeeVar)	log(FeeVar)	FeeTail	FeeTail
IC	1.69*** (0.240)		1.22*** (0.152)	
LQS	-0.576*** (0.094)		-0.396*** (0.071)	
qixhhi		0.720*** (0.170)		0.591*** (0.115)
qix_ior		-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 clustered by month and PERMNO.

*, **, *** denote 10%, 5%, 1% significance.

Lendable inventory concentration and recall risk. Table 4 documents analogous results on the utilization side. Higher *IC* predicts higher *RecallRisk* and *UtilTail*, consistent with a higher probability of effective scarcity and tightening locate constraints. Columns (2) and (4) show that `qixhhi` is also positively related to utilization risk, while higher quasi-indexer share is associated with lower utilization risk. In addition, *IC* is negatively related to average loan tenure (*AT*), suggesting that borrowing relationships are shorter-lived when the lending base is more concentrated. This pattern is consistent with a less stable borrowing environment, as short sellers face higher uncertainty about the continuation of their loans.

Table 4: Inventory concentration and recall risk

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	log(UtilVar)	log(UtilVar)	UtilTail	UtilTail	AT	AT
IC	1.17*** (0.136)		2.86*** (0.733)		-0.629*** (0.123)	
LQS	-0.369*** (0.068)		-1.56*** (0.356)		0.632*** (0.069)	
qixhhi		0.583*** (0.118)		4.31*** (0.796)		0.138 (0.108)
qix_ior		-0.863*** (0.061)		-2.47*** (0.344)		0.447*** (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 clustered by month and PERMNO.

*, **, *** denote 10%, 5%, 1% significance.

4.4 Summary and implications

Across specifications with stock and month fixed effects and controls for lender composition and quasi-indexer ownership, inventory concentration is systematically associated with tighter short-sale constraints. The evidence supports both channels emphasized above: concentrated lending supply is associated with higher *average* borrowing fees (consistent with market power) and with greater *instability* in borrowing conditions—higher fee and utilization risk and more extreme tail realizations (consistent with lender-base fragility). These results motivate the subsequent sections, which examine whether the same variation in lending-market structure translates into slower incorporation of negative information and stronger equity pricing anomalies.

5 Lendable Inventory Concentration and Information 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.

5.1 Hypothesis development and economic mechanism

I 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, where short selling is less central, the relation between inventory concentration and drift should be weaker.

5.2 Earnings announcement events and abnormal return measures

I use Compustat quarterly report dates (RDQ) to identify earnings announcements. For each earnings event, I compute CAPM-adjusted cumulative abnormal returns (CARs) in event time. I define the *announcement-window reaction* as $CAR_{i,t,[-1,+1]}^{CAPM}$ and study *post-announcement drift* using cumulative abnormal returns beginning after the immediate reaction window. Specifically, for each horizon h , I compute $CAR_{i,t,[+5,+h]}^{CAPM}$, which captures delayed adjustment beyond the first trading week.

In each month, I classify earnings announcements into *Good* and *Bad* news based on the sign and magnitude of the announcement-window return. Specifically, among events with *positive* $CAR^{CAPM}[-1, +1]$, I label the top 20% (largest positive CARs) as *Good* news. Among events with *negative* $CAR^{CAPM}[-1, +1]$, I label the bottom 20% (most negative CARs) as *Bad* news. All remaining events are excluded from the Good/Bad subsample analysis. In parallel, I 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 provides a first-order intuition for why lending-market structure should matter for price discovery. Following bad earnings news, prices continue to drift downward well beyond the announcement window, whereas the drift after good news is substantially smaller. Quantitatively, in the bad-news subsample the cumulative post-announcement CAR^{CAPM} over $[+5, +60]$ is **-11%** for high-*IC* stocks compared to **-4%** for low-*IC* stocks, implying a much larger drift when lendable inventory is more concentrated. The gap remains sizable at longer horizons: by $h = +120$, the cumulative drift reaches **-30%** (high *IC*) versus **-9%** (low *IC*). In contrast, following good news the corresponding $[+5, +60]$ drift is close to zero, and the High–Low *IC* difference is economically small.

These magnitudes are consistent with a short-sale-constraint channel. When inventory concentration is high, the borrowing environment is not only more expensive but also more fragile, which can deter short sellers from fully trading on bad

news immediately, leading to delayed adjustment and larger PEAD. Because short selling is less central for incorporating good news, the high-vs-low IC differences are correspondingly muted in the good-news subsample.

While Figure 2 is informative, it does not condition on other determinants of PEAD (size, liquidity, volatility, institutional ownership, or contemporaneous shorting demand) that may covary with IC . To quantify the incremental role of lending-market structure, I therefore estimate equation (5), 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.

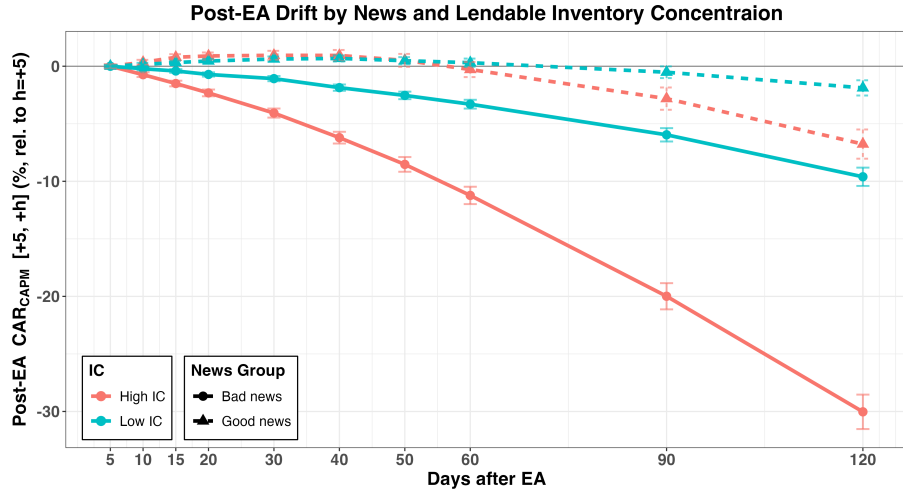


Figure 2: Asymmetric post-earnings-announcement drift by inventory concentration. Good news events are defined each month as the top 20% of *positive* announcement-window $CAR_{[-1,+1]}^{CAPM}$; Bad news events are defined as the bottom 20% of *negative* announcement-window $CAR_{[-1,+1]}^{CAPM}$.

5.3 Empirical specification

I estimate the following event-time panel specification:

$$CAR_{i,t,[+5,+h]}^{CAPM} = \alpha_i + \eta_t + \beta_h CAR_{i,t,[-1,+1]}^{CAPM} + \gamma_h (CAR_{i,t,[-1,+1]}^{CAPM} \times IC_{i,t}) + \delta_h X_{i,t} + \varepsilon_{i,t,h}, \quad (5)$$

where h indexes the post-announcement horizon. The coefficient of interest is γ_h , which captures how the mapping from announcement-window news to subsequent

drift varies with inventory concentration.

The specification includes firm fixed effects α_i and calendar-month fixed effects η_t to absorb time-invariant firm heterogeneity and common time-series variation in news environments and lending-market conditions. The control vector $X_{i,t}$ includes standard determinants of post-announcement drift and arbitrage frictions: market equity, turnover, illiquidity, return volatility and idiosyncratic volatility, institutional ownership, short interest, and utilization. To further separate inventory concentration from other constraint channels, I additionally allow the announcement-window news term to interact with key arbitrage-friction proxies (e.g., illiquidity, institutional ownership, and idiosyncratic volatility), so that γ_h is identified from variation in lending-market concentration beyond these standard dimensions.

5.4 Results: asymmetric drift under high inventory concentration

Figures 3 and 4 plot the estimated impulse-response profiles implied by equation (5) at horizons h , separately for Good and Bad news events. The central object is the interaction coefficient γ_h , which measures how inventory concentration changes the mapping from the announcement-window news shock $CAR_{[-1,+1]}^{CAPM}$ into subsequent post-announcement returns $CAR_{[+5,+h]}^{CAPM}$.

The results show a pronounced asymmetry. Following *good* earnings news, the estimated γ_h is economically small and statistically indistinguishable from zero at conventional horizons: at $h = +30$ the estimate is $\hat{\gamma}_{30} = \underline{0.15}$ (s.e. $\underline{0.32}$), and at $h = +60$ it is $\hat{\gamma}_{60} = \underline{0.30}$ (s.e. $\underline{0.59}$). Consistent with this, the implied High–Low *IC* difference in cumulative drift is modest. In contrast, following *bad* earnings news, inventory concentration strongly amplifies post-announcement drift. The interaction term is economically large and statistically significant over intermediate and longer horizons: for example, $\hat{\gamma}_{30} = \underline{0.58}$ (s.e. $\underline{0.32}$) and $\hat{\gamma}_{60} = \underline{2.03}$ (s.e. $\underline{0.64}$). Thus, conditional on the same announcement-window shock, bad news is incorporated more slowly when lendable inventory is concentrated among a few dominant lenders.

Overall, the regression evidence mirrors the nonparametric patterns in Figure 2: the relation between IC and delayed price adjustment is concentrated in negative-information events, where short selling is most relevant. This asymmetry is difficult to reconcile with purely symmetric trading-friction explanations and is consistent with a short-sale-constraint channel operating through a more fragile and riskier lending environment in high- IC stocks.

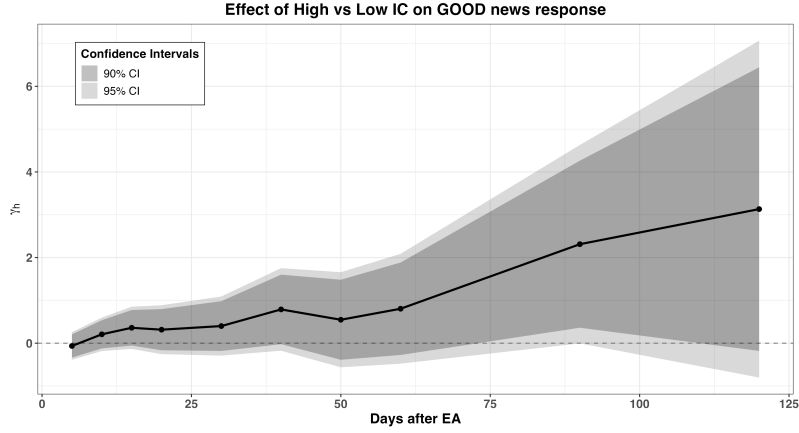


Figure 3: Impulse-response of post-announcement $CAR_{[+5,+h]}^{CAPM}$ to announcement-window news, Good news subsample.

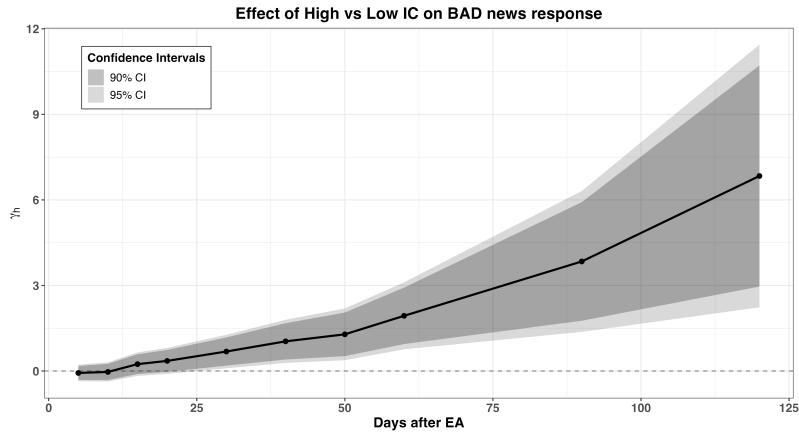


Figure 4: Impulse-response of post-announcement $CAR_{[+5,+h]}^{CAPM}$ to announcement-window news, Bad news subsample.

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.

5.5 Summary

In sum, earnings announcements provide clean, high-salience tests of information incorporation. I find that lending-market structure is an important state variable for price discovery: post-announcement drift is substantially more pronounced following *bad* earnings news when lendable inventory is concentrated among a few dominant lenders. The asymmetry between good and bad news supports a short-sale-constraint mechanism rather than a generic attention- or risk-based explanation, and motivates the next section, which studies whether the same lending-market structure also amplifies the profitability and persistence of cross-sectional equity pricing 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 ??), 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

I use monthly signed anomaly signals from [Jensen et al. \(2023\)](#) and restrict attention to the subset of signals that exhibit a positive and statistically significant CAPM alpha (10% level) in the merged CRSP–Markit universe over 2006–2023, after applying the baseline microcap and hard-to-borrow screens. This yields 62 anomalies.

For each anomaly, I form equal-weighted quintile portfolios each month and compute the long–short return spread (high-signal minus low-signal, with signal signs taken as provided in the library).

6.2 Double-sorts on inventory concentration and anomaly signals

The main portfolio design is a monthly double-sort that cleanly separates variation in anomaly strength across lending-market states. In month t , I first sort stocks into inventory concentration groups based on $IC_{i,t}$: Low IC (bottom quintile), Mid IC (middle three quintiles), and High IC (top quintile). Within each IC group, I sort stocks into quintiles based on a given anomaly signal $X_{i,t}$ and compute equal-weighted portfolio returns. Let $r_{jq,t}$ denote the return in month t for stocks in characteristic quintile $j \in \{1, \dots, 5\}$ within IC group $q \in \{L, M, H\}$. The within-group anomaly return is then

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

The key object is the high-minus-low IC amplification:

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

This construction ensures that anomaly spreads are always measured within comparable IC subsamples, so cross-IC differences are not driven mechanically by differences in the cross-sectional composition of stocks.

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

To summarize patterns across many signals, I group the 62 anomalies into standard clusters (e.g., profit growth, investment, momentum, accruals) and report average

Table 5: Double-sort design: inventory concentration and anomaly characteristics

Characteristic quintiles (within IC group)	Inventory Concentration (IC) groups		
	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 $r_t^q = r_{5q,t} - r_{1q,t}$.

anomaly spreads and CAPM alphas by cluster. Table 6 shows that anomaly returns are systematically larger in High IC stocks than in Low IC stocks. The High-minus-Low amplification is economically meaningful across several clusters, including profit growth (0.79% per month; $t = 4.03$), investment (0.64%; $t = 2.54$), and momentum (0.59%; $t = 1.88$). The corresponding CAPM alpha differentials are of similar magnitude, indicating that the effect is not simply compensation for market exposure.

Decomposing the amplification into long- and short-leg contributions suggests that the effect is driven primarily by the short side. In Table 6, the “LC S – HC S” column is typically large and positive, consistent with overvalued stocks being harder to arbitrage (via shorting) when inventory concentration is high.

6.4 Fee-adjusted implementations

Because borrow fees directly affect the feasibility and net profitability of short-selling-based strategies, I also compute *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 approximated by

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

Table 6: Average anomaly results by cluster (gross returns)

Cluster	HC–LC	HC–LC α_{CAPM}	HC L – LC L	LC S – HC S
Profit Growth	0.79 (4.03)	0.78 (3.91)	0.28	0.51
Investment	0.64 (2.54)	0.64 (2.50)	0.14	0.50
Momentum	0.59 (1.88)	0.53 (1.67)	0.12	0.47
Accruals	0.47 (1.86)	0.39 (1.54)	-0.02	0.49
Low Risk	0.47 (1.61)	0.57 (1.94)	0.09	0.39
Short-Term Reversal	0.39 (1.68)	0.43 (1.82)	-0.08	0.46
Value	0.33 (1.14)	0.53 (1.90)	-0.03	0.35
Debt Issuance	0.32 (1.16)	0.34 (1.25)	0.02	0.30
Quality	0.19 (0.61)	0.13 (0.38)	-0.05	0.24
Profitability	0.09 (0.28)	0.19 (0.58)	-0.06	0.16
Seasonality	-0.11 (-0.38)	-0.11 (-0.39)	-0.09	-0.02
<i>Counts across 62 anomalies</i>				
	Positive alpha	sig@10%	sig@5%	sig@1%
Full Sample	62	62	47	22
HC	60	52	43	34
HC–LC	58	30	27	15

For the long leg, lending income accrues only on the fraction of shares actually lent and is reduced by intermediary spreads. In the baseline adjustment, I therefore add $0.7 \times f_{i,t+1}$ scaled by utilization $u_{i,t+1}$, so that

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

I then form fee-adjusted long–short portfolio returns by taking the difference between the fee-adjusted long and short legs, and compute fee-adjusted CAPM alphas by regressing the resulting portfolio excess returns on the market excess return.

Table 7 shows that the High-minus-Low IC amplification remains strong after fee adjustment in several clusters (Profit Growth: 0.69% per month, $t = 3.67$; Investment: 0.59% per month, $t = 2.45$). Although fee adjustment reduces the number of statistically significant strategies in the full sample—consistent with borrow costs eroding implementable profits—it leaves a substantial set of economically meaningful returns in High-IC stocks and preserves the cross-IC gradient.

A useful benchmark implication is that if borrowing costs fully explain anomaly profitability, then net-of-fee abnormal performance should vanish conditional on fees.

Formally, under the null

$$E[\alpha + f \mid f] \approx 0 \quad \Rightarrow \quad E[\alpha \mid f] \approx -f,$$

so that strategies that load on high-fee short positions should not deliver positive fee-adjusted alphas. Instead, the persistence of large fee-adjusted returns in High-IC stocks indicates that lending-market structure captures an additional, state-dependent constraint—through fragility and short-selling risk—beyond fee levels alone.

Table 7: Average anomaly results by cluster (fee-adjusted returns)

Cluster	HC–LC	HC–LC α_{CAPM}	HC L – LC L	LC S – HC S
Profit Growth	0.69 (3.67)	0.66 (3.47)	0.41	0.27
Investment	0.59 (2.45)	0.60 (2.43)	0.36	0.23
Short-Term Reversal	0.49 (2.23)	0.55 (2.45)	0.21	0.28
Momentum	0.46 (1.53)	0.41 (1.34)	0.33	0.13
Accruals	0.46 (1.84)	0.37 (1.50)	0.26	0.20
Debt Issuance	0.30 (1.12)	0.34 (1.28)	0.23	0.07
Low Risk	0.10 (0.40)	0.19 (0.68)	0.14	-0.04
Quality	0.00 (0.01)	-0.07 (-0.24)	0.13	-0.13
Value	-0.03 (-0.11)	0.16 (0.60)	0.05	-0.08
Seasonality	-0.12 (-0.49)	-0.11 (-0.40)	0.03	-0.15
Profitability	-0.16 (-0.52)	-0.07 (-0.24)	0.10	-0.26
<i>Counts across 62 anomalies</i>				
	Positive alpha	sig@10%	sig@5%	sig@1%
Full Sample	62	37	24	11
HC	59	35	32	18
HC–LC	49	18	16	9

6.5 A summary mispricing measure: NetLeg portfolios

To aggregate information across many anomaly signals, I construct a NetLeg measure following [Engelberg et al. \(2018\)](#). Using the 62 anomaly signals, I count for each stock-month how often the stock appears in the long quintile and how often it appears in the short quintile across anomalies. 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, I sort stocks into NetLeg quantiles using the lagged NetLeg score and form a zero-cost portfolio that buys the highest NetLeg quintile and sells the lowest NetLeg quintile. I repeat this construction within Low, Mid, and High IC subsamples to test whether aggregate anomaly-based mispricing is more exploitable in concentrated lending markets.

Figure 5 plots the cumulative log returns of the NetLeg strategies (fee-adjusted) across IC groups. Consistent with the cluster-level results, performance is strongest in High IC stocks.

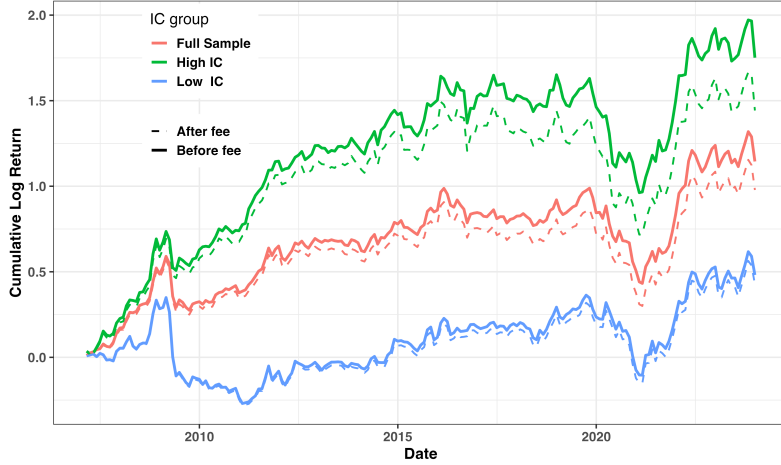


Figure 5: Cumulative log returns of NetLeg portfolios (fee-adjusted), 2007–2023.

Table 8 provides the corresponding portfolio-level statistics. In the High IC subsample, the NetLeg high-minus-low portfolio earns **102.18** b.p. per month ($t=2.39$) in excess returns and **147.00** b.p. per month ($t=3.86$) in CAPM alpha. After fee adjustment, the spread remains large: **86.85** b.p. per month ($t=2.04$) in fee-adjusted excess returns and **131.60** b.p. per month ($t=3.46$) in fee-adjusted CAPM alpha. In contrast, the same strategy in Low IC stocks earns only **33.94** b.p. ($t=1.00$) in excess returns and **75.26** b.p. ($t=3.00$) in CAPM alpha, with fee adjustment leaving a spread of **31.25** b.p. ($t=0.92$) and **72.55** b.p. ($t=2.89$). Thus, the aggregate anomaly signal produces substantially larger and more robust performance when

lendable inventory is concentrated.

Table 8: NetLeg quintile portfolios: returns, fees, and CAPM alphas in basis points (High vs. Low IC)

	Metric	Q1	Q2	Q4	Q5	Q5–Q1
High IC	r^e	28.40 (0.41)	58.38 (1.04)	109.33 (2.40)	130.58 (3.10)	102.18 (2.39)
	Fee	21.64	14.32	10.48	9.02	-12.62 (-20.49)
	r_{feeadj}^e	50.04 (0.73)	68.40 (1.22)	116.67 (2.56)	136.90 (3.25)	86.85 (2.04)
	α_M	-82.03 (-2.20)	-38.47 (-1.54)	38.69 (1.57)	64.98 (2.81)	147.00 (3.86)
	α_M^{feeadj}	-60.30 (-1.62)	-28.39 (-1.14)	46.06 (1.87)	71.30 (3.09)	131.60 (3.46)
	# stocks	102.00	98.00	111.00	94.00	–
Low IC	r^e	67.98 (1.17)	93.98 (2.08)	83.53 (2.24)	101.92 (3.13)	33.94 (1.00)
	Fee	4.95	3.55	3.23	3.23	-1.72 (-10.72)
	r_{feeadj}^e	72.93 (1.26)	96.46 (2.14)	85.79 (2.30)	104.18 (3.21)	31.25 (0.92)
	α_M	-49.53 (-2.07)	-5.74 (-0.42)	-1.37 (-0.12)	25.73 (2.84)	75.26 (3.00)
	α_M^{feeadj}	-44.54 (-1.87)	-3.25 (-0.24)	0.90 (0.08)	28.01 (3.09)	72.55 (2.89)
	# stocks	107.00	97.00	99.00	109.00	–

6.6 Connection to short-selling risk

Finally, Table 9 links the aggregate mispricing measure back to borrowing instability. In both High and Low IC subsamples, stocks in the lowest NetLeg quintile (those most frequently appearing on short legs) exhibit substantially higher fee and utilization risk than stocks in the highest NetLeg quintile. Importantly, the levels of short-selling risk are uniformly higher in the High IC subsample. For example, in High IC stocks the difference in $\log(\text{VarFee})$ between the lowest and highest NetLeg quintiles is 1.29, compared to 0.42 in Low IC stocks; similarly, the TailFee spread is 2.24 in High IC and 0.49 in Low IC. These patterns support the interpretation that anomaly amplification in High IC stocks is linked to a more fragile lending environment precisely where short positions are most needed.

6.7 Equity mispricing and inventory concentration: Fama–MacBeth evidence

The portfolio results above show that anomaly-based strategies earn larger returns in high- IC stocks and that the amplification is concentrated on the short side. To

Table 9: Short-selling risk across NetLeg quintiles for High vs. Low IC

	Metric	Q1	Q2	Q4	Q5	Q5-Q1
High IC	log(VarFee)	-2.36	-3.10	-3.40	-3.65	-1.29
	log(VarUtil)	2.62	1.56	0.53	0.17	-2.45
	TailFee	4.57	3.34	2.66	2.33	-2.24
	TailUtil	41.17	26.39	15.55	12.79	-28.38
Low IC	log(VarFee)	-5.89	-6.23	-6.31	-6.31	-0.42
	log(VarUtil)	1.46	0.43	-0.14	-0.31	-1.77
	TailFee	1.03	0.65	0.55	0.54	-0.49
	TailUtil	26.81	15.89	11.31	10.35	-16.46

quantify this mechanism in a unified cross-sectional framework, I estimate monthly Fama–MacBeth regressions of next-month excess returns on NetLeg, inventory concentration, and interactions that isolate the long- versus short-leg channel.

Short-leg intensity and subsample definitions. I construct $NetShort_{i,t}$ as a standardized measure of how frequently stock i appears on the short legs of the anomaly portfolios in month t . Specifically, I compute the within-month cross-sectional percentile rank of the short-leg frequency and rescale it to $[-1, 1]$:

$$NetShort_{i,t} = 2 \cdot \text{PercentRank}_t(\text{ShortLegCount}_{i,t}) - 1.$$

By construction, $NetShort_{i,t} = -1$ corresponds to stocks in the bottom of the month- t short-leg distribution, $NetShort_{i,t} = 0$ corresponds to the cross-sectional median, and $NetShort_{i,t} = 1$ corresponds to stocks at the top of the distribution. I define the *moderately shorted* subsample as stocks with $NetShort_{i,t} \geq 0$ (above-median short-leg intensity) and the *heavily shorted* subsample as stocks with $NetShort_{i,t} \geq 0.5$, which is equivalent to being in approximately the top quartile of the short-leg distribution in that month.

Specification. In each month t , I run the cross-sectional regression

$$r_{i,t+1}^e = \alpha_t + \beta_t NetLeg_{i,t} + \theta_t IC_{i,t} + \phi_t^L (NetLong_{i,t} \times IC_{i,t}) + \phi_t^S (NetShort_{i,t} \times IC_{i,t}) + \Gamma_t' X_{i,t} + \varepsilon_{i,t+1},$$

and report time-series averages of the coefficients with Fama–MacBeth t -statistics. $X_{i,t}$ includes the standard return-predictability controls used throughout the paper: market equity (ME), β_m , book-to-market (BM), return volatility (VOL), idiosyncratic volatility (IVOL), institutional ownership (IO), illiquidity, short interest, and turnover. *NetLong* and *NetShort* summarize a stock’s exposure to the anomaly long and short legs, so the interaction terms allow the effect of inventory concentration to differ precisely where short positions are most relevant.

Results. Table 10 reports the estimates for the full universe and for subsamples split by short-leg intensity (moderately versus heavily shorted). Three findings stand out.

First, the standalone NetLeg slope is not reliably different from zero once controls are included. This is consistent with the portfolio evidence that the predictive content of NetLeg is not uniform across lending-market states.

Second, inventory concentration is strongly positively related to subsequent returns, and the association strengthens with short-leg intensity. The coefficient on IC is 13.114 ($t=2.03$) in the full sample, 76.207 ($t=5.44$) among moderately shorted stocks, and 223.234 ($t=3.65$) among heavily shorted stocks.

Third, and most importantly, the interaction terms show that inventory concentration operates primarily through the *short side*. The coefficient on $NetShort \times IC$ is large and significantly negative in all subsamples: -33.685 ($t=-4.39$) in the full sample, -139.498 ($t=-4.74$) among moderately shorted stocks, and -315.276 ($t=-3.61$) among heavily shorted stocks. Because low NetLeg stocks are those most frequently on short legs (i.e., most “overvalued” by anomaly signals), a negative $NetShort \times IC$ implies that higher inventory concentration inflates expected returns *precisely* for the stocks that are hardest to arbitrage on the downside. Consistent with this interpretation, the magnitude of the short-leg interaction is most pronounced in the heavily shorted subsample.

Overall, the Fama–MacBeth results reinforce the main mechanism: lending inventory concentration is not merely correlated with higher average returns; it dispro-

portionately amplifies mispricing on the short side, where tighter and more fragile borrowing conditions impede negative-bet arbitrage.

Table 10: NetLeg and inventory concentration: Fama–MacBeth regressions

	All Stocks	Moderately Shorted	Heavily Shorted
<i>Dependent variable: Next-month excess return (%)</i>			
NetLeg	-12.458 (-1.10)	-4.454 (-0.25)	-29.781 (-0.75)
IC	13.114** (2.03)	76.207*** (5.44)	223.234*** (3.65)
NetLong $\times$ IC	29.154*** (3.98)	-3.736 (-0.29)	-34.940 (-1.46)
NetShort $\times$ IC	-33.685*** (-4.39)	-139.498*** (-4.74)	-315.276*** (-3.61)

Notes: Monthly Fama–MacBeth regressions. Controls: ME, β_m , BM, VOL, IVOL, IO, illiquidity, short interest, turnover.

Moderate shorting: $NetShort_{i,t} \geq 0$; heavy shorting: $NetShort_{i,t} \geq 0.5$ (approximately top quartile).

*, **, *** denote 10%, 5%, 1% significance.

6.8 Summary

Across a broad anomaly set, return predictability is systematically stronger when lendable inventory is concentrated. The amplification is visible in cluster averages and remains present after fee adjustment. A composite NetLeg strategy delivers substantially larger excess returns and CAPM alphas in High IC stocks, even after adjusting for borrowing costs, and the cross-sectional patterns align with elevated fee and utilization risk on the short side. Consistent with this mechanism, Fama–MacBeth regressions show that inventory concentration is positively related to subsequent excess returns, and that the effect operates primarily through the *short side*: the interaction between IC and the short-leg intensity ($NetShort \times IC$) is large and significantly negative, with the magnitudes strongest among heavily shorted stocks. Taken together, the evidence supports the interpretation that securities lending market structure is an important, state-dependent limit to arbitrage that sustains equity pricing anomalies, especially by impeding the correction of overpricing when negative bets are most needed.

7 Conclusion

This paper studies how the *structure* of the securities lending market shapes short-sale constraints, the incorporation of negative information into prices, and the strength of cross-sectional equity pricing anomalies. The central object is *lendable inventory concentration* (IC)—the concentration of lendable shares across lenders—measured directly from granular IHS Markit securities lending data. Conceptually, IC captures two complementary mechanisms emphasized in the lending literature: (i) concentrated supply can generate market power over fees, and (ii) a concentrated lender base is intrinsically more fragile, so shocks to large lenders translate into abrupt tightening of effective short-sale constraints.

The empirical results support three main conclusions. First, lending inventory concentration is strongly associated with tighter short-sale constraints. Stocks with higher IC exhibit higher average borrowing fees and, importantly, substantially greater instability in borrowing conditions—higher fee and utilization volatility and more extreme tail realizations—consistent with elevated short-selling risk that is not fully captured by fee levels alone. This pattern is robust to controlling for shorting demand (short interest and utilization) and a standard set of stock characteristics.

Second, inventory concentration matters for price discovery. Focusing on earnings announcements as clean, high-salience information events, I find that negative news is incorporated more slowly when lending supply is concentrated. High-IC stocks display larger and more persistent post-earnings-announcement drift following bad news, while drift following good news is comparatively small. The asymmetric nature of the result is consistent with a short-sale-constraint channel: when it is risky to maintain short positions because borrowing conditions are fragile, informed investors are less willing or able to trade aggressively on negative information, and price adjustment is delayed.

Third, these lending-market frictions translate into stronger anomaly profitability. Across a broad set of replicated anomaly signals, long-short strategy returns are systematically larger in high-IC stocks than in low-IC stocks, and this amplifica-

tion remains present after fee adjustment. A composite NetLeg strategy illustrates the economic magnitude: CAPM alpha is roughly 150 bps per month in high-IC stocks versus roughly 75 bps in low-IC stocks, and the fee-adjusted CAPM alpha in high-IC stocks remains sizable at about 130 bps per month—approximately twice the low-IC benchmark. Cross-sectional Fama–MacBeth regressions reinforce the mechanism: the effect of inventory concentration operates primarily through the *short side*. In particular, the interaction between IC and short-leg intensity is large and strongly significant, with the largest effects concentrated among stocks that are most frequently identified as short candidates by the anomaly set (i.e., the “heavily shorted” group based on the standardized *NetShort* measure). Taken together, the portfolio and regression evidence indicates that IC amplifies pricing errors precisely where negative-bet arbitrage is most required.

The broader implication is that securities lending market structure is an economically important, state-dependent limit to arbitrage. While prior work emphasizes borrowing-cost levels and short-selling risk as separate frictions, this paper shows that a simple and observable feature—the concentration of lendable inventory across lenders—helps unify these channels and organizes when and where mispricing persists. For anomaly-based tests of market efficiency, the findings suggest that the relevant constraint is not only the *level* of borrow fees but also the *fragility* of lending supply: mispricing is systematically larger in stocks whose lendable inventory is controlled by a small set of lenders and therefore more vulnerable to supply disruptions.

An important direction for future work is to sharpen causal interpretation by exploiting plausibly exogenous shocks to the lending structure—such as large exits or sudden lending contractions by major suppliers—and to further connect lender composition (e.g., quasi-indexers and other stable lenders) to the dynamics of IC, short-selling risk, and anomaly strength. These extensions would help distinguish market-power versus fragility mechanisms more sharply and deepen our understanding of how institutional lending supply shapes price informativeness in equity markets.

References

- Ian R Appel, Todd A Gormley, and Donald B Keim. Passive investors, not passive owners. *Journal of Financial Economics*, 121(1):111–141, 2016.
- Adem Atmaz, Suleyman Basak, and Fangcheng Ruan. Dynamic equilibrium with costly short-selling and lending market. *Review of Financial Studies*, 37(2):444–506, 2024. doi: 10.1093/rfs/hhad060.
- Victor L Bernard and Jacob K Thomas. Post-earnings-announcement drift: delayed price response or risk premium? *Journal of Accounting research*, 27:1–36, 1989.
- Jonathan Brogaard, Thanh Huong Nguyen, Talis J. Putnins, and Eliza Wu. What moves stock prices? the roles of news, noise, and information. *Review of Financial Studies*, 35(9):4341–4386, 2022. doi: 10.1093/rfs/hhab137.
- Brian J Bushee. The influence of institutional investors on myopic r&d investment behavior. *Accounting review*, pages 305–333, 1998.
- Shuaiyu Chen, Ron Kaniel, and Christian C Opp. Market power in the securities lending market. *Available at SSRN 4100699*, 2022.
- Lauren Cohen, Karl B Diether, and Christopher J Malloy. Supply and demand shifts in the shorting market. *The Journal of Finance*, 62(5):2061–2096, 2007.
- Zhi Da, Chengbo Fu, Nanying Lin, and Lei Lu. Short-selling profitability, stock lending fees, and asset pricing anomalies. *Working Paper*, 2025. Available as SSRN working paper.
- Douglas W Diamond and Robert E Verrecchia. Constraints on short-selling and asset price adjustment to private information. *Journal of financial economics*, 18(2):277–311, 1987.
- Xi Dong and Qifei Zhu. Equity lender base and limits to arbitrage: Position-level evidence from mutual funds. *Available at SSRN 4291572*, 2022.

- Gene D’avolio. The market for borrowing stock. *Journal of financial economics*, 66 (2-3):271–306, 2002.
- Roger M Edelen, Ozgur S Ince, and Gregory B Kadlec. Institutional investors and stock return anomalies. *Journal of Financial Economics*, 119(3):472–488, 2016.
- Joseph E. Engelberg, Adam V. Reed, and Matthew C. Ringgenberg. Short-selling risk. *Journal of Finance*, 73(2):755–786, 2018. doi: 10.1111/jofi.12601.
- Andrea Frazzini, Ronen Israel, and Tobias J. Moskowitz. Trading costs of asset pricing anomalies. *Ewing Marion Kauffman Foundation Research Paper Series*, 2012. URL <https://api.semanticscholar.org/CorpusID:44053212>.
- Jeremiah Green, John RM Hand, and X Frank Zhang. The characteristics that provide independent information about average us monthly stock returns. *The Review of Financial Studies*, 30(12):4389–4436, 2017.
- Campbell R Harvey, Yan Liu, and Heqing Zhu. ... and the cross-section of expected returns. *The Review of Financial Studies*, 29(1):5–68, 2016.
- Harrison Hong and Jeremy C Stein. Differences of opinion, short-sales constraints, and market crashes. *The Review of Financial Studies*, 16(2):487–525, 2003.
- Kewei Hou, Chen Xue, and Lu Zhang. Replicating anomalies. *Review of Financial Studies*, 33(5), 2020.
- Heiko Jacobs and Sebastian Müller. Anomalies across the globe: Once public, no longer existent? *Journal of Financial Economics*, 135(1):213–230, 2020.
- Theis Ingerslev Jensen, Bryan Kelly, and Lasse Heje Pedersen. Is there a replication crisis in finance? *The Journal of Finance*, 78(5):2465–2518, 2023.
- Charles M Jones and Owen A Lamont. Short-sale constraints and stock returns. *Journal of Financial Economics*, 66(2-3):207–239, 2002.
- Jonathan Lewellen. Institutional investors and the limits of arbitrage. *Journal of Financial Economics*, 102(1):62–80, 2011.

- Juhani T Linnainmaa and Michael R Roberts. The history of the cross-section of stock returns. *The Review of Financial Studies*, 31(7):2606–2649, 2018.
- Lei (Matthew) Ma. Short selling risk and hedge fund performance. *Working Paper*, 2019. Working paper, University of Connecticut.
- R David McLean and Jeffrey Pontiff. Does academic research destroy stock return predictability? *The Journal of Finance*, 71(1):5–32, 2016.
- Richard R Mendenhall. Arbitrage risk and post-earnings-announcement drift. *The Journal of Business*, 77(4):875–894, 2004.
- Edward M Miller. Risk, uncertainty, and divergence of opinion. *The Journal of finance*, 32(4):1151–1168, 1977.
- Dmitriy Muravyev, Neil D. Pearson, and Joshua M. Pollet. Anomalies and their short-sale costs. *Journal of Finance*, 80(6):3639–3694, 2025. doi: 10.1111/jofi.13501.
- Stefan Nagel. Short sales, institutional investors and the cross-section of stock returns. *Journal of financial economics*, 78(2):277–309, 2005.
- Robert Novy-Marx and Mihail Velikov. A taxonomy of anomalies and their trading costs. *The Review of Financial Studies*, 29(1):104–147, 2016.
- Darius Palia and Stanislav Sokolinski. Strategic borrowing from passive investors. *Review of Finance*, 28(5):1537–1573, 2024.
- Jeffrey Pontiff. Costly arbitrage and the myth of idiosyncratic risk. *Journal of Accounting and Economics*, 42(1-2):35–52, 2006.
- Melissa Porras Prado, Pedro A. C. Saffi, and Jason Sturgess. Ownership structure, limits to arbitrage, and stock returns: Evidence from equity lending markets. *Review of Financial Studies*, 29(12):3211–3244, 2016. doi: 10.1093/rfs/hhw058.
- Andrei Shleifer and Robert W Vishny. The limits of arbitrage. *The Journal of finance*, 52(1):35–55, 1997.

Dimitri Vayanos and Denis Gromb. Limits of arbitrage: The state of the theory.
Technical report, Financial Markets Group, 2010.

Andrew Y. Chen and Tom Zimmermann. Open source cross-sectional asset pricing.
Critical Finance Review, 11(02):207–264, 2022.