Inefficiencies in the Securities Lending Market*

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Abstract

In contrast with a general trend of declining trading frictions, over the last several decades the cost of borrowing securities for short-selling has increased dramatically. Using a portfolio approach, we show that as the borrow costs have increased so has the mispricing associated with portfolios of high-borrow-cost names. This decline in market efficiency has resulted from a lack of competition in the intermediation chain that links share lenders with borrowers, and a growing and rational unwillingness among institutional investors to hold and lend high-borrow-cost names. Since 2020, we estimate that the inefficiencies associated with these frictions have exceeded $300 Million/day.

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1 Introduction

By many measures, financial markets have become more efficient. As a result of improved technology, and entry and increased competition in the financial services sector, the costs of acquiring information and the transaction costs associated with buying and selling US common stocks have fallen dramatically (see e.g., Jones, 2002) and, at least by some measures, market efficiency has increased (Bai, Philippon, and Savov, 2016).[1]

In this paper we examine the securities lending market, and show that a variety of factors have instead led to the securities-lending market becoming far less efficient. Specifically, far more securities are now hard-to-borrow, and the aggregate borrow costs of these hard-to-borrow stocks are higher. We further document that these higher borrow costs have led to less efficient prices for these securities.

We begin with some data on borrow costs from D'Avolio (2002), which was among the earliest papers to directly examine borrow costs in the modern era.[2] D'Avolio obtained data from "a large financial institution" on lending fees for US common stocks at a daily frequency for the period from April 2000 through September 2001. He found that:

1. Most stocks could be borrowed: specifically, "…at most 16% (1,267 of 7,879) of the stocks found in the monthly CRSP file [were] potentially impossible to short," but that these issues accounted for "…less than 1% of the market by value (1,093 of these are in the bottom size decile and 719 are under $5)"
2. Borrowing a value-weighted portfolio of all stocks in the market costs 25 bps/year.
3. "Only 9% of stocks (about 206 stocks per day) have loan fees above 1% per annum. These 'specials' (stocks with high lending fees) have a mean fee of 4.3% per annum."
4. "Fewer than 1% of stocks (roughly seven per month) on loan become extremely special, demanding negative rebate rates (i.e., loan fees in excess of the risk-free rate)."

With regard to the final point, D'Avolio reports the most extreme negative rebate stocks in his Table 2. Across all the (firm-day) observations in his sample, the highest annualized fee ever observed is 79%, and only eight firms ever have an annualized fee higher than 35%.

[1] See however Asness (2024) for an alternative perspective.

[2] Jones and Lamont (2002) examine borrow costs recorded at the share lending desk at the NYSE in the 1930s. See also Jones (2012).

Table 1: Highest borrow costs for US securities as of Monday, June 30, 2025. This table shows the highest daily Indicative Fees reported by Markit for common stocks with CRSP share codes of 10 or 11, exchange codes of 1, 2, or 3, and a market capitalization of at least $100MM, in the time period 2024:01 to 2025:06. For each firm, we only pick the day with the most extreme fee, so that no firm appears more than once. The table reports the annualized *Indicative Fee* (in %, from Markit), the annualized *Rebate Rate*, and the equity *Market Capitalization* (from CRSP, in $MM).

Tick	Name	Date	Ind. Fee (%)	Rebate (%)	MktCap
ARMP	ARMATA PHARMACEUTICALS INC	2024/05/10	1000.00	−994.830	111.744
SBET	SHARPLINK GAMING INC	2025/06/13	940.96	−935.790	549.395
QXO	Q X O INC	2024/07/31	902.75	−897.580	5117.875
AIRJ	AIRJOULE TECHNOLOGIES CORP	2024/06/11	896.70	−891.530	431.273
SDST	STARDUST POWER INC	2024/08/12	881.04	−875.870	432.845
NUKK	NUKKLEUS INC	2024/12/18	859.60	−854.430	207.376
NXTT	NEXT TECHNOLOGY HOLDING INC	2025/06/26	799.13	−793.960	959.783
LASE	LASER PHOTONICS CORP	2024/10/14	747.85	−742.680	118.740
FBLG	FIBROBIOLOGICS INC	2024/02/15	731.13	−725.960	417.197
ZENA	ZENATECH INC	2024/12/16	731.01	−725.840	134.310
COCH	ENVOY MEDICAL INC	2024/03/12	722.24	−717.070	148.960
NMAX	NEWSMAX INC	2025/04/02	718.46	−713.290	4671.601
DJT	TRUMP MEDIA & TECH GRP CORP	2024/04/01	705.54	−700.370	6651.871
KIDZ	CLASSOVER HOLDINGS INC	2025/05/06	699.68	−694.510	108.830
BNAI	BRAND ENGAGEMENT NETWORK INC	2024/06/13	615.95	−610.780	146.950
OPTX	SYNTEC OPTICS HOLDINGS INC	2024/12/27	605.71	−600.540	122.538
LVWR	LIVEWIRE GROUP INC	2025/06/03	594.13	−588.960	814.264
AISP	AIRSHIP A I HOLDINGS INC	2024/03/19	590.19	−585.020	291.309
GATE	MARBLEGATE ACQUISITION CORP	2025/04/01	584.48	−579.310	190.308
ATLN	ATLANTIC INTERNATIONAL CORP	2025/01/03	553.83	−548.660	297.002
AIFF	FIREFLY NEUROSCIENCE INC	2025/02/12	545.60	−540.430	103.047
TVGN	TEVOGEN BIO HOLDINGS INC	2024/10/30	526.34	−521.170	420.104
CRWV	COREWEAVE INC	2025/04/01	515.99	−510.820	19 023.769
SIRI	SIRIUS X M HOLDINGS INC NEW	2024/07/23	513.47	−508.300	14 633.800
XBP	XBP EUROPE HOLDINGS INC	2024/05/14	499.62	−494.450	101.056
JNVR	DEFI DEVELOPMENT CORP	2025/04/16	499.13	−493.960	103.074
UPXI	UPEXI INC	2025/05/15	496.64	−491.470	356.884
STI	SOLIDION TECHNOLOGY INC	2024/03/22	488.19	−483.020	264.401
ANNA	ALEANNA INC	2025/05/12	477.63	−472.460	435.062
UP	WHEELS UP EXPERIENCE INC	2024/07/03	448.93	−443.760	2259.262

Today the picture is much different. Table 1 provides the 30 observations with the highest borrow costs among US common stocks listed on major US exchanges with at least $100MM market capitalization, over the last 18 months of our sample (2024:01–2025:06), a time period as long as D'Avolio's sample. The dramatic rise in these borrow costs over the last 25 years is clear. For the highest borrow cost security, ARMP, the annualized fee is 1000%. That is, the daily cost of borrow is almost 4%. For each of these 30 securities, the annualized borrow cost is greater than 400%. During that time, there were 42,978 observations with indicative fees greater than 100%/year in the universe of common US stocks on major exchanges, i.e., more than 113 stocks per day, on average.

Like D'Avolio, we find that the majority of US common stocks on NYSE, AMEX and NASDAQ today have a borrow cost that is at (or close to) the general collateral (GC) rate: during the 2024:01–2025:06 period, 68% of the 1.445 million observations had an annualized fee lower than 1%. However, today both the number of *specials*—stocks with a fee greater than 1% annualized—and the distribution of fees for these specials is far different. D'Avolio found that "... at most 9% of all stocks ... [had] loan fees above 1% per annum", and that "... these 'specials' ... [had] a mean fee of 4.3% per annum". Consistent with D'Avolio's findings, at the start of our sample in June 2003, only 10% of stocks with non-missing fees have an annualized borrow cost greater than 1%. However, by July of 2022, 43% have borrow costs greater than 1%. Over this same time period, the fraction of firms that have borrow costs above 10% increases from a handful of issues in 2003 to just under 20% in August of 2023.

To better understand the implications of this for pricing, in Section 5 we take a new approach to estimating the relationship between borrow costs and returns. We form portfolios on the basis of lagged borrow costs as reported by Markit.[3] We find that there is close to a one-to-one relationship between the borrow costs reported by Markit and the negative alpha of the security.

Our high-borrow-cost portfolio, formed based on one-day lagged borrow costs (as reported by Markit and available to Markit subscribers) earns an annualized CAPM alpha of -81.4% (t = -5.87).[4] Thus, an investor in this portfolio who did not lend out the securities would have earned a risk-adjusted return of -81.4%.

Given the large negative alpha earned by this portfolio, one might think a short position in this portfolio would have earned a high *positive* alpha of 81.4%. However, the *ex-post* cost of borrowing the shares over this period was approximately 84.8%, so net of the borrow cost

[3]As we discuss in Section 2, other papers in the literature employ the Markit share lending data to estimate the returns net of borrow costs to portfolios formed on the basis of other characteristics (see, e.g., Drechsler and Drechsler (2014))

[4]Here, we are forming the portfolios on the basis of the indicative fee as reported by Markit. However, we are calculating the raw portfolio returns using only CRSP data.

the return to shorting this portfolio was an annualized -3.4% (t-statistic: -0.25), based on the daily indicative fees reported by Markit.

A net-of-borrow-cost alpha of zero is consistent with a market in which short-sellers are rational, informed, and competitive.[5] The net return for our high-borrow-cost portfolio is statistically indistinguishable from zero, but for portfolios with slightly less extreme annualized borrow costs between 10% and 50%, short-sellers would have earned *positive* alphas over our 2010:01–2025:06 sample period.

As discussed above, we are also interested in the returns to investors who go long these high-borrow-cost stocks. For investors who purchased portfolios of these securities and did not lend their shares, the alphas are negative and highly statistically significant. And, because any borrowed shares are always sold short, the number of shares which are not lent out and are not earning a lending fee is always equal to the number of shares outstanding.

Another important question, though, is the alpha that would be earned by a sophisticated investor who chose to and did lend out all of the shares in these portfolios. If the fee earned by the lender of the shares were equal to the fee paid by the borrower, then the alpha from going long these portfolios would equal -1 times the alpha from going short. However, there are necessarily transaction costs—i.e., losses in the intermediation chain connecting lenders with borrowers—which result in the lending fee being lower than the borrow cost.

We estimate the efficiency of the intermediation chain between short sellers who borrow shares, and the funds that are the primary lenders of these shares. The N-PORT and N-CEN filings that the SEC has required since 2019 provide, for each fund that files these forms, snapshots of the exact security lending done by the fund, and that fund's income from share-lending over the year. By combining these data with the Markit data, we can estimate on a fund level basis what the eventual borrowers of the shares paid to borrow those shares. By comparing this borrow cost with the revenue received by the fund, we estimate that the intermediation costs are about 40% of the fees. Thus, the lender receives

[5] Short sellers may face other costs other than the explicit borrow costs we consider here; see, e.g., Engelberg, Reed, and Ringgenberg (2018).

only 60% of every dollar that a short-seller pays to borrow its shares. The intermediaries' share does shrink with the borrow cost but is still roughly 67% for even higher borrow cost names. Thus, once one accounts for the spread between the cost paid by the share borrowers (as reported by Markit), and the fee received by the lenders, the alpha from a strategy of holding and lending out a portfolio of high-borrow-cost names are strongly negative and highly statistically significant.

We argue that the increase in lending fees that we document results, at least in part, from the structure of the share-lending market, combined with a possible increased demand from short sellers and a lack of competition in the intermediation chain that links share lenders with borrowers. Specifically, we argue that the increase in borrow costs is consistent with a model in which, as some agents receive negative information about a security, these agents compete to short that security, driving up borrow costs. The result of this is that, as the negative information becomes apparent in the borrow costs of these securities, the funds holding these securities decide to sell rather than lend these securities. They sell rather than lend because the frictions in the intermediation chain mean that the lending fee the lenders receive is lower than the borrow cost the borrowers pay. As discussed above, our empirical estimates suggest that, even if they received the full borrowing cost, they would earn an alpha ≤ 0. Thus, given the intermediation costs, they have learned that they are far better off selling rather than holding and lending the high-borrow-cost securities (Evans, Ferreira, and Porras-Prado, 2017). So they sell, and generally sell to individual investors who choose not to lend the securities, leading to a decrease in supply, and a large increase in the borrow costs.

We investigate this hypothesis using data from the N-PORT filings. We show that in recent years even index funds underweight firms with higher borrow costs. Furthermore, we use 13F filings to compare the dollar holdings of institutional investors in high-fee securities with their holdings of similarly sized stocks. The ratio of the two is negative throughout the sample, suggesting that institutions always held a smaller amount of money in high-fee stocks than in similar-sized unconstrained ones. Furthermore, speaking directly to the increase in fees documented here, the ratio between dollar holdings in high-fee and general collateral stocks has significantly fallen since 2010, consistent with institutions avoiding high-fee stocks more over time and in line with the positive time trend in borrowing fees.

The evidence we present here, combined with much other evidence in the academic literature, suggests that there is substantial disagreement across market participants: optimists express this optimism through purchasing securities, and pessimists express their pessimism through short selling the same securities. A recent literature has attempted to explore the beliefs of investors by examining analyst forecasts (see, e.g., Bordalo, Gennaioli, La Porta, and Shleifer, 2024). An interesting question, given our evidence here, is whether the views of analyst better reflect the views of the optimists or of the pessimists. We examine this question by exploring the extent to which analyst forecast errors and forecast revisions can be predicted using borrow costs reported by Markit in advance of the time the forecast is made. If these forecasts are rational with respect to borrow costs, in the sense that the forecasts fully incorporate all information embedded in the reported borrow costs, then both forecast errors and revisions should be orthogonal to this information. Instead, we find that forecast-errors and revisions can be forecast with the information in *ex-ante* borrow costs at high levels of statistical significance.

Finally we estimate dollar inefficiency associated with mispricings resulting from the frictions in the share lending market. We estimate that, since 2020, this quantity has totaled more than $300 Million per day. Note that in a standard goods market, these costs would not exist. Generally, the price of a good rises if demand exceeds supply. Such price run-ups create profit opportunities and cause either existing or new suppliers to produce more of that good. The problem in the security lending market is that the supply of shares in the lending market is necessarily equal to the demand of lending institutions who purchase the security in the security market. If these institutions are not willing to buy more of the constrained security—it is not even necessary that they demand less of it—then we will observe a (partial) market failure. To the extent that inefficiencies in the lending market cause upward-biased prices in the security market (Miller, 1977), increasing borrowing fees are the flip-side of increasingly inefficient prices in the stock market.

2 Related Literature

Miller (1977) and Harrison and Kreps (1978) argue that asset prices can become inflated as a result of both heterogeneous expectations and constraints on short selling. Diamond and Verrecchia (1987) show that private information can be supressed by short-selling constraints. Duffie, Garleanu, and Pedersen (2002) develop a dynamic model of securities lending, shorting, and pricing. Their work demonstrates how search frictions in the lending market create impediments to short selling that can lead to overpricing of securities, consistent with Miller (1977) and Harrison and Kreps (1978).

D'Avolio (2002) and Geczy, Musto, and Reed (2002) provide empirical evidence about the equity lending market's structure and functioning. Their analysis reveals that many stocks are "special" in the lending market, with significant variation in borrow costs and availability across securities. This heterogeneity in lending conditions creates differential arbitrage constraints that vary systematically across stocks, providing a mechanism through which anomalies can persist in some securities while being arbitraged away in others. Cohen, Diether, and Malloy (2007) attempt to identify supply and demand shifts in the shorting market, and demonstrate that changes in short-selling constraints have predictable effects on stock prices, with tightening constraints leading to price increases and loosening constraints enabling price decreases.

Stambaugh, Yu, and Yuan (2015) examine the link between short-selling constraints and asset pricing anomalies. They demonstrate that arbitrage asymmetry—the differential ease of going long versus short—can explain the persistence of various market anomalies. Their theoretical model shows that when short selling is constrained, overpriced securities cannot be efficiently arbitraged, leading to persistent anomalies. Importantly, they show that this asymmetry can also explain the idiosyncratic volatility puzzle, demonstrating the broad explanatory power of short-selling constraints for multiple market phenomena. Drechsler and Drechsler (2014) provide additional theoretical support for this relationship by developing a model where a "shorting premium"—the additional return required to compensate for short-selling costs and risks—helps explain various asset pricing anomalies. Their framework suggests that many documented anomalies may actually reflect compensation for the costs and risks associated with implementing arbitrage strategies, particularly those requiring short positions.

Engelberg, Evans, Leonard, Reed, and Ringgenberg (2025) examine the role of borrow costs in explaining cross-sectional return patterns. They examine 102 asset pricing anomalies and found that borrow costs are the best predictor of cross-sectional returns, with the "loan fee anomaly" exhibiting the highest monthly long-short return (1.17%) and Sharpe ratio (0.40). Their analysis reveals that 72% of the loan fee anomaly's performance is due to unique information possessed by short sellers, suggesting that short sellers' willingness to pay high fees reveals their private information about future returns.

This finding is complemented by Muravyev, Pearson, and Pollet (2025), who examine the relationship between anomalies and short-sale costs across 162 documented anomalies. They argue that anomalies are concentrated in stocks that are expensive to short, and once stock borrow fees are accounted for, the alpha from anomaly strategies is eliminated. This result provides strong evidence that many documented anomalies may be "explained" by the limits to arbitrage imposed by high short-selling costs.(See also Drechsler and Drechsler, 2014)

A number of other papers have explored determinants of borrow costs. Sikorskaya (2024) shows that benchmark-driven institutional demand inflates prices and raises borrowing fees, a mechanism closely related to our focus on institutional frictions. Chen, Kaniel, and Opp (2025a) document market power in securities lending, with concentrated custodians extracting non-competitive fees. Cookson, Fos, and Niessner (2025) find that disagreement facilitates informed trading by activists and short sellers, especially when borrow costs are high. Banerjee and Smith (2025) show that loan fees spike around information events, depending on disagreement.

In this paper we will mostly use the Markit-reported indicative fee as a measure of borrow costs. There are a few caveats raised by the literature. First, Kolasinski, Reed, and Ringgenberg (2013) use panel data examining how borrow costs charged by 12 distinct lenders change in response to demand shocks. They demonstrate significant dispersion in the fees charged by the different lenders, consistent with a model in which search costs drive lending fees in a competitve share lending market. As discussed below, we argue that the share lending market is better describe by a model with market power (consistent with Chen, Kaniel, and Opp, 2025a).

We use the borrow-cost as a proxy for the all-in cost to short-selling. Engelberg, Reed, and Ringgenberg (2018) point out that there are significant risks to short selling that make the effective cost for some short-sellers far higher than the simple borrow cost.

Daniel, Klos, and Rottke (2023) focuses on the behavioral and information-theoretic foundations of short-selling patterns. They develop a dynamic model of disagreement that explains how differences of opinion about security values evolve over time and interact with short-selling constraints. This model demonstrates that disagreement creates natural demand for short selling from pessimistic investors, but when this demand is constrained, it leads to persistent overpricing.

Blocher and Ringgenberg (2018) show that after option market makers lost their exception with regards to the ban on naked short selling in a regulation change in 2008, equity borrow fees increased significantly. In 2013 that ban became even more binding for them, when a workaround was also prohibited, resulting in yet higher equity borrow fees. However, our focus is primarily on data starting in 2010. While the 2013 change could explain part of the increase in fees early in our sample, causal influence on the significant rise in the later part of our sample period is less plausible. Nonetheless, the ban certainly made simple fee mitigation using options less viable—Blocher and Ringgenberg (2018) argue that synthetic short sales using options became about as costly (even more costly in some cases) as physical short sales.

Reed (2013) and, more recently, Daniel, Klos, and Rottke (2024) provide reviews of the literature on securities lending and short-selling, with different emphasis. A new development not addressed in existing reviews is the use of position-level lending data from N-PORT. Our paper shares this approach with Gogar, Haushalter, and Pisciotta (2024), Dong and Zhu (2024), and Chen, Tran, and Wang (2025b). Related to our analysis of mutual funds and institutional holdings, Evans, Ferreira, and Porras-Prado (2017) use N-SAR data to demonstrate that equity-lending funds tend to underperform. Furthermore, Honkanen (2025) draw on N-Q and N-CSR filings to show that active funds systematically rebalance away from borrowed stocks.

3 The Structure of the Securities Lending Market

We provide a summary of the institutional features of the securities lending market. Good summaries of the market structure are given in Duffie, Garleanu, and Pedersen (2002), Reed (2013), and Kolasinski, Reed, and Ringgenberg (2013). We focus on institutional restrictions and features in the United States, though the basic structure is similar in other countries.[6]

3.1 Regulatory framework and market structure

US security market regulations require that, in order to take a short position in a common stock, most traders must first borrow that stock. Specifically, under SEC Regulation SHO, the borrower or the borrower's broker must first *locate* a willing lender—that is, establish a high probability of being able to borrow or otherwise locate share certificates by the

[6] See, e.g., Bris, Goetzmann, and Zhu (2007)

settlement date. [7] This "locate" requirement does not necessitate identifying specific shares, but rather demonstrating reasonable grounds to believe that shares can be borrowed when needed.

The SEC, granted authority to regulate short sales under Section 10(a) of the Securities Exchange Act of 1934, governs short selling primarily through Regulation SHO.[8] Per SEC Regulation SHO Rule 200(g), all sell orders must be marked as either a long sale, a short exempt sale (exempt from the up-tick rule and locate requirement), or a standard short sale (subject to the modified up-tick rule and requiring a locate).

Market makers historically enjoyed broad exemptions from Regulation SHO's locate and close-out requirements. However, regulatory changes in 2008 and 2013 significantly curtailed these exemptions. In September 2008, responding to concerns about abusive naked short selling during the financial crisis, the SEC eliminated the options market maker exception to the close-out requirement for all equity securities.[9] Subsequently, in February 2013, the SEC further restricted market maker exemptions by requiring that, to qualify for bona fide market making activity exemptions, firms must demonstrate that their trading activity is designed to facilitate customer orders and provide liquidity, rather than serving proprietary interests.[10] Under current rules, while market makers retain some exemptions from the up-tick rule, they must comply with locate requirements for most transactions and face more stringent close-out obligations than in the pre-2008 period.

Additional restrictions apply to threshold stocks—securities that have experienced significant settlement failures for more than five consecutive days. For these stocks, Regulation

[7] US equity markets transitioned from $T+2$ to $T+1$ settlement on May 28, 2024. Under $T+1$ settlement, sellers must deliver shares by market close one trading day after the trade date, at which point buyers must deliver cash. The clearing agent ensures simultaneous exchange unless the trade fails. Stock loan contracts typically specify that, once recalled, the borrower must return shares by 3pm the following day. This timing allows traders to sell shares that have been lent out and then recall the loans by the end of day $T+1$, ensuring settlement can occur on day $T+2$ (under the previous settlement regime) or $T+1$ (under current rules).z

[8] See Mackintosh (2022) for a summary of the rules around share lending and short selling, and SEC, Division of Trading and Markets (2015) for specific guidance on SEC Rule SHO.

[9] See SEC Release No. 34-58572 (September 17, 2008). Blocher and Ringgenberg (2018) document that this regulatory change led to significant increases in equity borrowing fees.

[10] See SEC Release No. 34-68950 (February 14, 2013). Blocher and Ringgenberg (2018) show that this additional restriction resulted in further increases in borrowing costs.

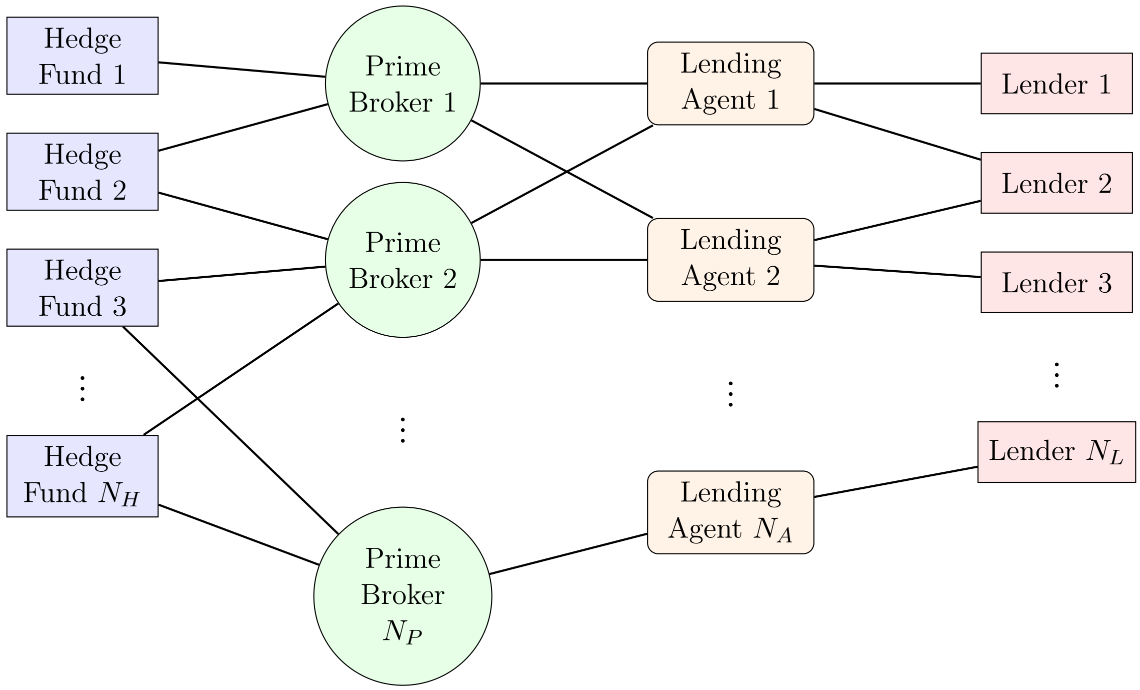

Figure 1: The Securities Lending Market

SHO specifies enhanced close-out requirements and more stringent locate requirements. Most importantly, brokers must pre-borrow (not merely locate) threshold stocks before executing new short sales for their customers.[11]

Securities lending between institutional investors and hedge funds operates outside any centralized clearinghouse or exchange structure.[12] Instead, prime brokers serve as intermediaries between share lenders and borrowers, as illustrated in Figure 1. Most of the time, asset managers engage lending agents to intermediate in between themselves and the prime brokers. This decentralized market structure has historically suffered from limited transparency, making it difficult for market participants to assess whether the terms they receive reflect prevailing market conditions.

[11] Exchanges publish lists of threshold stocks. See NYSE (2025) and Nasdaq Trader (2025) for the NYSE and NASDAQ lists.

[12] An exception was the NYSE lending post, which operated until the 1930s (Jones and Lamont, 2002).

3.2 Share lending mechanics

In the US, only shares held in *margin accounts*—which are held in *street name*—can be lent by brokerage firms for short selling purposes. Shares held in non-margin accounts typically cannot be lent.

Stock loans for short-selling purposes closely mirror repurchase agreements. Almost all loans are *open term*, meaning either party can cancel the loan with effectively overnight notice. When a lender recalls a loan, the borrower must return the shares the next day. Importantly, securities lent can be *rehypothecated*—that is, lent again by the party that purchased the borrowed shares. This rehypothecation feature means that short interest can and sometimes does exceed 100% of shares outstanding. However, given the US restriction that shares can only be borrowed for short-selling purposes, every single share outstanding—even if it is lent and sold short multiple times—must eventually end up in the hands of a party who does not lend it out further. This constraint is economically important: it means that 100% of all outstanding shares are not lent, and thus do not earn lending fees.

The open-term nature of stock loans exposes all short-sellers to *buy-in risk*—the possibility that their loan will be recalled, forcing them to buy shares on the open market to cover their short position. According to SEC Regulation T, a short sale requires an initial margin of 150% of the shorted shares' market value. This requirement is met by retaining the full short-sale proceeds (100%) in the account plus depositing additional equity collateral equal to 50% of the sale's value.

Within brokerage firms, a typical stock loan occurs between one margin account holding shares and another initiating a short sale. Retail investors have historically not received any portion of the lending fee revenue, though recently some brokerage firms have begun sharing a portion of this revenue even with retail beneficial owners of lent shares. Institutional investors generally participate actively in the securities lending market. Consequently, the combination of high short interest and high institutional ownership serves as a reliable indicator of whether a stock will be special (e.g., SIRIO in Drechsler and Drechsler, 2014).

When shares are lent, the borrower must compensate the lender for any dividends paid. However, this creates a tax inefficiency: qualified dividends received by shareholders are taxed at preferential rates, while payments in lieu of dividends from borrowers are taxed as ordinary income. This tax treatment can influence the lending behavior of taxable investors.

3.3 Reporting requirements and transparency

The SEC's reporting requirements for short positions and securities lending by US institutional investors have evolved significantly over the past several decades. Prior to the 1980s, institutional investment managers filing Form 13F were not required to report short positions, nor were there standardized disclosure requirements for securities lending activities.

The SEC introduced Semi-Annual Reporting (the *N-SAR* form) in the 1980s and used it until 2018. N-SAR required funds to report basic information about their security lending programs on a semi-annual basis, including whether they engaged in securities lending and the revenue generated from such activities. However, N-SAR provided limited granular detail about individual lending transactions.

Form N-PORT, introduced in 2019, replaced N-SAR and significantly enhanced transparency requirements for fund portfolios. N-PORT requires funds to report detailed quarterly (third-month) information about their securities lending activities, including the identity and value of securities on loan, collateral received, and counterparty information. This detailed data is only public with a 60-day lag. Complementing N-PORT, Form N-CEN (also introduced in 2018) requires funds to provide annual census-type information about their operations, including basic statistics about securities lending programs.

The SEC has subsequently adopted new Rules 10c-1a and 13f-2, effective January 2, 2024, intended to increase the transparency and efficiency of the securities lending market. These requirements expand transparency by requiring certain entities to report securities lending transactions to FINRA for public dissemination and mandating institutional investment managers to disclose short position data.[13]

The SEC's final report on Rule 10c-1a (U.S. Securities and Exchange Commission, 2023) explicitly acknowledges the market's opacity:

> The securities lending market is opaque. There is a general lack of comprehensive information on current market conditions in the securities lending market.... The lack of public information and data gaps creates inefficiencies in the securities lending market [and] ... make it difficult for borrowers and lenders alike to know whether the terms they receive are consistent with market conditions....
>
> Private vendors have attempted to address the opacity in the securities lending market by offering systems that provide data to borrowers and lenders of securities, such as systems that are only available to those who voluntarily provide their transaction data to the data vendor. However, data gaps remain. (pp. 5–6)

In our analysis below, we make use of data from both the N-PORT and N-CEN filings, available on the SEC's website.

4 Data

For our analysis of the returns of portfolios of hard-to-borrow securities, we use daily and monthly returns, market capitalizations, and trading volumes from the Center for Research in Security Prices (CRSP). Our sample consists of all common ordinary NYSE, AMEX, and NASDAQ stocks.[14]

Short interest comes from two sources: from April 1980 to May 1988 and after June 2003, we get short-interest data at the security level from Compustat. From June 1988 through June 2003, our short-interest data come directly from the exchanges (NYSE, AMEX and NASDAQ). However, prior to June 2003, if short-interest data from an exchange is missing for a given firm-month, we use short interest as reported by Compustat if that is available.

[13] From SEC (2023c). See also SEC (2023a) and SEC (2023b).

[14] Specifically, we only consider stocks with exchange code 1, 2, or 3, and share code 10 or 11. Returns are adjusted for delisting (Shumway, 1997) using the CRSP delisting return, where available. Where the delisting return is missing, we follow Scherbina and Schlusche (2015) and assume a delisting return of -100%, or, if the delisting code is 500, 520, 551-573, 574, 580, or 584, we assume a delisting return of -30%.

After June 2003, if Compustat short-interest data is missing for a given firm-month, we use data from the exchanges if available.[15]

Aggregated institutional ownership data is constructed using Thomson-Reuters Institutional 13-F filings through June 2013, and on WRDS-collected SEC data after June 2013.[16] Our data on stock borrow costs comes from IHS Markit. Prior to August 2004, Markit data frequency is monthly. From August 2004 until July 2006, the data is weekly, and daily coverage is available starting in July 2006. We use both the *indicative fee* (a proxy for marginal costs) and *simple average fee* (an equal-weighted average of all contracts for a particular security) in our analyses.

Most of our analyses using the Markit stock loan database begin in January 2010. While the Markit data is available starting in 2002, coverage is poor prior to 2010. Figure 2 shows a number of statistis on the coverage based on the Markit borrow cost data, short-interest, and other variables.

Analyst forecasts of quarterly and fiscal-year-end earnings comes from IBES. We use the summary file unadjusted for stock splits, to avoid the bias induced by ex-post split adjustment, as pointed out by Diether, Malloy, and Scherbina (2002).

We obtained the N-PORT and N-CEN data set—used in the analyses of individual fund holdings—directly from the SEC website.[17] The first date at which N-PORT filings are available from the SEC as structured data is 2019:q4. Compliance dates differed among smaller and larger fund families. All funds should be included by 2020:q2.[18]

Finally the source for the US (equity) market returns, Fama-French indstry returns, and the monthly risk-free rate is Ken French's data library.

[15]See the data section in Daniel, Klos, and Rottke (2023) for more details on our calculation of short interest.

[16]See note issued by WRDS in May 2017. We do substantial cleaning of these data, as described in the data section in Daniel, Klos, and Rottke (2023).

[17]See https://www.sec.gov/data-research/sec-markets-data/form-n-port-data-sets and https://www.sec.gov/data-research/sec-markets-data/form-n-cen-data-sets.

[18]See https://www.sec.gov/about/divisions-offices/division-investment-management/accounting-disclosure-information/investment-company-reporting-modernization-frequently-asked-questions for further details.

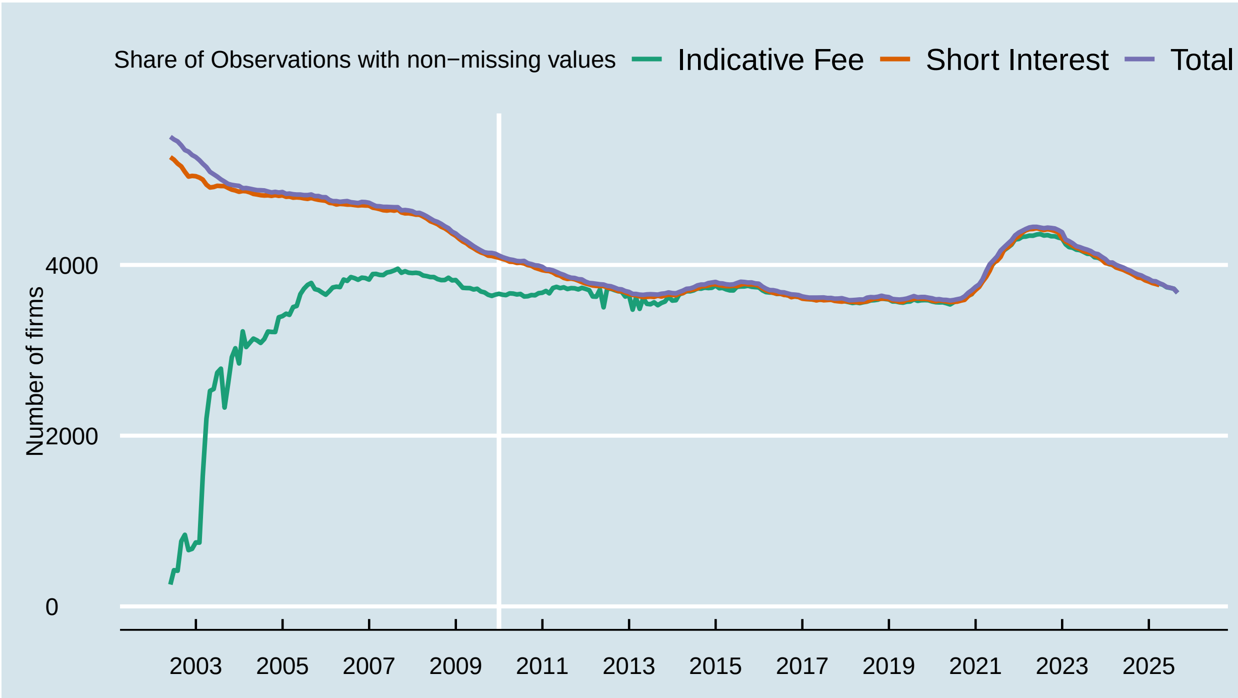

Figure 2: Markit Coverage, May 2002 through May 2025
This figure presents statistics on data coverage over the period from 2002:05–2025:05. The baseline universe consists of all stocks in CRSP with a valid market cap, share code 10 or 11 and exchange code 1, 2, or 3, and the line labeled "Total" plots the total number of stocks in that baseline universe. The line labeled "Short Interest" is the number of stocks in the universe for which we have non-missing short interest data (from Compustat, NYSE, Amex or NASDAQ). The line labeled "IndicativeFee" is the number of stocks in the universe for which Markit reports a valid indicative fee.

5 Empirical Findings

5.1 Changes in Borrow Costs and Short Interest over time

In this section we examine how borrow costs have changed for US common equities in the last several decades. Figure 3 presents cumulative distribution functions (CDFs) for *Markit* Indicative Fees for US common stocks listed on the major US exchanges on four selected dates. The earliest CDF, using early Markit data, shows that as of 2003:10:22, 99% of US common stocks have borrow costs of 5% or less (annualized). For both 2003:10:22 and 2007:01:03, 35% is the maximum indicative fee observed in the data. Already by 2007, the fees have started to increase.

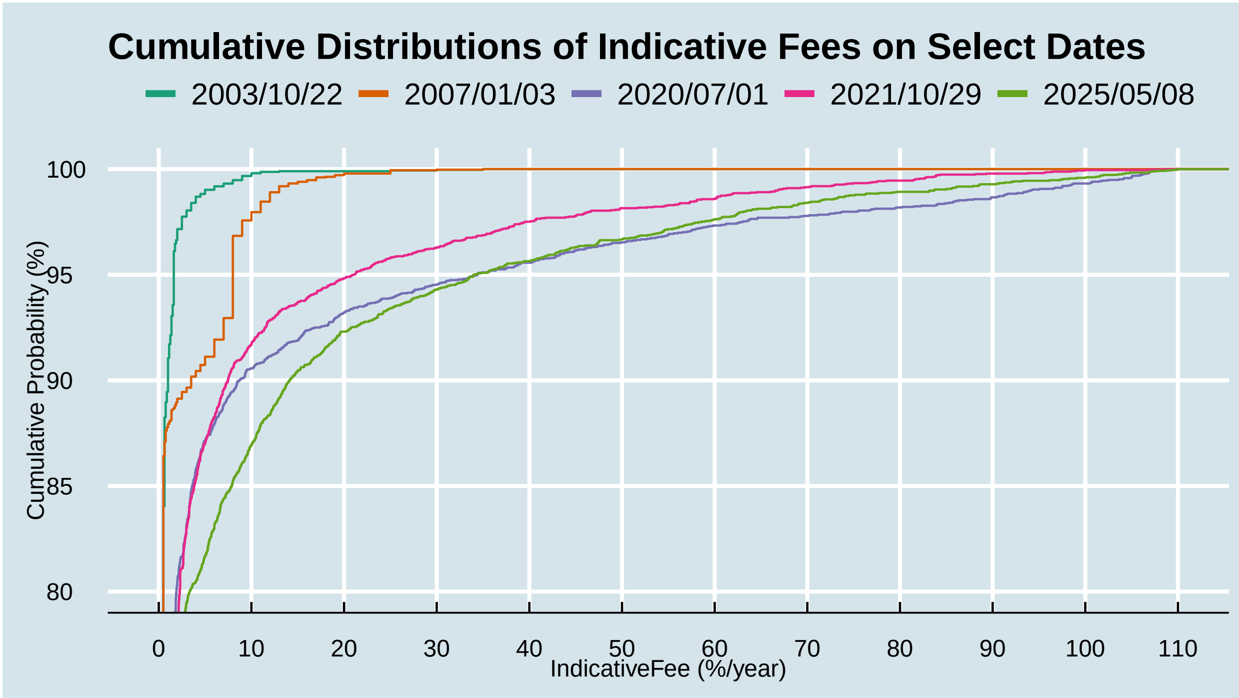

Figure 3: CDFs of *Markit* Indicative Fees for US common stocks
This figure presents cumulative distribution functions (CDFs) for *Markit* Indicative Fees for US common stocks listed on the major US exchanges on five selected dates: 2003/10/22, 2007/01/03, 2020/07/01, 2021/10/29, and 2025/05/08.

For the last three dates at which cumulative distribution functions are calculated, the picture is far different. The 99th percentile cutoffs for these three dates are 105%, 72% and 192% (annualized fee), respectively.

Figure 4 plots quantiles of the distribution of the annualized Indicative Fees over time. While the median is at a low level and falls slightly over time, the other quantiles trend upward. The 99th percentile starts at 5% in October 2003, and rises to over 192% by the May 2025. Note that Markit has changed their algorithm in 2018 to produce a smooth distribution of Indicative Fees, whereas before that date, fees were reported in coarse buckets, such as 37.5 bps, which is reflected in the lines jumping between these predefined coarse buckets pre-2018.

Figure 5 shows the evolution of fees in a different way. Here, we plot the fraction of stocks with indicative fees above one percent and above 10% over the period from January

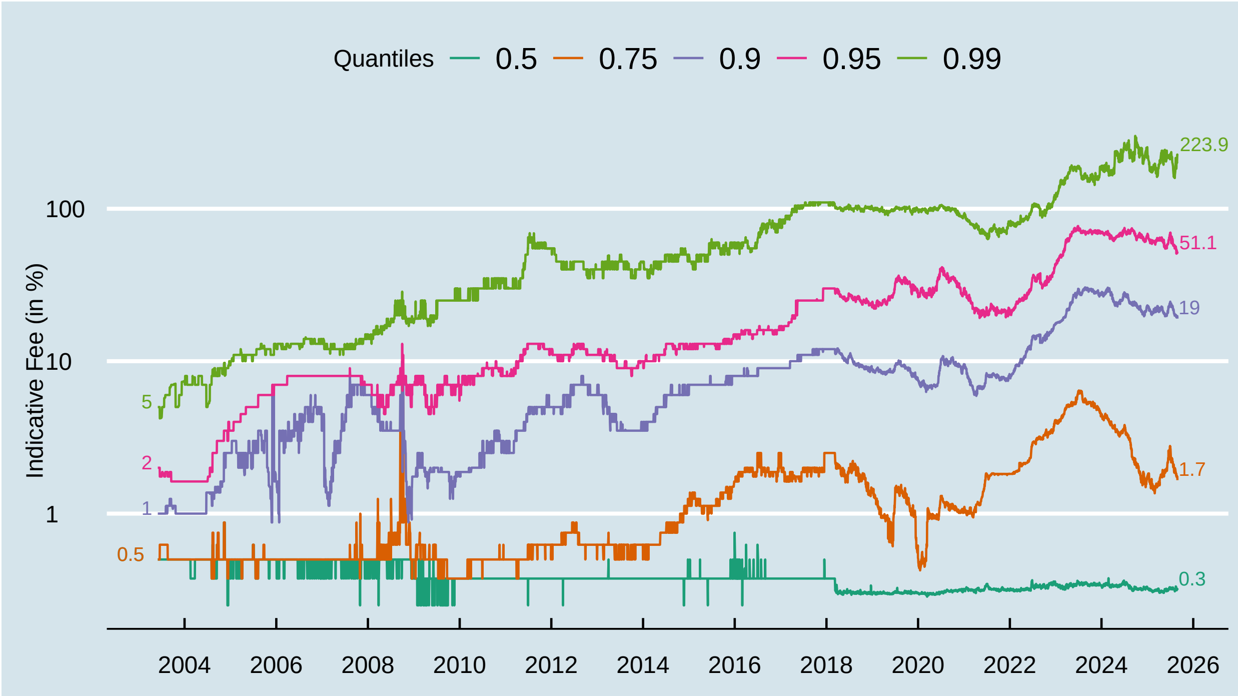

Figure 4: Indicative fee quantiles over time
This figure presents various quantiles of the distribution of *Markit* Indicative Fees for US common stocks listed on the major US exchanges over time. The sample period is 2003:10–2025:06.

2010 (where data coverage is better - see Figure 2) through May 2025. The fraction of stocks with a fee above 1% has increased from 11% in 2010 to over 40% in 2022, and, as of May 2025, has come down slightly, to 29% in May 2025. In 2010, only 3% of stocks had a fee >10%. That number was up to just under 20% in 2023 and is about 15% in May 2025.

In the following, we first sort all US common stocks on each date into ten groups, using NYSE breakpoints. That is, the bottom decile portfolio contains all US common stocks, traded on any of the three major exchanges, for which the equity market capitalization is less than the market capitalization of the 10th percentile NYSE firm. Figure A.9 gives an overview of the proportion of these buckets. As a result of using NYSE breakpoints, there are far more firms in the bottom decile portfolio than in any other bucket. In fact, decile 1 makes up around 40% of names in the universe. The large stocks (decile 10) only account for roughly 5% of all names though, particularly by the end of the sample, it contains most

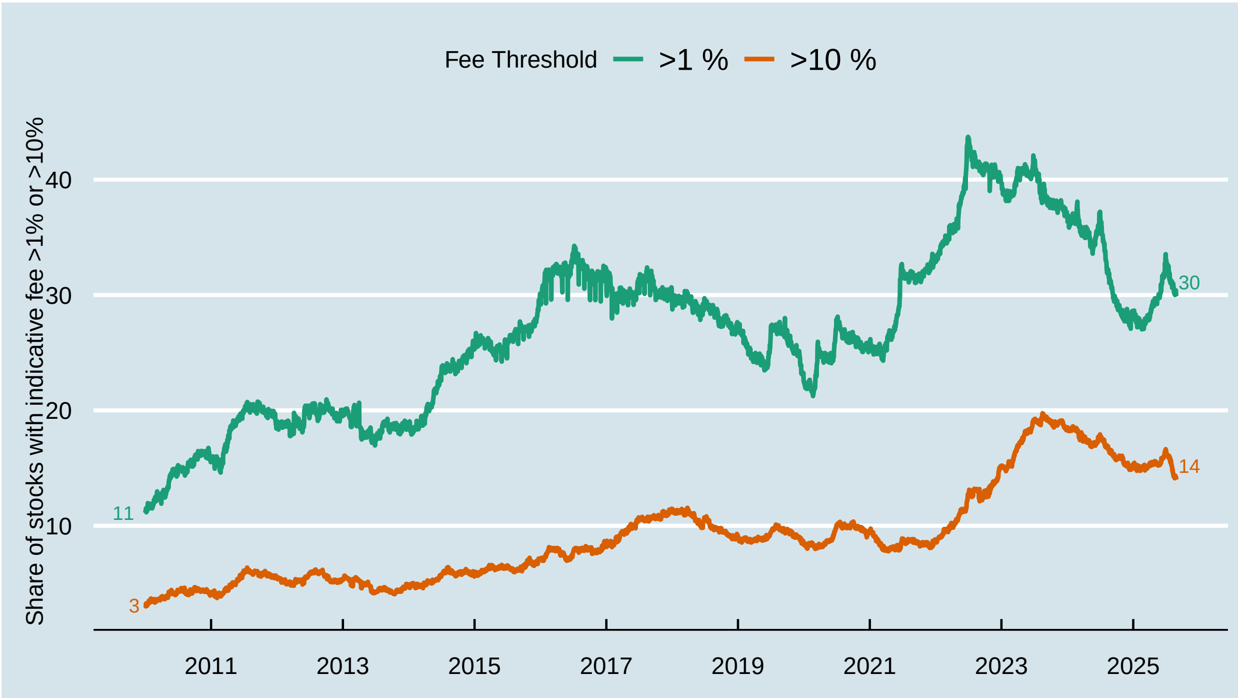

Figure 5: Share of stocks with indicative fee above 1% and 10% over time
This figure presents the share of US common stocks on the major exchanges with indicative fees above 1% and 10% over time. The sample period is 2010:01–2025:06.

of the market capitalization. In the following analyses, we combine size deciles 4 to 9 for clarity.

Figure 6 shows the fraction of specials (fees >1%) within NYSE size deciles. Figure A.10, in the Appendix, shows this analysis for a 10% fee cutoff. The figure shows that among bottom decile market capitalization firms, the fraction of firms for which the fee is greater than one percent has risen from about 15% to above 75%. The fraction for which fees are > 10% has risen from just over 5% in 2010 to well over 40% in 2023. Even for deciles 2 and 3, the share of specials (i.e. a fee >1%) rose above 50% and 30%, respectively, in 2022. These have since come down but are still much higher than they used to be in 2010 (17% vs. 10% and 8% vs. 6%). For the share of stocks with lending fees >10% in deciles 2 and 3, it is also higher in 2025 compared to 2010 (4% vs. 3% and 3% vs. 1%)

Figure 7 plots the time series of average borrow costs, by size decile. For small decile stocks, the average fee increased from just above 2% in early 2010 to above 20% in May 2025.

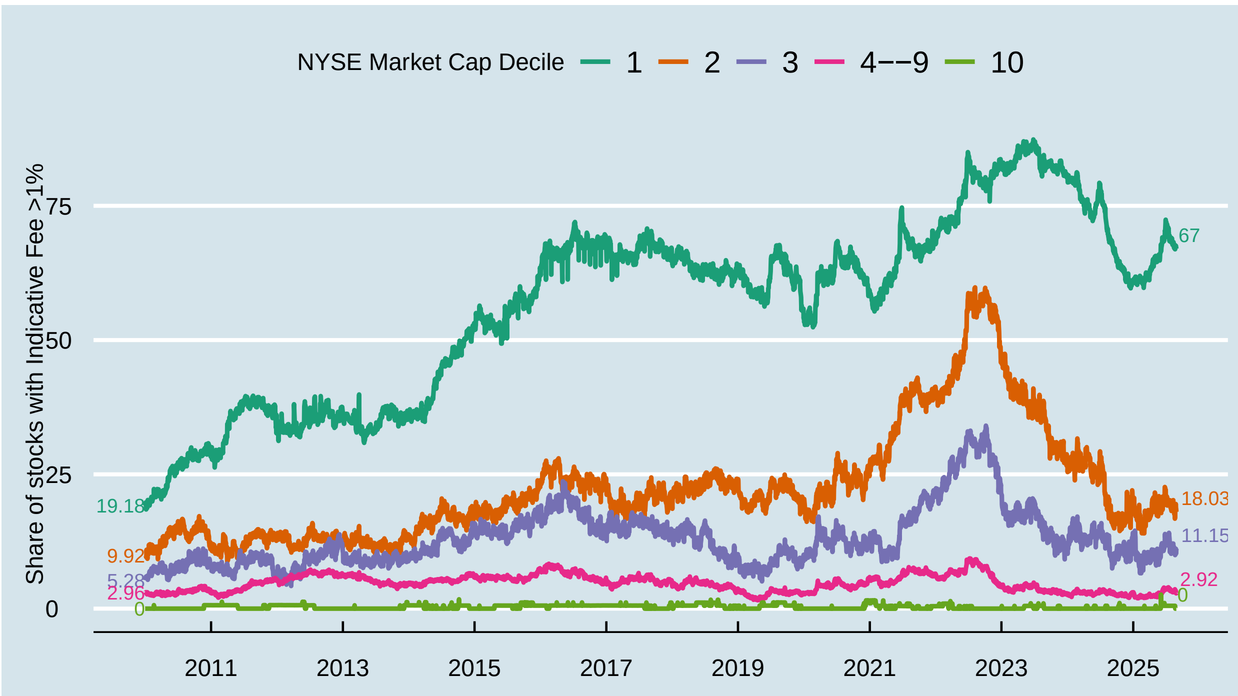

Figure 6: Fraction of stocks with an inidicative fee > 1%, by ME quintile
This figure presents the share of US common stocks on the major exchanges with indicative fees above 1% and 10% in each NYSE-sorted market capitalization decile over time. Deciles 4–9 are merged for readability. The sample period is 2010:01–2025:06.

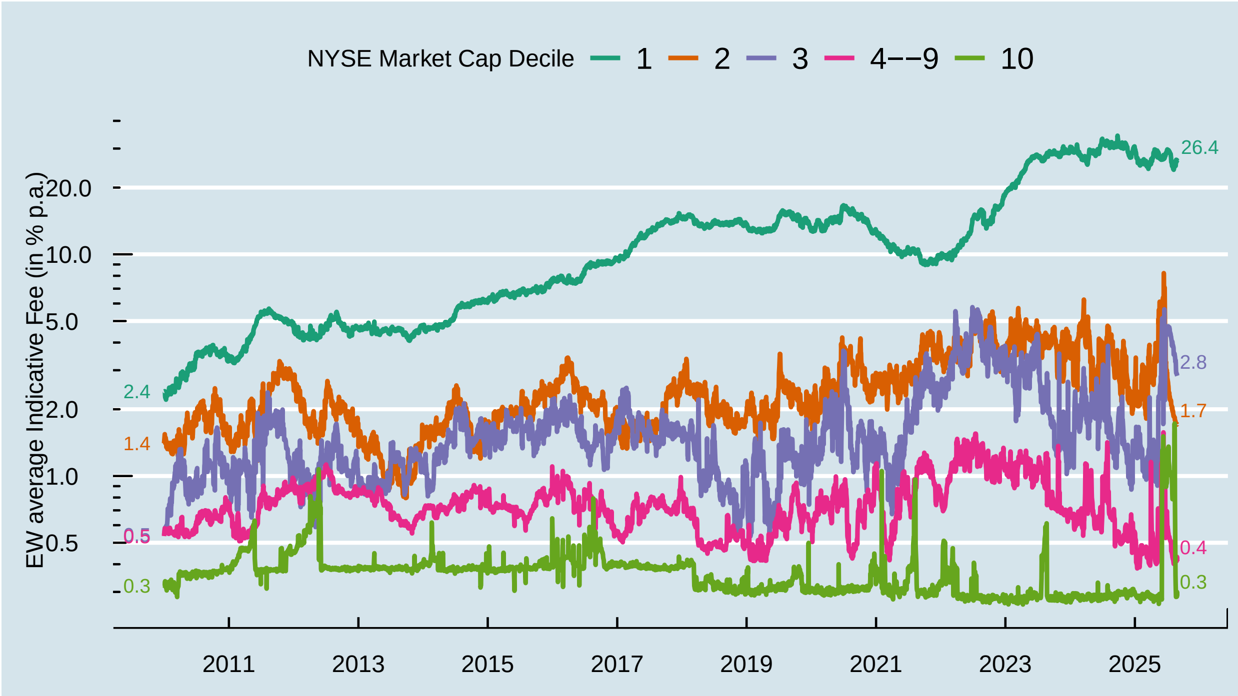

Figure 7: Average borrow cost, by size decile
This figure presents the equal weighted average of the indicative fees of all US common stocks on the major exchanges in each NYSE-sorted market capitalization decile over time. Deciles 4–9 are merged for readability. The sample period is 2010:01–2025:06.

Most, but not all, of the increase in fees is concentrated in NYSE decile 1 stocks. For deciles 2 and 3, the average fee has also increased (1.4% to 1.7%, and 0.5% to 2.8%, respectively).[19] rem

5.2 Persistence of fees

The analysis presented above supports the hypotheses that fees have risen, on average, over our sample period. One additional question one could ask is whether these high fees are predominantly driven by occasional jumps that quickly revert back to fees around the general collateral rate, or whether they are persistent.

In order to answer this question, we look at fees in event time, defining a "fee shock" event for a stock as an increase in borrow cost from GC ($\leq 1\%$) at $t = -21$ days to $\geq 10\%$ as

[19]Note that the trends in fees seem not to be driven by IPOs or SPACs, as excluding stocks recently listed (see Appendix A.1) does not change the results materially.

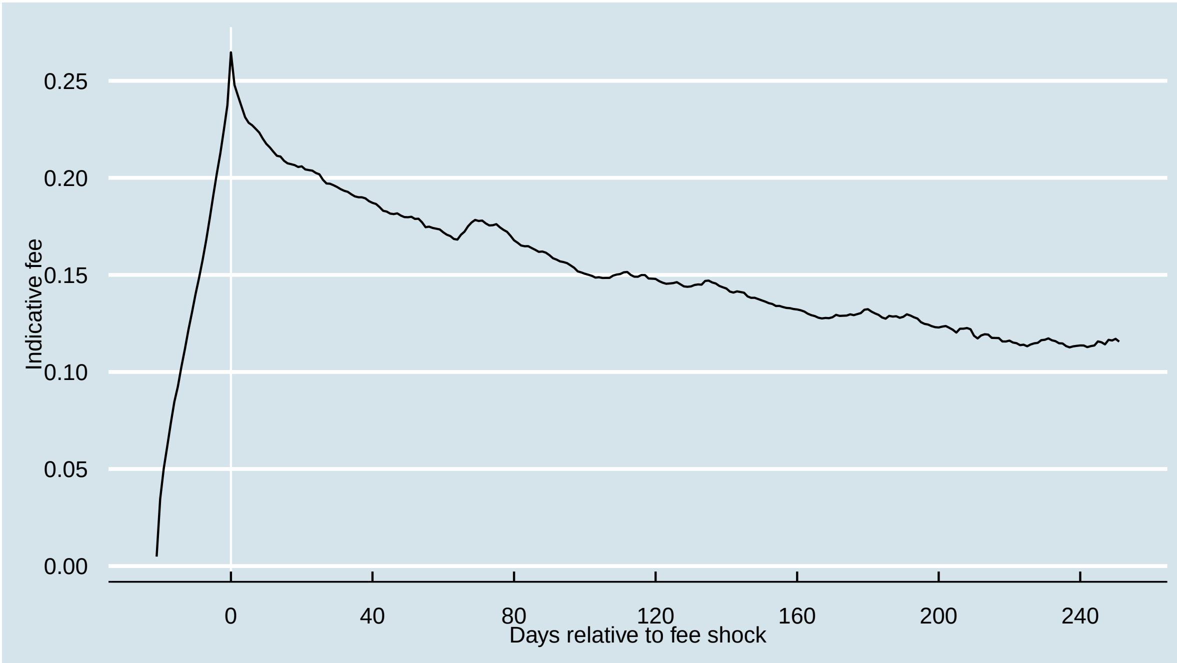

Figure 8: Indicative fee for 10% threshold shock. For this figure, on each day, we form a portfolio of all stocks whose indicative fee goes from below 1% to above 10%. We then plot this portfolio's market-cap weighted average indicative fee over event time, averaged over calendar time. The sample period is 2010:01–2025:06.

of $t = 0$. On each day we form portfolios of all stocks meeting this criterion and then track their market-cap weighted average indicative fee over time. We then average the fees of all portfolios in event time. For example, there are 3,869 days in our sample, and on each one of them we form one portfolio—day 0 in event time. For 3,868 of them, we can observe day 1 in event time (we do not have data for $t = 1$ for the portfolio that was formed on the last day of our sample). The point in the plot at $t = 1$ is the average indicative fee of the 3,868 portfolios formed on different calendar dates at day $t = 1$ in event time.

We can see that, on average, the fee jumps from somewhere below 1% at day $t = -21$ to over 26%, on average, at day $t = 0$. From there, the fee gradually falls, but even after a year, it does not dip below 10%.

5.3 Abnormal Returns for long- and short-investors in special stocks

In the previous sections, we document that borrowing costs have increased and remain persistently high. To the extent that short-sellers are rational and there is competition between short-sellers, the risk-adjusted returns to short-selling should be zero. Our evidence below is broadly consisten with this hypothesis. As we discuss below, this also means that agents in the economy who choose hold high-borrow-cost securities and not lend them out will necessarily earn *negative* risk-adjusted returns equal to the borrow-cost. Again we emphasize that the nunber of share of each stock that are not lent out is always equal to the number of shares outstanding. Finally, if security owners who lent out their securities received the full borrow cost, they would earn zero risk-adjusted returns. However, as a result of losses in the intermediation chain, they do not. Thus, the lenders also earn negative risk-adjusted returns equal to these losses.

We estimate the relation between the indicative fee reported by Markit on a given stock and the subsequent return to that stock. As discussed in Section 4, the Markit data comes pretty close to having full coverage starting in about January of 2010. Therefore, we start our examination in January of 2010. We use the CRSP return data merged with the Markit share lending data as described in Section 4. Our sample is all US common equities traded on major exchanges. Specifically, we require that the CRSP exchange code be 1, 2, or 3, and the CRSP sharecode be 10 or 11. We also require that the stock have a valid indicative fee in the Markit data.

At the start of each month from January 2010 through June 2025, we form portfolios based on the indicative fee provided by Markit for that stock as reported final day of the preceding month. We form these portfolios monthly rather than daily, and calculate value- rather than equal-weighted returns to avoid having microstructure effects (e.g, bid-ask bounce and short-term reversal) play a role in determining the returns of these portfolio.[20]

[20] In Appendix A.2.1, we report the results of analyses for daily-rebalanced portfolios.

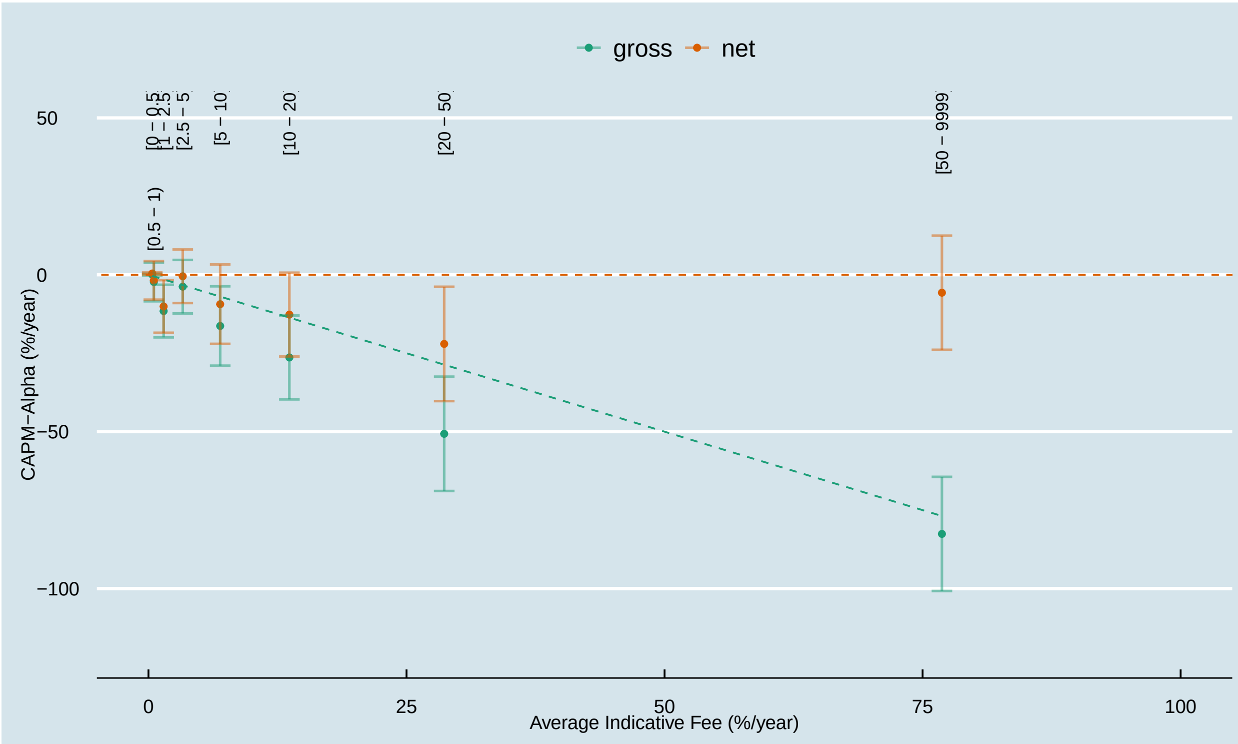

Figure 9: Performance of borrow-cost sorted portfolios – Monthly formation Each month, we sort all US common stocks traded on major US exchanges into portfolios based on the Indicative fees reported by Markit on the last day of the preceding month, using breakpoints of 0.5, 1, 2.5, 5, 10, 20, and 50% (annualized indicative fee). The green dots in this scatterplot represent, on the y-axis, the annualized CAPM alpha for the portfolios over the sample period, and on the x-axis the annualized borrow cost based on the indicative fee reported by Markit. The green dots represent the "gross" returns, and the green whiskers represent the ±1.96 standard errors, based on Newey and West (1987, 1994) standard errors with automatic lag selection. The net returns —represented by the orange dots—are calculated by adding the fee to each stock's daily return the daily borrow cost for that security. The CAPM alphas for each portfolio is calculated by running a time series regression of the return, net of the risk-free rate on the excess market return. The sample period is 2010:01:01–2025:06:30.

We form eight portfolios, using indicative fee breakpoints of 0.5, 1, 2.5, 5, 10, 20, and 50% (annualized indicative fee). That is, portfolio 1 (the lowest fee portfolio) on January 4, 2010 (the first trading day of 2010) contains all stocks that, as of the last trading day in December 2009 had an annualized indicative fee of less than 0.5%. Portfolio 2 contains all stocks that had an annualized indicative fee between 0.5% and 1%, and so on. The high fee portfolio contains all stocks that had an annualized indicative fee that was above 50%. The securities in these portfolio remain fixed until the first trading day of February 2010. The weights each day on each security is proportional to that security's market-capitalization (from CRSP).

We then regress these returns, in excess of the risk-free rate, on the excess market return to get CAPM alphas for each of these eight portfolios.[21] Figure 9 plots these "gross-of-fee" alphas, with green dots, against the average indicative fee for each of the eight portfolios.[22] The error bars represent the ± 1.96 standard errors.[23] That is, these are the average annualized returns for these portfolios. That is, the alphas are based on the CRSP data only, and make no adjustment for borrowing cost.

The orange dots, labeled "net", are based on analyzing the returns net of borrow costs. Here, we add the individual stocks's daily borrow cost (from Markit) to its daily return (from CRSP) to get the stock's net return. Note that the net alphas are always higher than the gross return by approximately the borrow cost. The orange error bars represent the ± 1.96 standard errors around these point estimates of the net returns.[24] To make the chart easier to read, we have added an orange dashed line at $y = 0$, and a green dashed line with a slope of -1 and an intercept of zero. Several interesting regularities are evident in Figure 9:

1. The average net alpha—that is, the returns of the portfolios based only on CRSP returns, and ignoring and lending revenue—is approximately -1 times the fee, meaning that the high-fee portfolios suffer dramatic and consistent losses: the value-weighted portfolio of the high-fee stocks underperforms by 81.4%/year. This is somewhat shocking, because of course 100% of the shares outstanding in these firms are not lent out. (Recall that, for every share that is lent and sold, it has to eventually be bought by an entity who holds it without lending). So the investors who are holding these shares are losing a remarkable amount of money.

2. Historically, shorting moderate-fee stocks was a good bet. For example, the 6th portfolio had an average fee of about 13.5%, but lost 30.9% (on average over this entire period) relative to the CAPM. So you would have made an alpha of about 17.4%/year had you shorted these stocks. This of course means that, if you had gone long these

[21] Both the excess market return and the daily risk-free rate are taken from Ken French's database.

[22] To calculate the average indicative fee for the portfolio, we assume that the indicative fee on each stock is paid from close on the trading day on which it appears in the Markit database, to the close of the following trading day. We calculate the daily borrow cost by dividing the annualized indicative fee by 252.

[23] Based on Newey and West (1987, 1994) standard errors with automatic lag selection.

[24] Again based on Newey and West (1987, 1994) standard errors with automatic lag selection.

stocks and lent them out, AND captured the full fee, you would have lost 17.4%/year. Based on our estimate that you would have captured only roughly 60% of the fee, you would have lost 22.8%/year.

3. Based on conversations with an individual involved in share lending at at a major asset management firm, it appears that this firm and some others have begun monitoring fees, and if they get at all high, they just sell the stock rather than lend it out. This is a hypothesis we explore formally in Section5.5.

4. For the very highest fee stocks, it looks like the short sellers are paying too much. This suggests that there are a set of overly-aggressive individuals with margin accounts who are willing to pay massive fees to short sell some securities. Related to this, two decades ago the highest fees were always on the order of 20-30%. Now, there are over a hundred securities with fees $>$ 100% (annualized).

In Appendix A.2, we document some additional characteristics of these portfolios. First, note that in the high-borrow-cost portfolio the number of names is initially quite low (≤ 10), but by the end of the sample is reliably over 200 names. This is consistent with the rise in fees we have documented.

We also document how the value of $1 invested in each of these evolves over time, both gross and net of the borrow cost. We see that there is no apparent time trend in the returns to these portfolios. However, we do note that most of the losses in the moderate borrow-cost (10%-50%) portfolios are incurred between 2022–2025.

5.4 Inefficiency

The analysis of Section 5.3 suggests that the high lending fees we document result in significant wealth losses for long investors holding shares of constrained stocks—particularly for those who do not fully capture the lending fee. To the extent that fees above the general collateral rate reflect market inefficiencies, we can quantify the wealth losses for these investors that result from these frictions. In our calculations, we rely on the observation that 100% of outstanding shares are not lent and therefore do not earn the borrow-cost, regardless of the actual percentage of shares that is lent out and the lintermediation-chain losses.

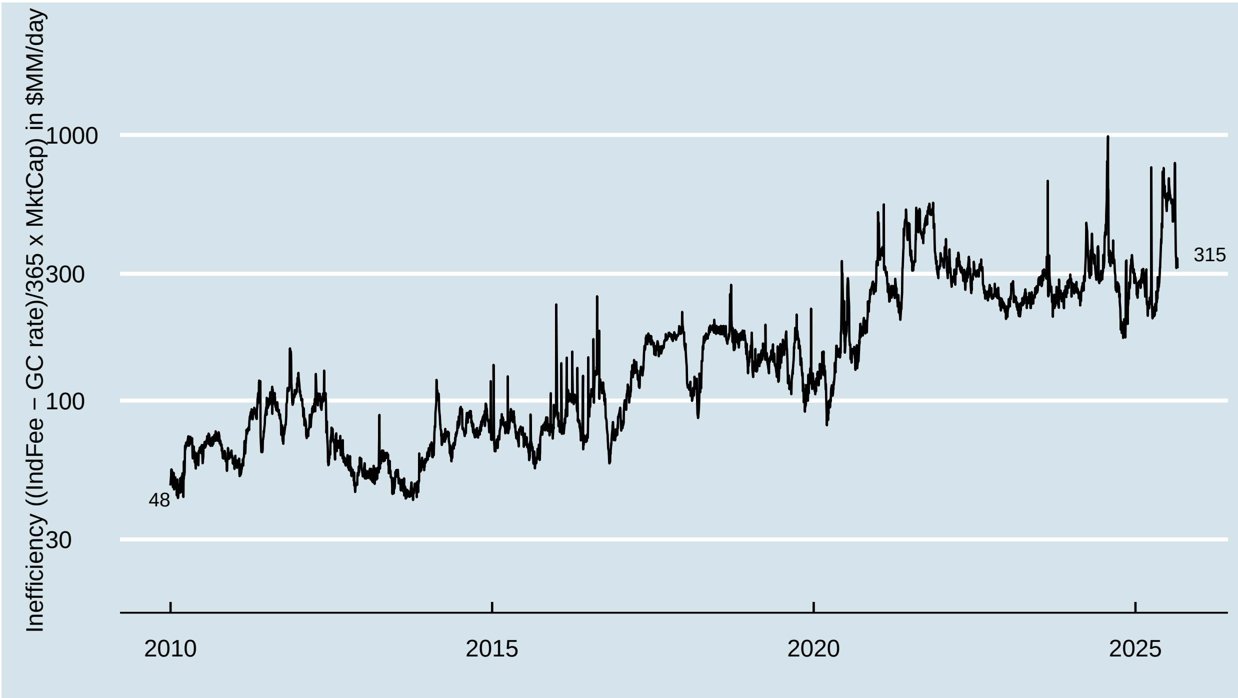

Figure 10: Inefficiency over time
The figure plots inefficiency as a function of time, where inefficiency is measured as: $\text{Ineff}_t = \sum_i \text{ME}_{i,t} \cdot (\text{fee}_{i,t} - \text{fee}_t^{GC})$, where $\text{ME}_{i,t}$ is the market-capitalization for firm i at time t in dollars, $\text{fee}_{i,t}$ is the daily indicative fee for stock i on day t, and fee_t^{GC} is the general collateral rate.

Figure 10 plots inefficiency as a function of time, where inefficiency is measured as:

$$\text{Ineff}_t = \sum_i \text{ME}_{i,t} \cdot (\text{fee}_{i,t} - \text{fee}_t^{GC}),$$

where $\text{ME}_{i,t}$ is the market-capitalization for firm i at time t in dollars, $\text{fee}_{i,t}$ is the daily indicative fee for stock i on day t, and fee_t^{GC} is the general collateral rate, defined as the one percent quantile of indicative fees on a given day.

Figure 11 plots the aggregate excess borrow costs as a function of time, where aggregate excess borrow costs are measured as:

$$\text{Costs}_t = \sum_i \text{SI}_{i,t} \cdot \text{P}_{i,t} \cdot (\text{fee}_{i,t} - \text{fee}_t^{GC}),$$

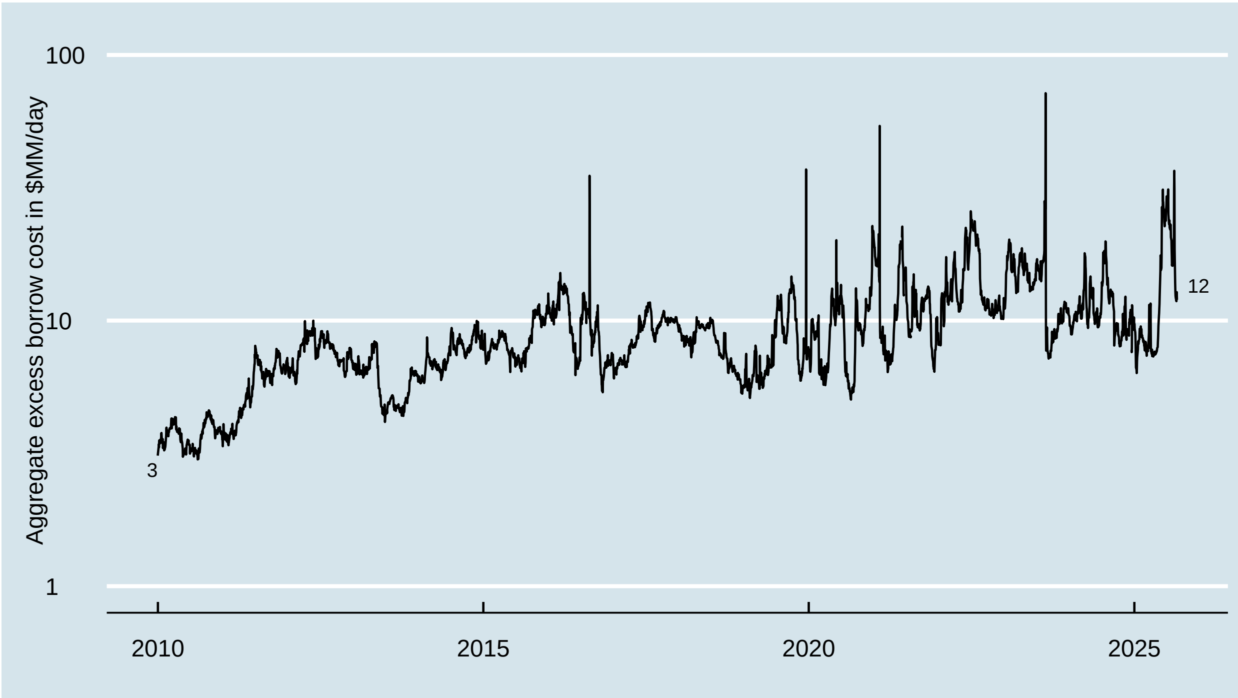

Figure 11: Aggregate borrow costs over time
The figure plots the aggregate excess borrow costs as a function of time, measured as: $\text{Costs}_t = \sum_i \text{SI}_{i,t} \cdot \text{P}_{i,t} \cdot (\text{fee}_{i,t} - \text{fee}_t^{GC})$, where $\text{SI}_{i,t}$ is the short-interest in shares for firm i at time t, $\text{P}_{i,t}$ is the price in dollars per share, and $\text{fee}_{i,t}$ is the daily indicative fee for stock i on day t, and fee_t^{GC} is the general collateral rate.

where $\text{SI}_{i,t}$ is the short-interest in shares for firm i at time t and $\text{P}_{i,t}$ is the price in dollars per share, $\text{fee}_{i,t}$ is the daily indicative fee for stock i on day t, and fee_t^{GC} is the general collateral rate.

These two figure in combination show that the aggregate borrow cost is higher by about a factor of four today relative to what it was in January 2010, while the measure of inefficiency plotted in Figure 10 has increased by about a factor of 7. Note also that "inefficiency", as defined here, is a factor of 25 larger than the aggregate borrow costs. Again, this is explained by the fact that short interest is small relative to shares outstanding for these firms with high borrow costs, and that this trend has worsened over time.

5.5 Why isn't there more lending?

A striking finding from the analysis in this paper is that, with the very high borrow costs we observe, there is not more lending of high fee names. In this section, we explore the holding of high-borrow-cost securities by institutional investors, and in particular, we examine how these holdings vary with the fees on the securities. We restrict ourselves to US common equites, and in this section we utilize the data available from the SEC's N-PORT filings from 2019:q4.

Table 2: Largest Lenders – 2024:q4
This table shows the largest lenders of shares as of the final quarter of 2024.

Fund Name	Lent($)	AUM($)	ratio
iShares Russell 2000 ETF	6,478,828,734	72,093,428,512	0.090
iShares Core S&P Small-Cap ETF	3,983,488,985	85,836,927,634	0.046
iShares Core S&P 500 ETF	3,575,614,374	584,398,561,119	0.006
Vanguard total stock mkt index fund	3,072,685,466	1,772,368,654,393	0.002
iShares Core MSCI Emerging Mkts ETF	2,808,831,783	80,072,853,241	0.035
Vanguard total intl stock index fund	2,797,110,492	437,351,714,892	0.006
iShares Core S&P Mid-Cap ETF	2,776,593,040	94,310,766,143	0.029
Vanguard developed mkts index fund	2,119,483,377	190,020,993,881	0.011
Fidelity Sml Cap Index Fund	2,110,345,840	26,820,629,983	0.079
Invesco S&P 500 EW ETF	1,999,590,011	65,616,385,655	0.030

Table 2 reports the ten funds with the largest total dollar lending of securities as of 2024:q4. The table lists the dollar amount on loan, the total AUM of the fund, and finally the ratio of the amount lent to the AUM. At this point in time, the largest lender was the iShares Russell 2000 ETF, which lent out 9% of its holdings. We note that this is far below the mandated upper limit on lending of 33%.

Table 3 reports, for the iShares Russell 2000 ETF as of 2024:q4, the holdings, the amount lent out of each holding in dollars, and the fraction lent for each holding for which the annualized indicative fee was greater than 20%. The table shows that 17 securities meet this 20% criterion. Interestingly, the fraction of these names lent is now, on average, close to 100%. This report also shows that there are a few problems with the filing, in that the

Table 3: iShares R2000 ETF lending – fee > 20% – 2024:q4
This table shows holdings (in \$), amount lent (in \$), and the average annualized borrow cost over the preceding 90 days (labeled "fee") for all holdings of the iShares R2000 fund for which the fee was greater than 20%/year. The borrow cost is calculated using the indicative fee as reported by Markit. The table entries are sorted by the indicative fee.

Holding Name	Holdings (\$)	lent (\$)	fraction	Ind. Fee
CervoMed	314,474.900	280,881.900	0.893	1.199
NANO Nuclear Energy	3,103,734.000	3,075,055.000	0.991	1.047
Galectin Therapeutics	503,772.100	507,756.900	1.008	0.731
FuelCell Energy	4,355,038.000	4,318,281.000	0.992	0.729
Airship AI Holdings	1,927,930.000	1,899,660.000	0.985	0.582
Roadzen	1,861,513.000	1,314,039.000	0.706	0.539
Tenaya Therapeutics	2,143,601.000	2,114,025.000	0.986	0.504
BioAge Labs	1,915,037.000	1,899,682.000	0.992	0.411
Critical Metals	1,259,117.000	794,484.300	0.631	0.404
B Riley Financial	2,915,600.000	2,598,266.000	0.891	0.363
SolarMax Technology	795,799.100	112,946.400	0.142	0.355
Beyond Meat	6,094,031.000	6,156,135.000	1.010	0.283
Humacyte	12,222,682.000	12,139,296.000	0.993	0.274
Candel Therapeutics	5,012,197.000	3,079,933.000	0.614	0.274
Luminar Technologies	3,196,699.000	1,422,800.000	0.445	0.264
IGM Biosciences	2,571,925.000	2,525,544.000	0.982	0.225
Verrica Pharmaceuticals	397,372.500	59,745.700	0.150	0.203
Cartesian Therapeutics	4,672,092.000	3,941,633.000	0.844	0.201

amount reported lent for two names—Galectin Therapeutics and Beyond Meat—are greater than the dollar holdings reported, resulting in calculated fraction lent of > 100%.

The largest holding reported in Table 3 is Humacyte, in which the iShares Russell 2000 ETF has holdings of \$12.2 Million as of this reporting date. In Table 4, we report the largest 20 holders of Humacyte across all N-PORT 2024:q4 filings. The table shows that the fund with the largest position in Humacyte at this time was the SPDR S&P(R) Biotech ETF, with a position of \$13.3 million. In the table we also report the dollar amount of this holding lent out as of the reporting date, the fraction lent, and finally the total dollar amount of securities lent by that fund as of 2024:q4.

Again in this table we see that, given the high borrow cost for Humacyte over the preceding quarter, a number of funds elect to lend out a large fraction of their holdings. Across all

Table 4: Humacyte (fee = 27.4%) – Top holdings 2024:q4

Fund	Holdings ($)	lend?	lent ($)	frac.	tot lent ($)
SPDR(R) S&P(R) Biotech ETF	13,291,115	Y	12,645,780	0.951	975,439,502
Vanguard Total Stock Mkt Index Fund	13,093,716	Y	12,291,483	0.939	3,072,685,466
iShares Russell 2000 ETF	12,222,682	Y	12,139,296	0.993	6,478,828,734
Vanguard extended mkt index fund	7,797,599	Y	6,784,170	0.870	1,451,145,428
iShares Russell 2000 Growth ETF	4,127,612	Y	3,964,704	0.961	1,634,287,005
iShares Biotechnology ETF	3,412,280	Y	3,100,084	0.909	441,983,984
iShares Micro-Cap ETF	1,016,676	Y	1,006,505	0.990	170,617,586
TIFF Multi-Asset Fund	836,502	N			32,760,076
Master Small Cap Index Series	761,413	Y	761,413	1	386,110,541
Putnam Dynamic Asset Alloc. Gr. Fnd	602,672	N			0
EQ/2000 Managed Volatility Portfolio	505,242	Y	458,318	0.907	196,855,125
Putnam Dynamic Asset Alloc. Bal. Fnd	417,316	N			0
CREF - Equity Index Account	386,224	Y	382,360	0.990	139,148,899
LVIP SSGA Small-Cap Index Fund	329,260	N			0
Fidelity Small Cap Growth Index Fund	270,437	Y	264,620	0.978	62,394,843
Vanguard balanced index fund	257,171	Y	254,520	0.990	39,085,903
Vanguard inst. tot stock mkt index fund	255,742	Y	253,005	0.989	14,689,272
Small Cap Index Fund (Northern Funds)	197,066	N			0
EQ/Small Company Index Portfolio	182,355	Y	165,419	0.907	75,613,837
State St. Sm/Mid Cap Eq Index Port	164,125	Y	155,994	0.950	386,521,077

of the non-zero entries in this table, the lowest is 87%. Interestingly, there is one fund, the TIFF Multi-Asset Fund, that reports zero lending of Humacyte, despite doing a substantial amount of lending of its other holdings. In addition, there are four funds that do no lending of any securities.

We began this analysis by showing that borrow costs have increased over the last several decades. A key question is why the fees have increased so much. One hypothesis is that institutional owners who hold high-fee firms have come to appreciate that, when the borrow costs on these securities become large, they are far better off selling these holdings than lending them out (consistent with the findings in Evans, Ferreira, and Porras-Prado, 2017). If these holdings are sold by the funds/institutional investors to individual investors with non-margin accounts, then this will downward shift the supply curve of shares in the share lending market, resulting in an increase in fees, consistent with the increase documented in Section 5.3.

To investigate this hypothesis statistically we next examine, for a set of index-based ETFs, whether they deviate from market weights in a way that is consistent with this hypothesis. In Table 5, using the SEC's N-PORT filings merged with the Markit fee data, we examine whether index ETFs downweight high fee stocks. Of course, if index funds do indeed downweight these high fee stocks, this will result in higher tracking error but, based on the results in Section 5.3, it will also result in an increased alpha relative to the index. If asset managers have concluded that it is optimal for them (and for their customers) to increase their alpha by getting out of the high fee names, at the cost of increased tracking error, this would be support for the hypothesis that this behavior is indirectly leading to lower lending supply, higher borrow costs, and decreased market efficiency.

To ensure that we use only funds that track an index in proportion to market weights—and that we focus on sizeable positions—we apply several data filters. First, funds must self-report as both ETFs and index funds in their N-CEN filings. Second, we consider only positions larger than \$500,000. Third, we include only funds on report dates where they hold at least 10 such positions. Finally, for each fund and each report date, we run a regression of the log of the portfolio weight on the log of the market weight. The market weight for asset i in fund j at time t is defined as $w^m_{i,j,t} = \frac{ME_{i,t}}{\sum_{k \in j(t)} ME_{k,t}}$, where $ME_{i,t}$ is the equity market capitalization of stock i at time t. If a fund holds all positions in proportion to market weights, the regression coefficient should be one. We include only funds on report dates for which this coefficient lies between 0.95 and 1.05. This final filter ensures that we exclude index ETFs that do not track a value-weighted index.

All panel data regressions are estimated with quarter fixed effects. By construction of the sample, market weights alone explain most of the variation in portfolio weights (Model 1). In Models 2 and 3, we test whether borrow fees help explain the remaining variation. The coefficient on the fee can be interpreted as the elasticity of fund holdings with respect to long-term borrow costs. The elasticity is highly statistically significant: when borrow costs for a security increase, funds tend to reduce their holdings of that security. Moreover,

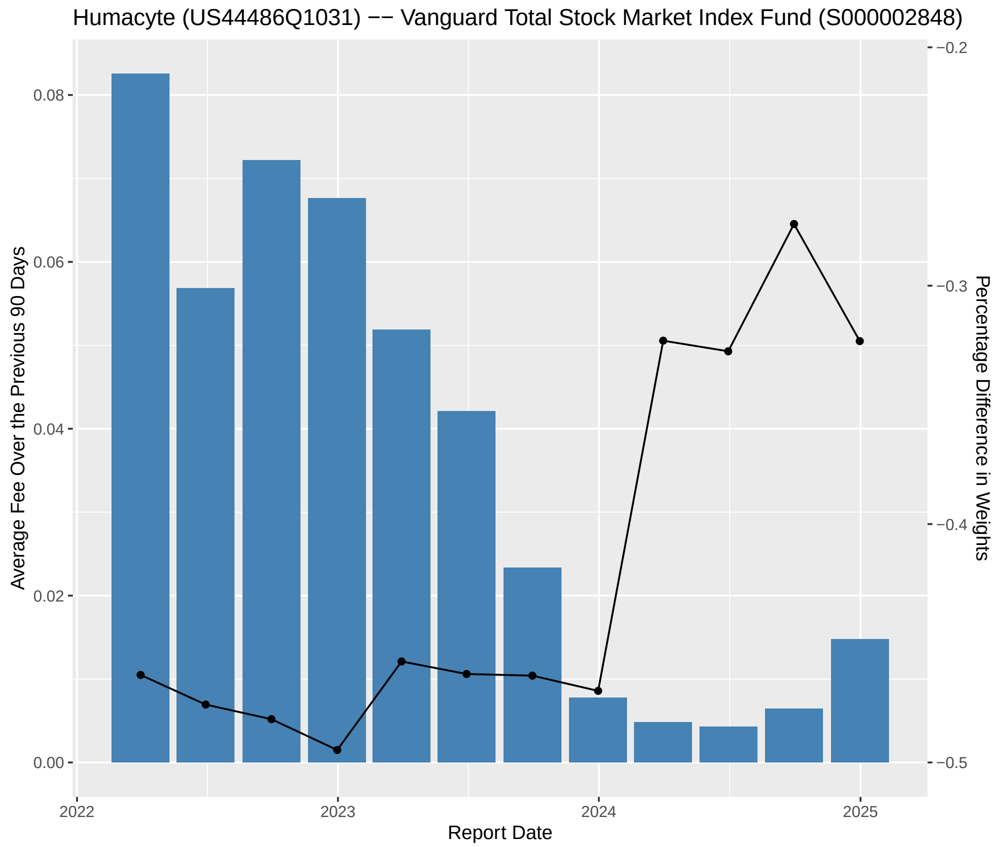

Figure 12: Example: Humacyte and the Vanguard Total Stock Mkt Index Fund The figure shows the average indicative fee over the previous 90 days for Humacyte as a bar chart. The figure further plots the average deviation of the Vanguard Total Stock Market Index Fund from Humacyte's market weight. This deviation, called percentage difference in weights in the graph, is compute as the difference between the fund's portfolio weight and their market weight divided by the market weight.

the estimated elasticity of -0.12 suggests that the effect is economically meaningful. The elasticity is largest for stocks with borrow fees exceeding 10%.

Figure 12 illustrates the result by setting an example. We look at the Vanguard Total Stock Market Index Fund, the largest fund in the database and the lender with the second-largest holding of Humacyte as of December 2024. The figure shows the percentage deviation of Vanguard's portfolio weight from the market weight (as defined in the caption of Table 5). This negative deviation suggests that Vanguard underweights Humacyte relative to their market capitalization. However, they underweight more strongly if fees were high over the previous 90 days.

Table 5: Borrow Costs and Fund Weights – Index-ETFs
This table reports the results of a panel data regression used to assess the effect of fund fees on portfolio weights in index funds. The dependent variable is the log of the weight of asset i in fund j as of the reporting date. The independent variables are the log of the market weight for asset i in fund j, and the log of the average borrow cost for asset i over the preceding 90 calendar days. The market-weight for asset i of fund j is defined as $w^m_{i,j,t} = \frac{ME_{i,t}}{\sum_{k \in j(t)} ME_{k,t}}$, where $ME_{i,t}$ is stock i's equity market capitalization at time t. We run regressions with quarter fixed effects. Standard errors are clustered at the fund and reporting quarter level. Fund holdings come from the quarterly N-PORT filings available from the SEC between 2019:q1 and 2025:q1. We restrict our sample to funds that self-report that they are both ETFs and index funds–taken from that fund's N-CEN filing from the same year. We additional include only observations on a report date for which the coefficient of a linear regression of the log of the weight of asset i in a given fund on the market-weight for asset i of the fund lies between 0.95 and 1.05. We merge the N-PORT data with indicative fee data from Markit, and with market capitalizations from CRSP. We require at least 50 valid fees in the preceding 90 days for each asset. We only look at positions worth at least half a million and require that a fund holds at least 10 positions larger than half a million. $I_{0.01 \leq fee < 0.1}$ is an indicator variables equal to one if the fee of a stock lies between 1% and 10% at the report date. $I_{fee \geq 0.1}$ is in indicator equal to one if the fee is larger than 10%.

	Dep. Var: log(port-wt)		
	(1)	(2)	(3)
log(mkt-wt)	1.017	1.004	1.004
	(0.006)	(0.003)	(0.003)
log(avg-fee)		−0.121	−0.123
		(0.008)	(0.009)
log(avg-fee):$I_{0.01 \leq fee < 0.1}$			0.007
			(0.004)
log(avg-fee):$I_{fee \geq 0.1}$			−0.041
			(0.014)
Quarter Fixed Effects	Yes	Yes	Yes
Observations	964,301	964,301	964,301
Adjusted R^2	0.970	0.972	0.972

We note that this test will have little power against the alternative hypothesis that funds completely sell out of holdings when the fees become large, in that we only examine the changes when funds reduce, but not eliminate, their positions in these securities.

5.6 Propensity to hold high-fee stocks: 13F analysis

In Section 5.5, we used N-PORT and N-CEN data to provide evidence suggesting that funds, including some index funds, will underweight a stock, relative to its market weight, following a large rise in the borrowing costs of that stock. While these data allow us to take a detailed look into specific funds' holdings of specific names, the data limits our ability to determine whether the patterns we document have changed over time.

In an attempt to examine how funds' overall willingness to hold contrained stocks has changed over time, we turn to the quarterly 13F data from Thompson Reuters. 13Fs are only filed by asset managers with more than $100 million in assets under management. Also the institutional managers file one 13F for all of the funds run by that institutional management company, unlike for the N-PORT and N-CEN data. Also, the 13F data is just quarterly snapshots of holdings, and doesn't give us any insight into the lending behavior of the fund, and certainly not the lending of individual securities.

Nonetheless, if institutions' tendency to sell high-fee stocks rather than lend them out has increased over time, we should see that such stocks have increasingly been avoided in institutional portfolios.

The challenge is that one of the most important determinants of the inclusion of a stock in an institutional portfolio is market capitalization—which is highly correlated with lending fees. We tackle this by employing a matching procedure, in which, for every high-fee stock, we pick a stock that is similar (but never bigger) in size from a universe of unconstrained (GC) stocks. The fee is measured as the average daily indicative fee over the previous calendar quarter. We then look at the ratio of the dollar amount invested in constrained stocks held by institutions relative to similarly sized unconstrained stocks. If that ratio is below 1, it indicates that institutions dislike constrained stocks over and above the fact that they are small. More importantly, the 13F data allow us to assess if and how this ratio changes over between December 2009 and June 2022.

To be more precise, for the last trading day of each calendar quarter, the matching process begins by selecting the largest constrained stock (lending fee above a threshold of 10%) and identifying the next smaller unconstrained (lending fee <1%) stock to form the initial matched pair. This procedure is then repeated for the second-largest constrained stock, continuing in descending order. Previously matched stocks are not excluded from subsequent pairings, i.e., they can be matched multiple times. If a fund holds an unconstrained stock that was matched n times, its investment amount will be multiplied by n. Constrained stocks for which no smaller unconstrained counterpart can be found (constrained stocks at the very bottom of the size distribution) are omitted from the analysis, slightly biasing the results towards a ratio of 1.

For both the constrained and matched unconstrained stocks, we sum up the quarterly dollar holdings of the selected institutions. This yields the total capital allocated to constrained stocks and, correspondingly, to matched unconstrained stocks by these institutions. Our primary statistic is the ratio of these two quantities, reflecting the relative allocation of capital between constrained stocks and their size-matched counterparts.

Figure 13 shows the result. We observe a (noisy) downward trend over time. The slope of the trend line is significantly negative in statistical (t=-2.23) and economic terms (-.31% per quarter).

This at least suggests an increasing sell-rather-than-lend behavior over time, which could explain part of the increase in lending fees.

5.7 Lenders' share of the borrowing costs

Our analysis aims to estimate the buy-side cost of borrowing a fund's portfolio and compare it to the fund's self-reported securities lending income. In a frictionless market where

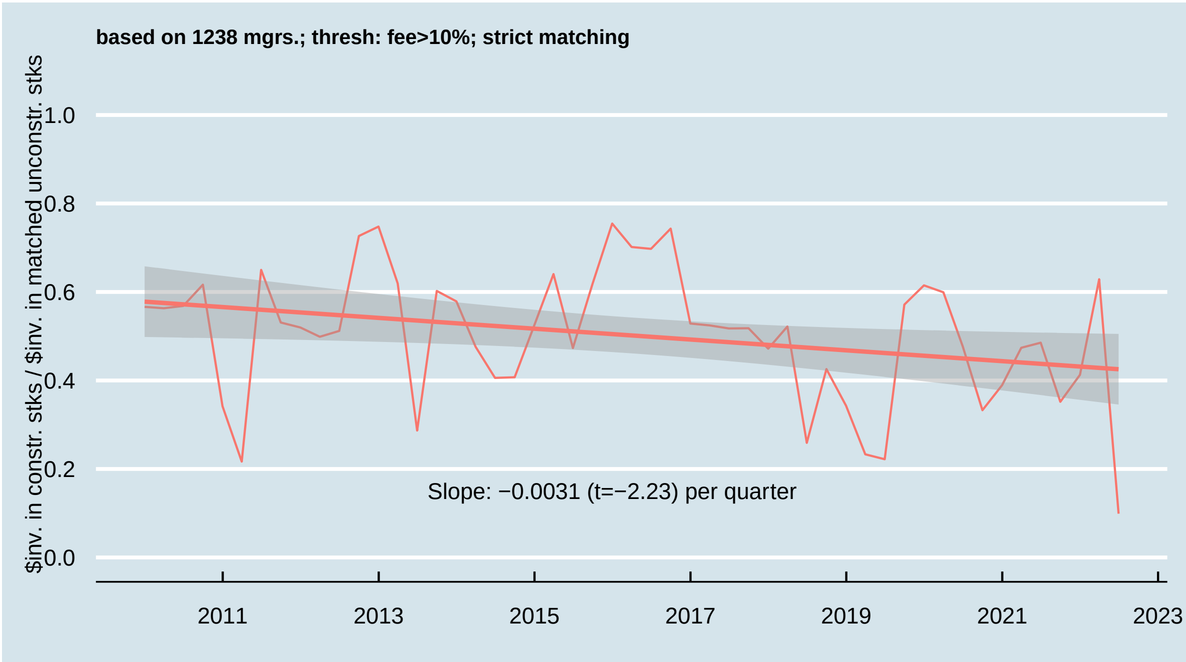

Figure 13: Ratio of investment in constrained vs. matched unconstrained stocks Each quarter, we sum up all dollar holdings of stocks whose lending fee averaged $\geq 10\%$ over the previous calendar quarter reported in 13F filings and divide it by the sum of all dollar holdings in stocks matched on size whose fee was $< 1\%$. The sample period is 2009:12–2022:06.

intermediaries receive no compensation, this ratio—referred to as the lending share—would equal one. In practice, we expect values below one. One minus the lending share represents the proportion of each dollar paid by short sellers captured by intermediaries such as lending agents and prime brokers. These numbers are important as the demand of lending institutions in the security market determines the supply in the lending market. The smaller the lender share, the higher the incentive to sell a high-fee stock.[25]

We use quarterly information on portfolio holdings, positions on loan, and borrowers from N-PORT-P, and annual information on net assets, funds characteristics, net lending income, and basic information about lending agents from N-CEN. From Markit, we use indicative fees of national and international stocks (matched by ISIN).[26] A key variable from

[25] We are unaware of an empirical examination of the lender share. Muravyev, Pearson, and Pollet (2025) assume that 70% of the fee can be captured by the lender.

[26] Please note that, unlike the rest of the paper, we expand our scope here to include both international holdings and U.S. equity holdings in securities not listed on major exchanges. To estimate the lender share,

the N-CEN reports is the annual net income from security lending, which is defined as the gross income from securities lending activities minus the aggregate fees/compensation for securities lending activities.[27]

We estimate the annual borrowing costs BC_{it} for equity mutual fund i in year t using buy-side lending fee data from Markit. Our approach begins with quarterly portfolio holdings from N-PORT-P, focusing exclusively on funds with 100% equity lending. The lending portfolio is defined as the full set of reported outstanding loans. We assume that portfolio holdings remain constant throughout each quarter and that the fund pays the Indicative Fee, as of the holding's report date, for the entire quarter. For each quarter, we calculate the dollar cost of borrowing the fund's entire lending portfolio. Summing these quarterly costs yields the fund's total annual borrowing cost.[28]

The data is drawn from fund self-reports submitted to the SEC. We apply filtering criteria as outlined in Appendix A.3. Nonetheless, some reported values are still implausible. For instance, certain funds report a net securities lending income below 2 basis points relative to their average value on loan — well below the lending fee for even the least expensive stocks. Others report lending income exceeding 1.5% of the average value on loan in N-CEN, despite reporting lendings with a value-weighted buy-side fee below 0.5% in N-PORT-P. Due to these outliers, we consider the median to be the most reliable statistic in this context. Notably, when we tighten constraints at both ends of the distribution, the median lender share remains relatively stable.

we compare the estimated buy-side borrowing costs with the fund's self-reported lending income. Since many funds hold securities outside the major U.S. stock exchanges, excluding these would lead to a downward bias in the lender share. The reported median lender share is based only on funds for which we observe an indicative fee for every outstanding security loan. Further details on the applied filters can be found in Appendix A.3.

[27]Fees and compensations are broken down as fees paid to securities lending agent from a revenue split, fees paid for any cash collateral management service (including fees deducted from a pooled cash collateral reinvestment vehicle) that are not included in the revenue split, administrative fees not included in revenue split, indemnification fee not included in revenue split, rebate (paid to borrower), and other fees not included in revenue split, see page 316 in https://www.sec.gov/files/rules/final/2016/33-10231.pdf. Note that the difference between gross and net lending income is typically not the total fee paid. There are brokers in addition to lending agents, see Figure 1.

[28]More realistic assumptions—namely, that each position gradually shifts to the value of the next quarter's position, and that we update the indicative daily—yield similar results.

The median lender share across all yearly observations without any missing fees and 100% equity lendings is 0.587 (N=9,603), and the median across yearly observations that pass all plausibility filters in Appendix A.3 is 0.577 (N=4,194).[29] The central implication of our analysis is that lenders incur losses by lending constrained stocks rather than selling them. We previously demonstrated that holding and lending constrained stocks generates zero alpha when the beneficial owner fully captures all lending fees. However, since approximately 40% of these fees are retained by intermediaries, the net result is a negative alpha after accounting for fees and commissions. This finding is consistent with Evans, Ferreira, and Porras-Prado (2017), who use N-SAR data to show that lending funds underperform otherwise similar non-lending funds.

5.8 Do analyst expectations reflect short seller beliefs?

The evidence presented in Section 5.3, combined with much other evidence in the academic literature, suggest that there is substantial disagreement across market participants: optimists express this optimism through purchasing securities, and pessimists express their pessimism through short selling securities. A recent literature has attempted to explore the beliefs of investors by examining analyst forecasts (see, e.g., Bordalo, Gennaioli, La Porta, and Shleifer (2024)). An interesting question given our evidence here is whether the views of analyst better reflect the views of the optimists or of the pessimists. We examine this question by exploring the extent to which analyst forecast errors and forecast revisions can be predicted using borrow costs reported by Markit in advance of the time the forecast is made. If these forecasts are rational with respect to borrow costs, in the sense that the forecasts fully incorporate all information embedded in the reported borrow costs, then both forecast errors and revisions should be orthogonal to this information.

[29] Unreported analysis reveals that median lending share tends to be higher for certain types of funds. Specifically, it is higher among index funds, funds with affiliated lending agents, and those that lend a greater proportion of high-fee stocks or lend out more stocks on average. Additionally, funds that avoid concentrated lending to a small number of financial institutions also exhibit higher lending shares.

Table 6: Forecasting forecast errors

Analyst 1-quarter-ahead forecast errors regressed on past forecast errors and past lending fees. 2010:01–2024:12

	1	2	3	4
Intercept	-0.00			
	(-1.11)			
fee	-0.02	-0.02		-0.02
	(-11.02)	(-11.01)		(-11.01)
error (t-1)			0.18	0.18
			(17.82)	(17.74)
R^2	0.0105	0.0169	0.0376	0.0451
Fixed Effects		qtr	qtr	qtr
Clustering	permno,qtr	permno,qtr	permno,qtr	permno,qtr
N	170,525	170,525	170,525	170,525

Table 7: Forecasting Revisions

Revision in analyst 1-quarter-ahead forecasts regressed on lagged lending fees, 2010:01–2024:12

	1	2	3	4	5
Intercept	-0.02	-0.02	-0.02	-0.02	
	(-233.55)	(-31.04)	(-26.03)	(-4.92)	
fee	-0.41	-0.41	-0.41	-0.41	-0.41
	(-100.87)	(-11.00)	(-10.84)	(-11.60)	(-12.11)
R^2	0.0020	0.0020	0.0020	0.0020	0.0088
Fixed Effects					year
Clustering		permno	permno, analyst	permno, analyst,yr	permno analyst,yr
N	5,093,157	5,093,157	5,093,157	5,093,157	5,093,157

Table 6 presents the results of panel regressions in which we regress analyst's 1-quarter-ahead consensus forecast errors on past consensus forecast errors and past lending fees over the period from 2010:01–2024:12. What this indicates is strong predictability, consistent with the information in *ex-ante* borrow costs not being reflected in the analysts' forecasts.

Table 7 presents the results of panel regressions in which we regress analyst's 1-quarter-ahead forecast revisions on lagged lending fees over the period from 2010:01–2024:12. This again indicates strong predictability for forecast revisions, consistent with the information in *ex-ante* borrow costs not being reflected in the forecasts.

6 Conclusions

We document a marked deterioration in the efficiency of the securities lending market over the past several decades. While financial markets have generally become more efficient through technological advances and increased competition, the securities lending market represents a notable exception to this trend. The evidence we present shows that borrow costs have increased dramatically, with particularly pronounced effects in smaller capitalization stocks where the average fee has increased by approximately a factor of ten since 2010.

Our portfolio-based analysis demonstrates a strong relationship between borrow costs and subsequent negative returns, with the highest fee portfolio earning an annualized CAPM alpha of approximately -75% over our sample period. This near one-to-one correspondence between borrow costs and negative alpha represents a substantial departure from market efficiency and suggests significant losses to those who purchase these securities when the borrow costs are elevated.

Short sellers cannot profit from this inefficiency, as they have to pay the borrow costs. Even the investors in these hard-to-borrow securities who lend out the shares cannot benefit, as it appears that institutional investors who lend their securities only receive 50–60% of the borrow cost. Who benefits from the inefficiency in the share lending market? Investors who sell when the borrow cost is high, and the intermediaries in the share-lending intermediation chain, who capture a large fraction of the borrow costs.

Since all shares outstanding are necessarily not lent, we can calculate the “cost” of this inefficiency as the product of the number of shares outstanding times the price times the fee (which is also approximately equal to the negative alpha). Summing over all common stocks in the US market, we estimate that, since 2020, the cost has averaged about $300 million per day. These estimates suggest that the inefficiencies in the securities lending market impose significant costs on market participants and reduce the overall efficiency of capital allocation. The dramatic increase in aggregate borrow costs over our sample period represents a deadweight loss to the economy, as resources are being allocated to rent-seeking activities in the intermediation chain rather than productive uses. Furthermore, the failure of the market to efficiently process negative information likely leads to persistent overvaluation of some securities, potentially distorting investment decisions and capital allocation throughout the economy. An interesting but open question is how much the frictions in the share lending market, and the resulting inefficiencies in the pricing of the equity of the hard-to-borrow firms leads to inefficient capital allocation to the underlying firms.

Direct evidence that market participants fail to incorporate the informational content of borrowing fees comes from financial analysts. The strong predictability we document in both forecast errors and forecast revisions suggests that the high borrow costs we observe reflect genuine negative information about firms' prospects, yet this information is not being efficiently incorporated into consensus expectations or market prices. This represents a failure of one of the market's key information aggregation mechanisms and suggests that the impediments to short selling are preventing the market from efficiently processing negative information.

Our investigation into the supply side of the lending market reveals a potential explanation for the dramatic increase in borrow costs. Using newly available N-PORT data, we show that even passive index funds have begun systematically underweighting high-fee stocks relative to market weights. This behavior, while individually rational for fund managers seeking to avoid the negative alpha associated with holding high-fee securities reduces the supply of lendable shares precisely when demand from short sellers is highest. The resulting supply-demand imbalance drives borrow costs even higher, further incentivizing institutional holders to exit these positions rather than lend them out. Consistent with our analysis of position-level mutual fund data and the observed trend of rising fees, we find that aggregated holdings reported in 13F filings for constrained stocks have declined over time relative to holdings in similarly sized unconstrained stocks.

These findings have important implications for both market participants and policymakers. For institutional investors, our results suggest that the traditional approach of lending out all available securities may no longer be optimal when borrow costs rise. The evidence that index funds are already adapting their behavior by underweighting high-fee stocks indicates that market participants are beginning to recognize and respond to these changed market conditions. For policymakers, our findings raise questions about the current regulatory framework governing securities lending and whether additional measures are needed to ensure that this critical market infrastructure continues to support efficient price discovery and market functioning.

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A Appendix

A.1 Analyses excluding recently listed stocks

In this section, we perform analyses of both the trends in fees and the returns/alphas of high portfolios sorted on the basis of Markit's reported indicative fee. However, we perform this analysis *only* for firms that have been in CRSP for more than five years. Our objective here is to remove firms that are either recent IPOs, or SPACs (see, e.g., Huang, Ritter, and Zhang, 2023; Gahng, Ritter, and Zhang, 2023).

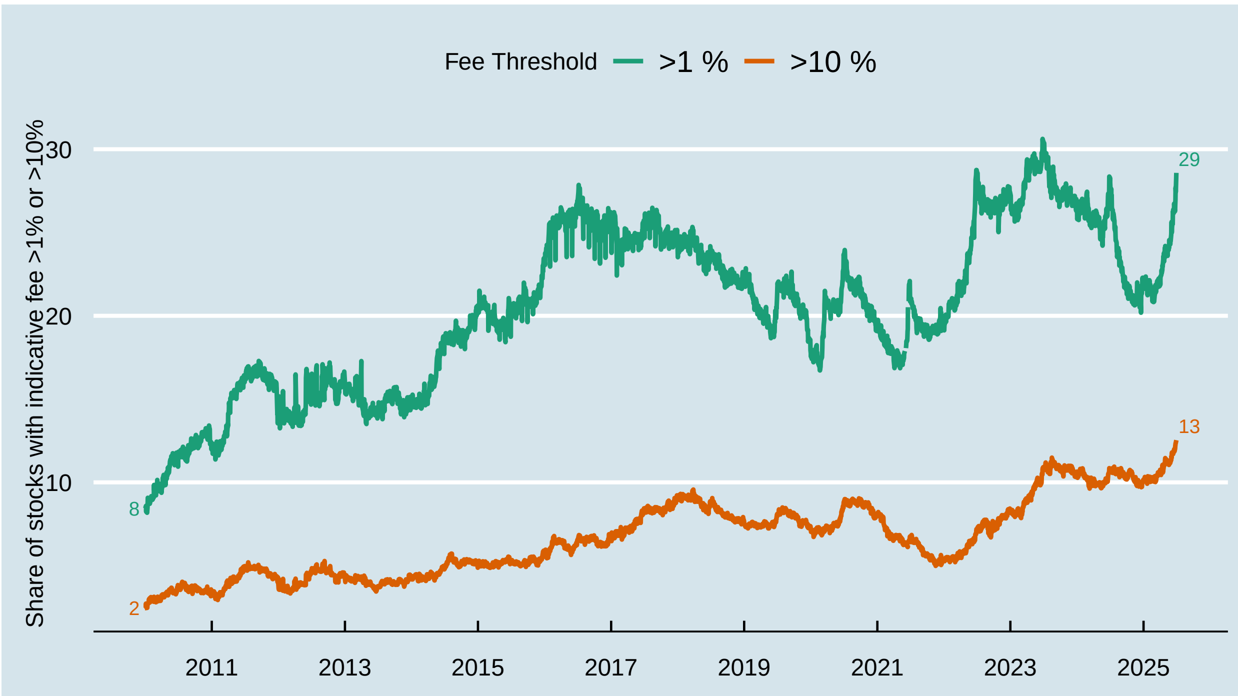

Figure A.1: Share of stocks with indicative fee above 1% and 10% over time – excluding stocks less than 5 years old
This figure presents the share of US common stocks on the major exchanges with indicative fees above 1% and 10% who have been listed at least 5 years over time. The sample period is 2010:01–2025:06.

Figure A.1 plots the fraction of stocks older than 5 years that have indicative fees >1% and >10% by date. A comparison with Figure 5 shows that excluding younger stocks makes almost no difference in this analysis.

Figure A.2 plots the quantile breakpoints for stocks that have been listed for >5 years. Again, a comparison with Figure 4 shows that excluding younger stocks makes almost no difference.

Finally Figures A.3 and A.4 repeat the portfolio return analyses described earlier, but using only firms which have been listed for more than 5 years. Again, the results are comparable.

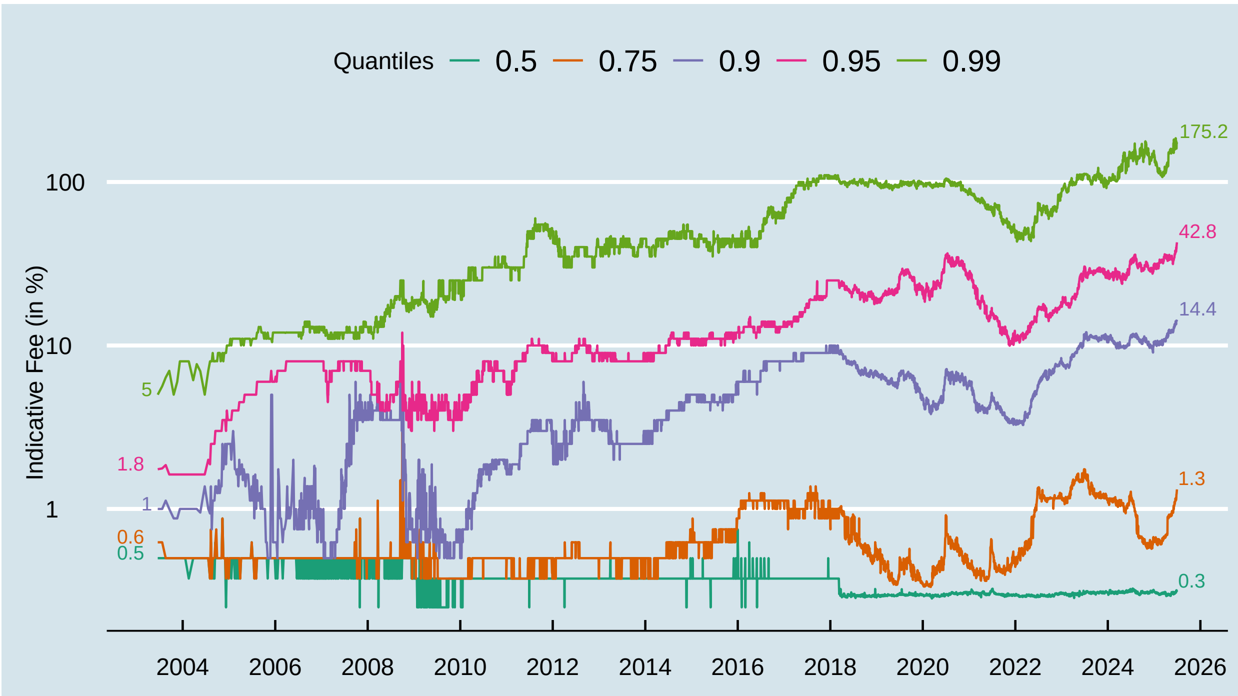

Figure A.2: Indicative fee quantiles over time – excluding stocks less than 5 years old
This figure presents various quantiles of the distribution of *Markit* Indicative Fees for US common stocks listed on the major US exchanges who have been listed at least 5 years over time. The sample period is 2003:10–2025:06.

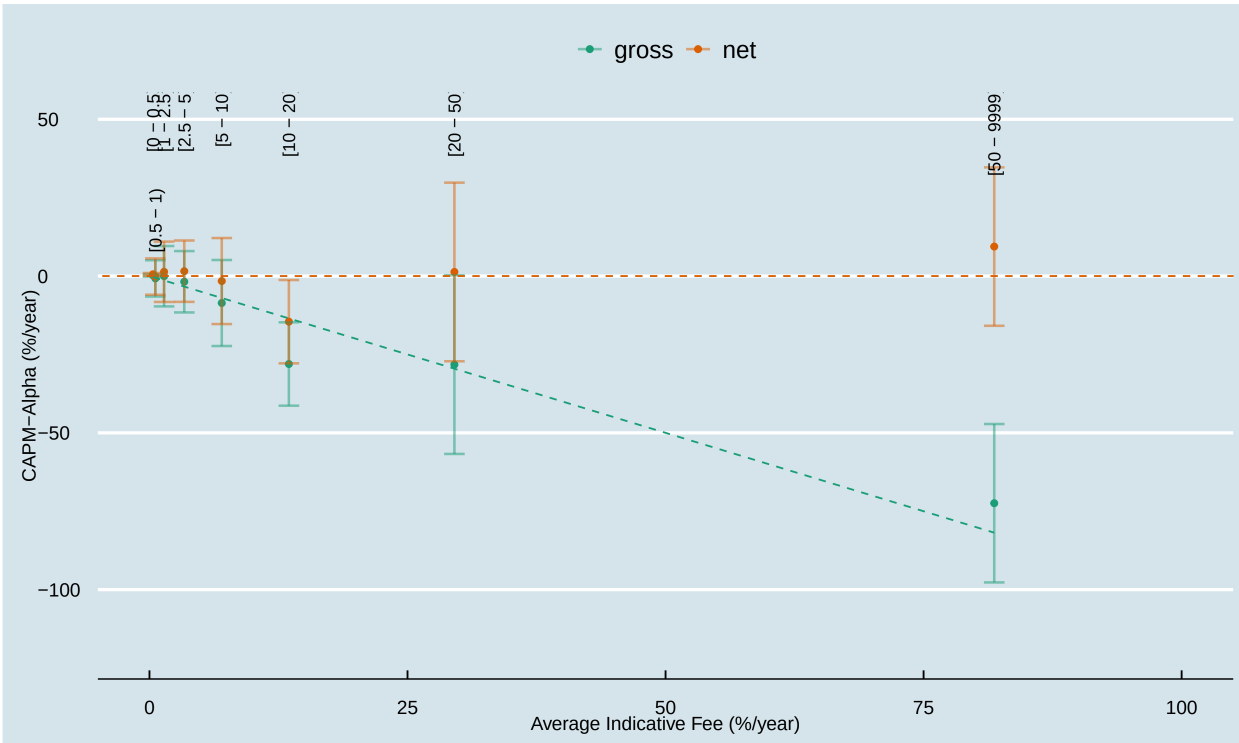

Figure A.3: Performance of borrow-cost sorted portfolios – Daily formation – excluding stocks less than 5 years old

The green dots in this scatterplot represent, on the y-axis, the annualized CAPM alpha for the portfolios over the sample period, and on the x-axis the annualized borrow cost based on the indicative fee reported by Markit. Note that these orange dots represent the "gross" returns, and the green whiskers represent the ±1.96 standard errors, based on Newey and West (1987, 1994) standard errors with automatic lag selection. The net returns — represented by the orange dots—are calculated by adding to each stock's daily return the daily borrow cost for that security. The CAPM alpha for each portfolio is calculated by running a time series regression of the return, net of the risk-free rate on the excess market return.

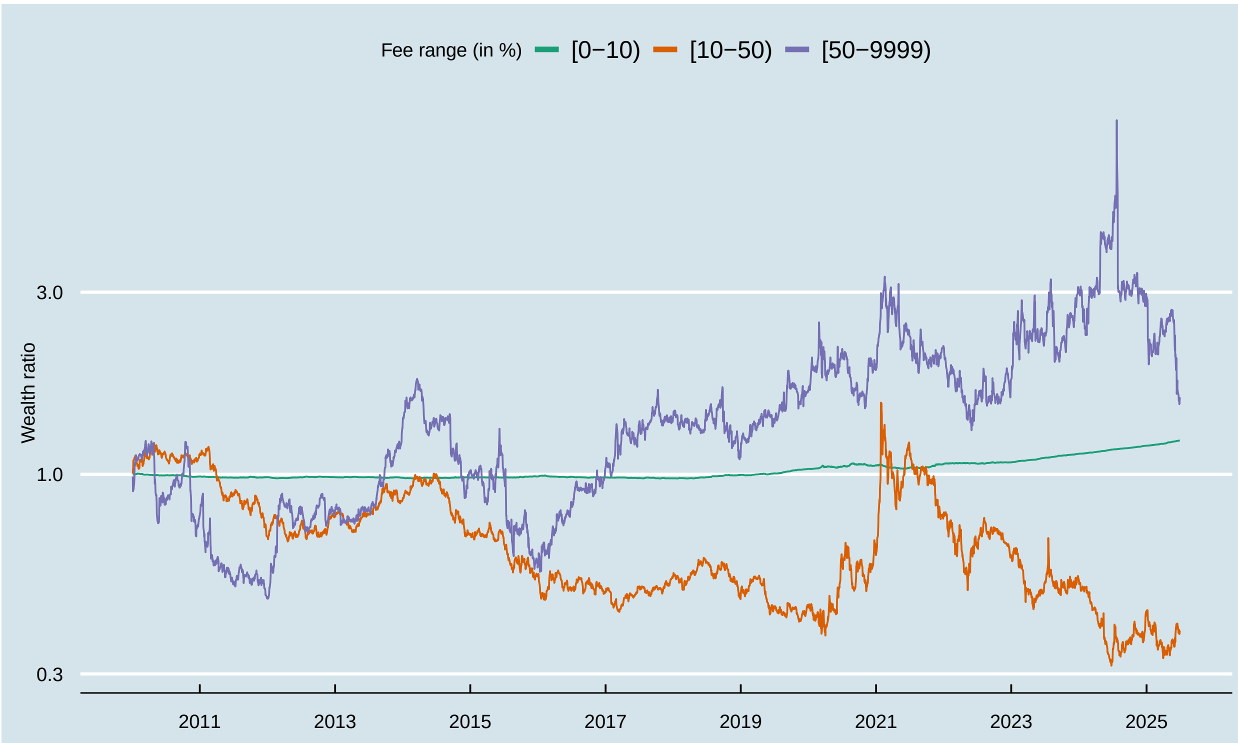

Figure A.4: Value of fee-sorted portfolios, net-of-indicative fee, and market hedged – excluding stocks less than 5 years old

We plot the value of 1 dollar invested in three (daily-rebalanced) value-weighted portfolios consisting of all stocks with fees in the 0–10%, 10%–50% and more than 50% range, respectively, excluding stocks that have been listed for less than 5 years. We add the indicative fee to each stock's return before calculating the portfolio return. Additionally, we market-hedge each portfolio by going short the CRSP VW-market portfolio and investing the short proceeds at the 1-month T-Bill rate.

A.2 Additional analyses for fee-sorted portfolios

A.2.1 Performance of fee-sorted portfolios, daily formation

On each trading day from January 3, 2010 to June 30, 2025, we form portfolios based on the indicative fee provided by Markit for that stock on the preceding day. We form eight portfolios, using indicative fee breakpoints of 0.5, 1, 2.5, 5, 10, 20, and 50% (annualized indicative fee). That is, portfolio 1 (the lowest fee portfolio) on January 4, 2010 contains all stocks that, as of January 3, 2010, had an annualized indicative fee of less than 0.5%. Portfolio 2 contains all stocks that, as of January 3, 2010, had an annualized indicative fee between 0.5% and 1%, and so on. The high fee portfolio contains all stocks that had an annualized indicative fee on January 3, 2010 that was above 50%.

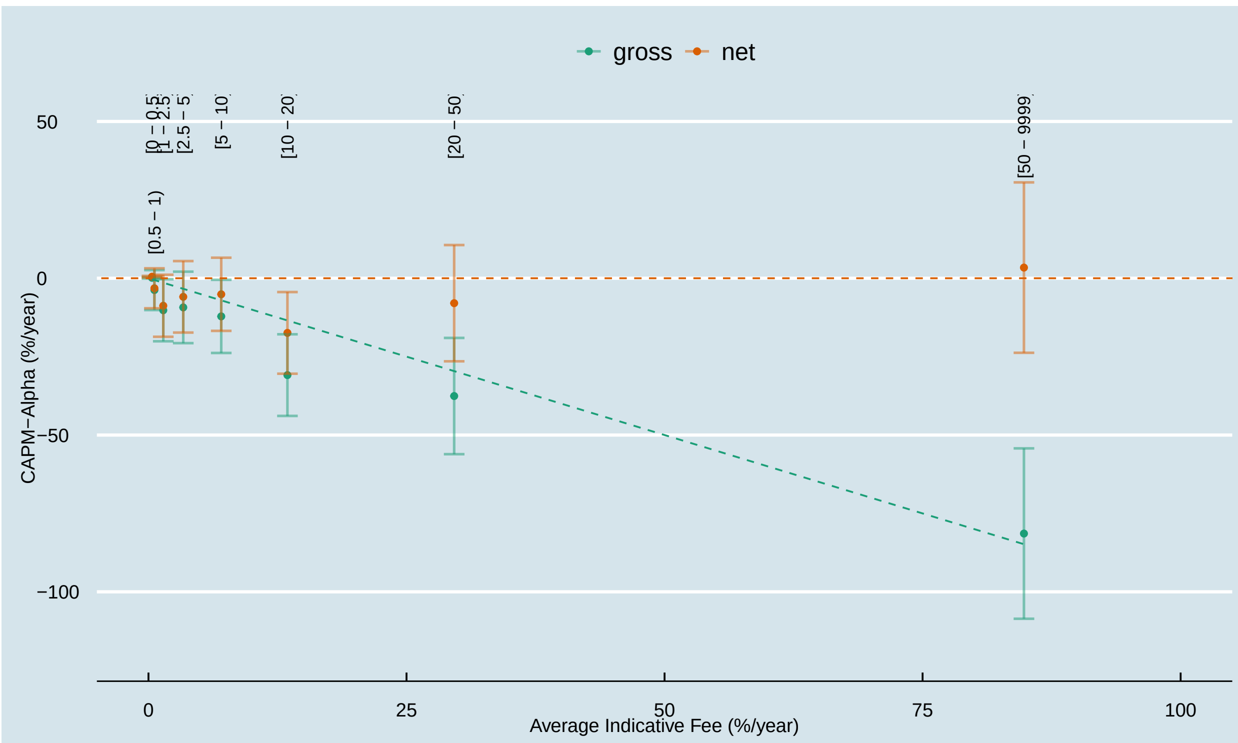

Figure A.5: Performance of borrow-cost sorted portfolios – Daily formation
The green dots in this scatterplot represent, on the y-axis, the annualized CAPM alpha for the portfolios over the sample period, and on the x-axis the annualized borrow cost based on the indicative fee reported by Markit. Note that these orange dots represent the "gross" returns, and the green whiskers represent the ±1.96 standard errors, based on Newey and West (1987, 1994) standard errors with automatic lag selection. The net returns — represented by the orange dots—are calculated by adding to each stock's daily return the daily borrow cost for that security. The CAPM alpha for each portfolio is calculated by running a time series regression of the return, net of the risk-free rate on the excess market return. The sample period is 2010:01:01–2025:06:30.

A.2.2 Number of Stocks in fee-sorted portfolios

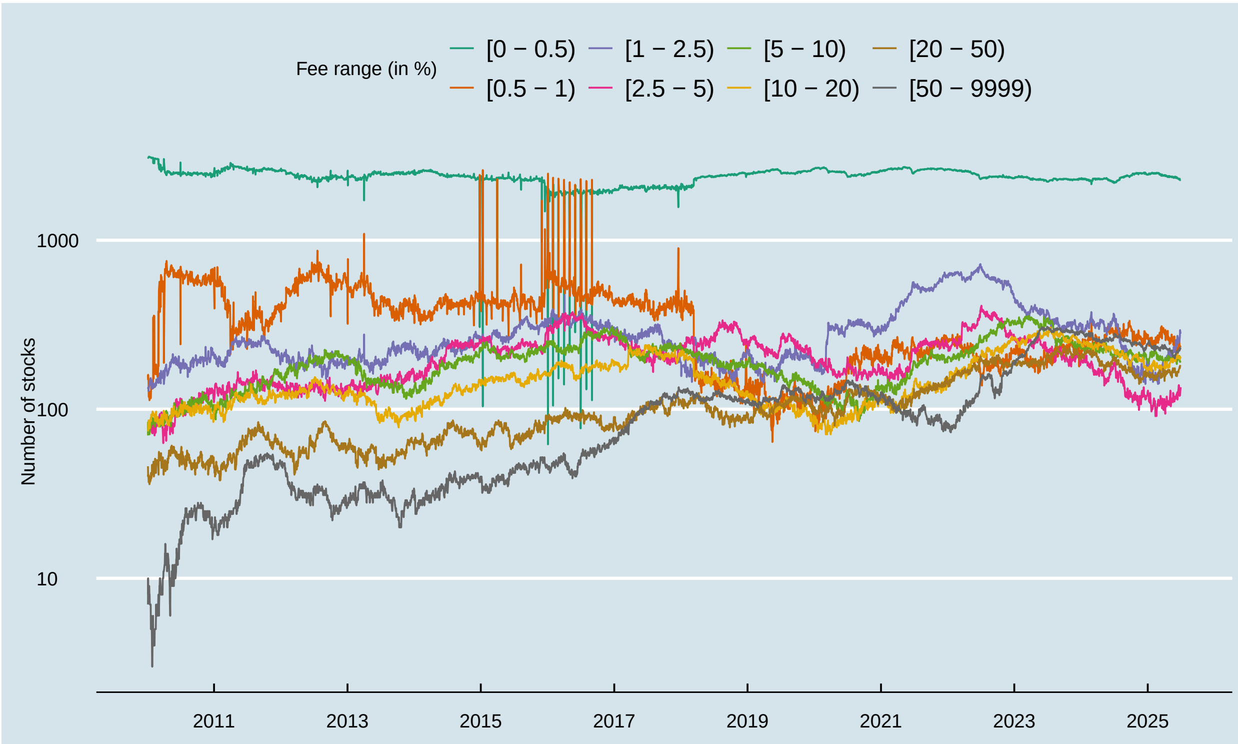

Figure A.6: Number of stocks in fee-sorted portfolios over time
This figure presents the number of stocks in each of the eight daily-formed fee-sorted portfolios over time. The sample period is 2010:01–2025:06.

Figure A.6 plots the number of stocks in each fee portfolio over time. There is a clear upward trend in the number of stocks in the high-fee portfolios. The portfolio of stocks with fees $> 50\%$ carries less than 10 stocks in 2010 and well over 200 stocks towards the end of the sample. Note that there is a bit of back-and-forth between the two lowest-fee portfolios in 2016, when the mode of the fee distribution sometimes increases to 50 bps and a large number of stocks gets allocated to the [0.5-1) portfolio temporarily. This probably relates to Markit calculating the Indicative Fee in a way that results in relatively coarse buckets of rounded fee levels (such as 37.5 bps and 25 bps) up until 2018.

A.2.3 The value of the fee-sorted portfolios over the sample period

Figure A.7 plots the values of the three (daily-rebalanced) value-weighted portfolios consisting of all stocks with fees in the 0–10%, 10%–50% and more than 50% range, respectively. These portfolios are all scaled to have an initial value of $1. Also, here we market-hedge each portfolio by going short the CRSP VW-market portfolio (and investing the short proceeds at the 1-month T-Bill rate).

In Figure A.8, we generate the returns in exactly the same way, except that we add to each individual stock's daily return the Markit indicative fee. Note that, in Figure A.7, the final value of the high-fee portfolio is about $\$10^{-6}$. In Figure A.8, where the the fee is added

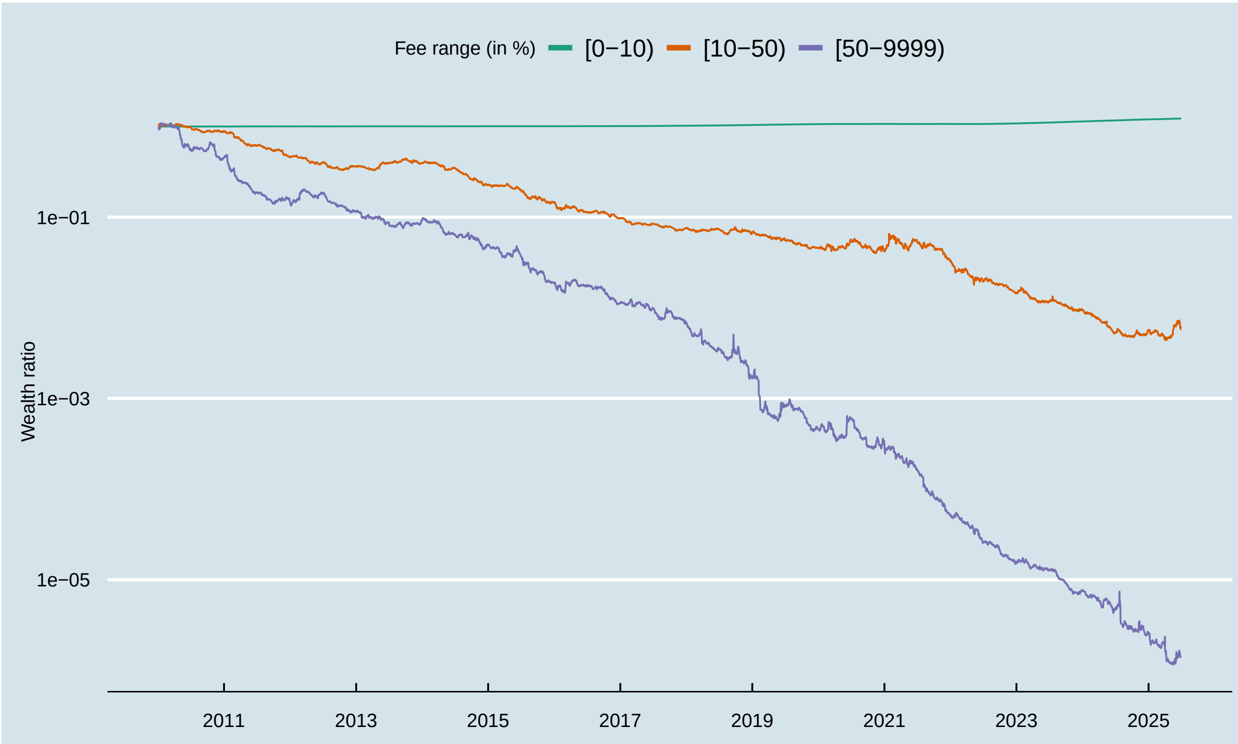

Figure A.7: Value of fee-sorted portfolios, market hedged.
We plot the value of 1 dollar invested in three (daily-rebalanced) value-weighted portfolios consisting of all stocks with fees in the 0–10%, 10%–50% and more than 50% range, respectively. Additionally, we market-hedge each portfolio by going short the CRSP VW-market portfolio and investing the short proceeds at the 1-month T-Bill rate.

to the CRSP returns, the final value of the high-fee portfolio is almost exactly the value of a portfolio which invested in T-Bills over this period.

The [0-10) portfolio has very little volatility, and rises at roughly the risk-free rate over the entire time period. This is expected as this is a value-weighted and industry hedged portfolio. While the [50-9999) portfolio exhibits considerably more volatility, it ends up at a wealth ratio of about 1—basically where it began, indicating that short-selling this portfolio would have cost about as much in fees as the abnormal returns it generated over the sample period.

While short-sellers of the high-fee portfolio broke even over this sample period, they seem to have been able to make some money off stocks in the [10-50) portfolio. From 2014–2020, that portfolio lost in value, and after a short volatile rebound, rapidly fell sharply again from 2022 until the end of the sample.

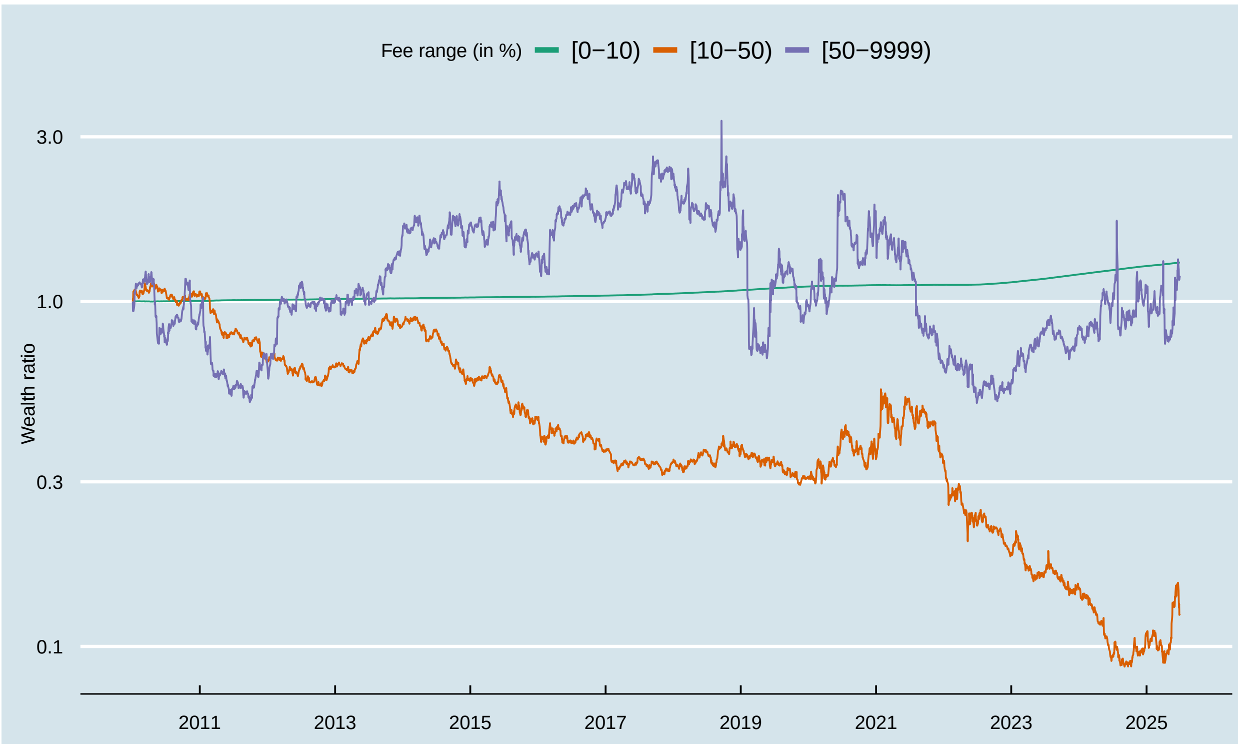

Figure A.8: Value of fee-sorted portfolios net-of-indicative fee, market hedged. We plot the value of 1 dollar invested in three (daily-rebalanced) value-weighted portfolios consisting of all stocks with fees in the 0–10%, 10%–50% and more than 50% range, respectively. We add the indicative fee to each stock's return before calculating the portfolio return. Additionally, we market-hedge each portfolio by going short the CRSP VW-market portfolio and investing the short proceeds at the 1-month T-Bill rate.

A.3 Lender Share

This appendix describes the construction of the sample and the plausibility filters applied in estimating the lender share introduced in Section 5.7. We begin with a complete download of all structured N-CEN and N-PORT-P data files provided by the SEC through the end of 2024.

For the N-CEN data, we remove all observations with a missing SERIES_ID, defined by the SEC as "a unique identifier assigned to each series of an investment company" (see SEC Investment Company Series and Class Information). If multiple entries exist for the same combination of SERIES_ID and reporting period end date, we retain the record with the most recent filing date.

From N-CEN, the variables used in the analysis (see also Form N-CEN Instructions) are:

- NET_INCOME_SEC_LENDING: Net income from securities lending activities
- AVG_VALUE_SEC_LOAN: Monthly average of the value of portfolio securities on loan during the reporting period
- MONTHLY_AVG_NET_ASSETS: Monthly average net assets during the reporting period

In the N-PORT-P data, we remove all holdings with a missing ISIN. Fewer than 1% of all (fund, report date) observations involve a missing ISIN in a position that is on loan. We flag cases where the reported amount on loan exceeds 110% of the reported position value. For each snapshot of the holdings data, we compute both the share of equity holdings and the share of equity lendings. Asset classes are identified using the SEC variable ASSET_CAT.

From Markit, we obtain securities lending fees for U.S. and international equities. For each security, we retain the last available observation in a given month to transform the daily dataset into a monthly one. The resulting monthly dataset is merged with the holdings data using ISIN identifiers. Our sample covers all quarters from Q4 2019 through Q4 2024. To compute annual borrowing costs, we require four observed quarters per fund and reporting year.

The generated dataset contains several extreme cases, such as funds reporting zero securities lending income despite having multiple positions on loan. To partly address these anomalies, we introduce a set of plausibility checks in addition to requiring that (i) no loan values have missing fees and (ii) all securities on loan are equities.

We start by approximating the average value on loan by taking the mean of the four quarterly sums of all values on loans in N-PORT-P. We compare this number to the self-reported monthly average on loan from N-CEN, and require:

1. The estimate average value on loan (N-PORT-P) must be between 75% and 125% of the self-reported monthly average value on loan (N-CEN).

Similarly:

2. The estimate average value of all holdings (N-PORT-P) must be between 75% and 125% of the monthly average net assets (N-CEN).

In N-PORT-P, funds are also required to report the aggregate value of all securities on loan to each individual borrower. We construct the sum of these reported values and impose the following condition:

3. The average quarterly sum across all borrowers in N-PORT-P must lie between 75% and 125% of the self-reported monthly average value on loan in N-CEN.

Additionally, we require:

4. The reported net income from securities lending, divided by the reported average value on loan (N-CEN), must be less than the maximum of all observed fees on the fund's outstanding loans (N-PORT-P).
5. The number of positions with loan values exceeding 110% of the reported position value must be zero.
6. There must be no holdings with a reported value of zero.
7. The average percentage of equity holdings must exceed 90%.

A.4 Additional Plots

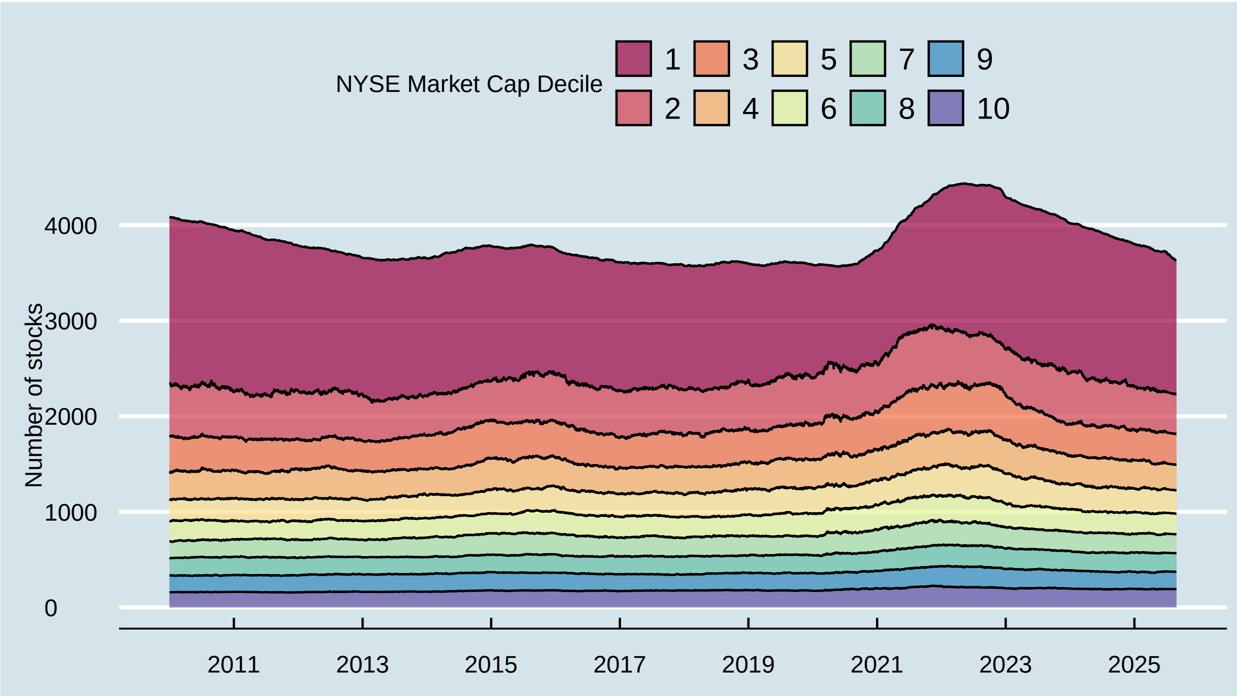

Figure A.9: Number of stocks in NYSE market capitalization deciles
This figure presents the number of US common stocks on the three major exchanges in each NYSE market capitalization decile over time.

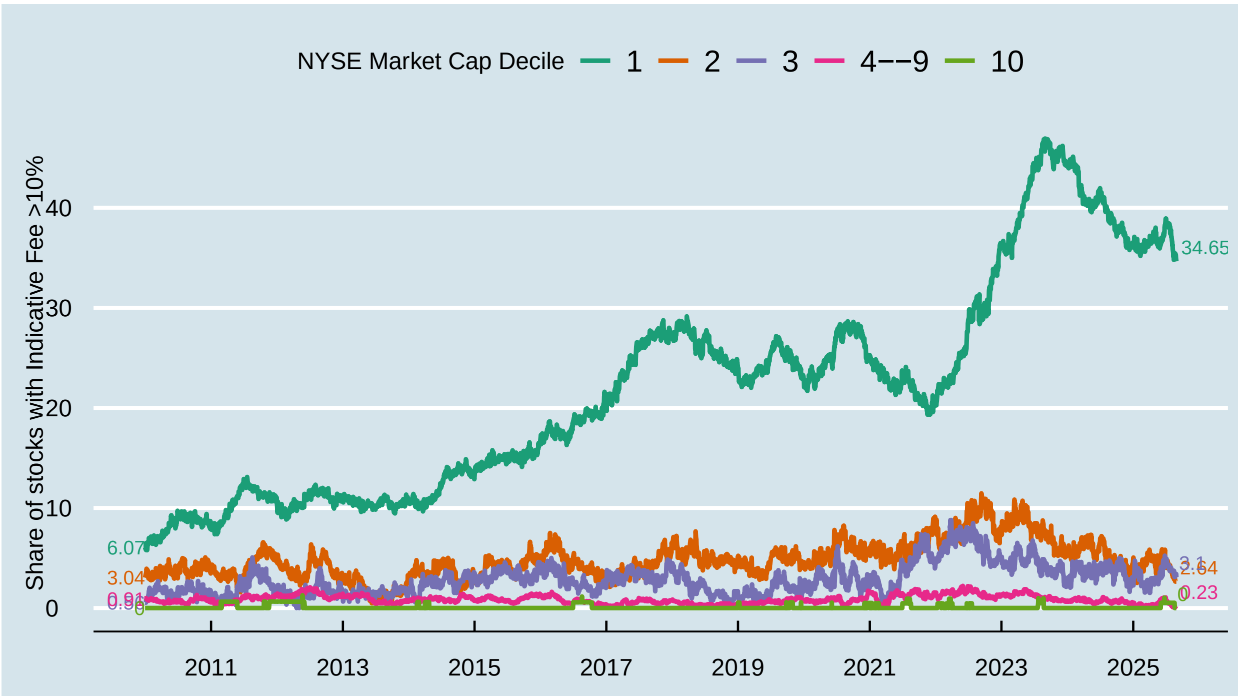

Figure A.10: Fraction of US common stocks with an indicative fee $> 10\%$, by ME quintile

This figure presents the fraction of US common stocks on the three major exchanges with indicative fees above 10% in each NYSE market capitalization decile over time. Deciles 4–9 are merged for readability. The sample period is 2010:01–2025:06.