Institutional Investors, Securities Lending, and Short-Selling Constraints*

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Abstract

Institutions facilitate short-selling by lending from their holdings, but what they hold is endogenous. This paper examines how institutional demand, driven by investment mandates (benchmarking), affects short-selling. In a model where benchmarked managers lend from their holdings, both lending supply and equilibrium price are higher for the benchmark asset, as is shorting demand (due to inflated price). A quasi-natural experiment using Russell index reconstitution shows that stocks with more benchmarked capital have greater lending supply and demand. Ultimately, such stocks are *costlier* to short. In theory and data, results are driven by incomplete pass-through from institutional holdings to lending supply.

JEL Classification: G11, G12, G14, G15, G23

Keywords: Benchmark, lending supply, borrowing fee, short sales, index effect, Russell

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1 Introduction

Short-selling is key to price discovery in financial markets. Yet, the securities lending market, in which most investors must first borrow assets to sell them short, is opaque (U.S. Securities and Exchange Commission (2021)). It is still an open question what determines the cost of short-selling despite nearly six decades of academic research in this area (Seneca (1967)). At the same time, an increasing number of studies are linking asset pricing anomalies to securities with binding short-selling constraints, or those that are expensive to borrow.[1]

The conventional view in the literature is that institutional ownership alleviates short-selling constraints by increasing the supply of lendable shares (D'Avolio (2002) and Asquith, Pathak, and Ritter (2005)). According to S&P Global (2023), short-sellers borrowed an average value of over \$0.6 trillion per day in U.S. equities in 2022, where institutional investors were the primary lenders.[2] Institutions, with their long-term investment horizons, are well-suited to lend their holdings and generate significant revenue by doing so.[3] At the same time, institutions can only lend what they own, and hence the same asset characteristics that drive institutional demand also influence the level of supply of the asset available to short-sellers in the lending market. For instance, one can expect larger and more liquid assets, which are typically held by institutions, to have a larger lending supply. However, if institutional demand affects asset prices, for example, by inflating them, it must change the short-selling demand as well. Therefore, it is not clear ex-ante how institutional ownership should affect the cost of short-selling, that is, the borrowing fee.

In this paper, I bring together the demand and supply effects of institutional ownership in the stock lending market, thereby shedding new light on the role of institutions in shaping short-selling constraints. In particular, I isolate changes in institutional holdings stemming from investment mandates and study the resulting changes in lending supply, shorting demand, and borrowing fees. Benchmarking, which involves evaluating fund manager performance against a market index (benchmark), is a key mechanism for enforcing investment mandates and has been shown to influence asset prices.[4] Despite this, the potential of mandate-bound institutional investors to

[1]See, for example, Chen, Hong, and Stein (2002), Geczy, Musto, and Reed (2002), Stambaugh, Yu, and Yuan (2012), Drechsler and Drechsler (2016), and Muravyev, Pearson, and Pollet (2022a).

[2]In the United States, over 90% of equity loans are sourced from institutions, as reported by the Federal Reserve (Baklanova, Caglio, Keane, and Porter (2016)) and The Investment Company Institute (2014).

[3]For instance, the 2022 N-CSR filing for Vanguard Index Funds reports net securities lending income of over \$0.57 billion, nearly 60% of net expenses. The Financial Times reports a 40% reduction in fees due to lending for selected BlackRock funds: https://www.ft.com/content/866171e2-1916-4c55-bdc2-2d6c6cb56609.

[4]See Ma, Tang, and Gómez (2019), who document that over 80% of manager compensation contracts in the United States are tied to an index such as the S&P 500 or the Russell 1000. Institutions tilt their portfolios toward stocks included in their benchmark indexes, raising these stocks' prices and inducing excess correlations in returns (Basak and Pavlova (2013)). Tight mandates contribute to market segmentation and

inflate asset prices and hence increase short-selling demand has been largely overlooked in the literature on short sales. I explicitly incorporate this channel and show, theoretically and empirically, that it is strong enough to challenge the conventional view on the role of institutions in short-selling markets.

I build intuition using a tractable model with benchmarked fund managers who supply their risky holdings for lending. These managers optimally tilt their portfolios to the asset in their benchmark index, increasing both the price of the asset and its lending supply. Simple intuition suggests that a larger supply should alleviate short-selling constraints and reduce the borrowing fee (*supply effect* of benchmarking). However, the model shows that benchmarking may increase the fee because it inflates the asset price and hence also attracts higher shorting demand (*demand effect* of benchmarking). I test the model's predictions using a quasi-natural experiment based on the Russell index reconstitution, in which there are shocks to how much capital is benchmarked against specific stocks. I find that the demand effect of benchmarking dominates the supply effect because it becomes costlier to short stocks that experience an increase in capital benchmarked against them. Finally, combined with my model, insights from novel regulatory filings suggest that both explicit lending limits and frictions in the lending market depress the pass-through from institutional holdings to lending supply, resulting in a weak supply effect of benchmarking.

The model allows me to characterize asset prices and borrowing fees in the presence of benchmarking and securities lending. It introduces a lending market to an economy with fund managers benchmarked to a market index. Other agents include direct investors, who are net long, and hedgers, who are net short. Because fund managers' performance is evaluated relative to the index, they always allocate a fraction of their holdings to the benchmark asset, thereby inflating its price. This results in the asset being overvalued compared to an economy without benchmarking.

A unique aspect of the model is that the benchmark-induced holdings contribute to the lending supply. Fund managers can lend their risky holdings to hedgers, up to an exogenous lending limit,[5] in exchange for a fee, while direct investors are not permitted to lend. The shorting demand of hedgers is upward-sloping in price so it is also higher for the benchmark asset due to its inflated price. Because both the supply and demand effects of benchmarking coexist, it is not immediately apparent how borrowing fees (short-selling costs) relate to benchmarking. By clearing the asset spot and lending markets at the same time, I demonstrate that this relationship in equilibrium

capital immobility (He and Xiong (2013)) and are closely related to preferred-habitat models of the term structure of interest rates (Vayanos and Vila (2021)).

[5]In the United States, there is a regulatory limit on the total value on loan relative to the fund value. I discuss this and other drivers of limited lending below. Furthermore, allowing funds to choose the lending limit endogenously to balance lending costs yields the same key findings. See Internet Appendix E.

depends on a simple condition related to the fund managers' lending limit. When the managers are too constrained in lending (that is, when the lending limit is relatively tight), the demand effect prevails, resulting in a higher borrowing fee for the benchmark asset.

The model features different predictions for an asset that is free to short, referred to as a *general collateral* asset, and an asset that is costly to short, referred to as an asset on special (or simply as a *special* asset). For a general collateral asset, the lending market clearing condition is slack, which means that the equilibrium lending supply is higher than the shorting demand and the borrowing fee is zero. While benchmarking increases both lending supply and shorting demand for such an asset, the borrowing fee remains unchanged. For a special asset, the lending market clearing condition binds, resulting in a strictly positive borrowing fee. Whether this fee increases or decreases with benchmarking depends on the lending limit as described above.

The contribution of the paper is primarily empirical. An ideal test of the model would require variation in benchmarking that is independent of stock fundamentals. Obtaining such variation in data is challenging because index membership is typically related to factors like company size and liquidity of its shares. Additionally, as stocks in major indexes often attract more analyst coverage, index membership may be related to analyst disagreement, which the literature has associated with short-selling. I therefore turn to a quasi-natural experiment.

To test predictions of my model, I exploit changes in the index membership of U.S. stocks due to the reconstitution of Russell indexes. Utilizing the composition of 34 U.S. equity indexes and the assets of mutual funds and exchange-traded funds (ETFs) benchmarked against them, I construct a comprehensive measure of the amount of capital benchmarked against a stock, expressed as a fraction of its market value. This measure is called *benchmarking intensity*, or BMI (Pavlova and Sikorskaya (2023)). I argue that the mechanical nature of the Russell reconstitution creates a plausibly exogenous change in BMI, allowing me to test the predictions of the model.[6] I first confirm that a stock's price goes up when the stock moves down from the Russell 1000 to the Russell 2000 index (see Chang, Hong, and Liskovich (2015)). Such stocks experience an average BMI increase of 8.6 percentage points (pp) because there is more capital benchmarked to the Russell 2000 index.

Using comprehensive S&P Global (Markit) buyside data, I provide new insights into the securities lending market during the Russell reconstitutions. I find that both a stock's lending supply (inventory) and shorting demand (short interest) go up with its BMI. This is true for both general collateral stocks and stocks on special, which I define empirically as those with annualized borrowing fees below and above 1%, respectively, following the literature (for example, Aggarwal,

[6]By using the proprietary ranking variable and constituent files from FTSE Russell, I circumvent certain known issues with the test design (see, for example, Appel, Gormley, and Keim (2021)). I provide the details in Section 5.2.6 and Internet Appendix A.5.

Saffi, and Sturgess (2015)).[7] However, the pass-through to lending supply seems weak, as a dollar of new benchmarked capital translates only to around 18 cents of new lending inventory. I observe no change in borrowing fees for general collateral stocks, which is consistent with my model because the short-selling constraint does not bind for these stocks. Conversely, the fees of stocks on special increase, revealing that the demand effect of benchmarking is dominant. The magnitude is economically significant, with the borrowing fee increasing by 21 basis points (bps) for each pp increase in BMI. This means that, on average, it becomes 25% more expensive to short stocks added to the Russell 2000. Finally, using changes in BMI as an instrument for changes in institutional ownership (following Pavlova and Sikorskaya (2023)), I document that a 1 pp increase in institutional ownership leads to a 77 bps higher fee for special stocks.

These findings do not depend on how borrowing fees and special status are measured. While the main analysis uses a borrower-side measure of short-selling costs, the results hold for lender-side fees and option-implied short-selling costs. Importantly, I show that a change in BMI shifts lending supply and shorting demand curves, rather than causing a movement along the supply curve. Potential changes in analyst disagreement and borrowing risk measures do not explain my findings, as demonstrated with other robustness tests in Section 5.2.6. Finally, I show that, even further away from the Russell cutoff, funds mostly lend stocks within their benchmark indexes, and provide additional evidence from the Japanese equity market supporting my model.

So why does the demand effect of benchmarking dominate in the data? In my model, this is primarily influenced by the lending limits that fund managers face. When these lending limits are too restrictive, managers tend to undersupply their holdings for lending. Meanwhile, shorting demand continues to rise due to the impact of benchmarking on asset prices.

To explore how restrictive lending limits are in the data, I collect lending information for U.S. investment management companies from their N-PORT and N-CEN filings, which are available from 2019. I find that the regulatory portfolio-level limit, set at one-third of total fund value by the regulators in the United States,[8] is not binding. At the same time, position-level data from major investment managers like BlackRock, Fidelity, J.P. Morgan, State Street, T. Rowe Price, and Vanguard reveal soft lending limits that are often at or above 80% of how much the manager holds in a given stock (see Figure 3).

The same regulatory filings allow me to study lending around the recent Russell reconsti-

[7] The borrowing fees in Markit data are typically derived from the quoted rebate rates. To borrow a stock, short-sellers usually provide cash collateral, on which lenders pay interest, called the rebate rate. The borrowing fee is the difference between the market short-term interest rate and the rebate rate paid on the cash collateral.

[8] See the regulations of the U.S. Securities and Exchange Commission (SEC) at https://www.sec.gov/investment/divisionsinvestmentsecurities-lending-open-closed-end-investment-companieshtm.

tutions by funds benchmarked to the Russell indexes. I find that these funds often lend out over 90% of their holdings in special stocks transitioning between Russell indexes, with borrowing fees positively correlated with the amount lent. However, benchmarked funds often forgo lending certain special stocks, contrary to model predictions. Known frictions in the lending market, such as participation constraints and search costs, do not fully explain this sparse lending. Instead, the data suggests the presence of securities lending habitats, as also observed in other N-PORT studies (Dong and Zhu (2022)).

Finally, I show that lending limits have broader implications beyond their impact on borrowing fees. In my model, lending limits influence both the likelihood of an asset being classified as special (that is, how likely the lending market clearing constraint binds) and the special asset's price sensitivity to benchmarking. As lending limits are relaxed, asset price sensitivity to benchmarking generally decreases. Without lending limits–when fund managers can lend the full value of their holdings–the model predicts that benchmarking has no effect on special asset prices. These findings underscore the significant and novel role of lending limits in designing and applying investment mandates, including central banks purchases and sustainable investing.

Related literature. This paper is related to several strands of the literature encompassing investment mandates and index effect, theoretical and empirical work on short-selling constraints, and, in general, empirical research on investment managers and securities lending.

A large body of empirical literature recognizes the importance of institutional ownership for lending markets. D'Avolio (2002) shows that the main suppliers of stock loans are institutional investors. So not surprisingly, the literature has used measures based on institutional ownership to proxy for short-selling constraints (Chen, Hong, and Stein (2002) and Nagel (2005)) and supply specifically (Asquith, Pathak, and Ritter (2005)).[9] A classical result in this literature is that institutional ownership increases lending supply, while the concentration of ownership reduces it (Prado, Saffi, and Sturgess (2016)). I exploit benchmarking to offer a new perspective on how institutional ownership impacts short-selling constraints. Although benchmarking increases supply, I find that borrowing fees rise when BMI increases. I provide position-level evidence of the weak pass-through from institutional ownership to supply and link it to the prevalence of the demand effect of benchmarking. My model takes into account the price pressure induced by institutional demand, which is typically not considered in the literature.

[9]Another approach is offered by Cohen, Diether, and Malloy (2007), who isolate directional shifts in supply and demand for shorting using proprietary data. They find that shorting demand predicts future returns while lending supply has only minor effects. Similarly, Kaplan, Moskowitz, and Sensoy (2013) use experimental evidence to argue for the limited importance of lending supply for stock prices and liquidity. At the same time, Beneish, Lee, and Nichols (2015) argue that shocks to supply are important when it is limited.

Ample lending supply has also been linked to higher price efficiency (Saffi and Sigurdsson (2011)), with several contemporaneous papers debating how lending by passive funds contributes to it. Specifically, Palia and Sokolinski (2024) argue that passive ownership reduces risks associated with stock borrowing (Engelberg, Reed, and Ringgenberg (2018)), attracting additional short-selling and increasing borrowing fees for special stocks. My empirical setting features a plausibly exogenous change in BMI, and short-selling demand and borrowing fees increase even without any observed improvement in borrowing risk measures.[10] My findings are therefore more consistent with Coles, Heath, and Ringgenberg (2022), who find no change in price efficiency around Russell reconstitutions.[11] Finally, Beschwitz, Honkanen, and Schmidt (2022) study lending and borrowing around Russell reconstitutions in the full sample of stocks. I separately consider special stocks and document large changes in their borrowing fees, for which my model has direct predictions.

This paper naturally relates to the vast literature on short-selling constraints and securities lending markets. Short-selling constraints are recognized as a limit to arbitrage,[12] but they bind only for certain (special) stocks.[13] Furthermore, beginning with Miller (1977) and Jarrow (1980), the literature has predominantly relied on the differences of opinion to explain the coexistence of short-sellers and investors who hold a long position in the asset, with the latter group typically supplying securities for lending. This is also true for the search-based models of the securities lending markets that endogenize the specialness of securities (see Duffie, Gârleanu, and Pedersen (2002) and Vayanos and Weill (2008)) and the recent theoretical literature with dynamic short-selling (Atmaz, Basak, and Ruan (2024)). Securities that are subject to more disagreement are usually more special in these models. Models in Blocher, Reed, and Van Wesep (2013) and Banerjee and Graveline (2013) are agnostic with respect to the trading rationale, and yet the prediction for specialness is similar. My model is first to provide a microfoundation for the effect of institutional incentives on lending supply. Furthermore, benchmarking generates short-selling demand by inflating the asset price (independent of disagreement). Its contribution to asset specialness is ambiguous and crucially depends on the lending limit.

[10] In my sample of special stocks, I observe no decrease in measures of borrowing risk suggested by the literature, such as borrowing fee volatility, loan utilization volatility, loan tenure, and failures to deliver. These results are reported in Internet Appendix A.15.

[11] Yet, the literature has also suggested that benchmarking and passive ownership may reduce price efficiency (see for example, Breugem and Buss (2019), Bhojraj and Zhao (2021), and Sammon (2023)).

[12] See, for example, Diamond and Verrecchia (1987), Hong and Stein (2003), Dow and Gorton (1994), and the reviews in Gromb and Vayanos (2010) and Reed (2013).

[13] The granular empirical evidence for that is first provided in D'Avolio (2002) and Geczy, Musto, and Reed (2002) and further extended in Kolasinski, Reed, and Ringgenberg (2013), all based on proprietary data from large lenders. Jones and Lamont (2002) document the same for U.S. stocks in 1926–1933. Studies of bond specialness include those of Duffie (1996), Krishnamurthy (2002), Nashikkar and Pedersen (2007), and Asquith, Au, Covert, and Pathak (2013). Also see the review in Daniel, Klos, and Rottke (2024).

There is extensive theoretical literature on the asset pricing effects of benchmarking, mandates, and investor habitats. The first equilibrium model with a benchmark is offered by Brennan (1993), while Cuoco and Kaniel (2011), Basak and Pavlova (2013), Buffa, Vayanos, and Woolley (2022), and Buffa and Hodor (2023) investigate equilibrium asset pricing effects in dynamic economies with benchmarks. Similarly, the literature considers the implications of investor styles (Barberis and Shleifer (2003)) and investment mandates in delegated asset management (for example, Binsbergen, Brandt, and Koijen (2008), He and Xiong (2013)).[14] None of these papers has examined how benchmarking or mandates affect the lending market. My model suggests that the feedback through this market has the potential to alter the effects of benchmarking on price.[15]

Finally, this paper is related to literature quantifying the effects of index membership for financial securities. Shleifer (1986) and Harris and Gurel (1986) were first to document abnormal returns to additions to the S&P 500 index. Index effects were later found in many other markets and asset classes.[16] In this strand of literature, my paper is closest to Chang, Hong, and Liskovich (2015), who document the Russell index effect, or an average price increase of stocks added to the Russell 2000 index from the Russell 1000 index, and to Pavlova and Sikorskaya (2023), who propose BMI as a measure of how much capital is benchmarked against a stock. I show that index reconstitutions trigger large changes in both lending supply and shorting demand as well as changes in short-selling costs, which this literature typically abstracts away from.

2 The Market for Lending and Borrowing Stock

The stock lending market plays a pivotal role by bridging the gap between short-sellers and stock owners willing to lend their shares in exchange for a fee. Four distinct groups of participants operate within this market: (i) beneficial owners such as institutional investors, (ii) professional lenders such as custodians or in-house lending agents of institutions, (iii) borrowers, comprising hedge funds, proprietary trading desks, and market makers, and (iv) prime brokers. Typically, hedge funds and market makers procure securities from their prime brokers, who subsequently

[14] Closely related literature investigates preferred habitats in fixed income markets (for example, Greenwood and Vayanos (2014) and Vayanos and Vila (2021)). Jappelli, Subrahmanyam, and Pelizzon (2023) integrate a repo market into a preferred-habitat model.

[15] There is also developing literature that incorporates downward-sloping demand curves for stocks in the asset pricing and macro-finance models (Koijen and Yogo (2019) and Gabaix and Koijen (2020)). My results imply that the asset pricing effects of institutional investors' inelastic demand may be influenced by their role as major lenders in the securities lending market.

[16] For example, Greenwood (2005) explores index effects of a redefinition of the Nikkei 225 index in Japan. Further examples include Kaul, Mehrotra, and Morck (2000), Wurgler and Zhuravskaya (2002), Chakrabarti, Huang, Jayaraman, and Lee (2005), and Boyer (2011).

borrow from lenders representing mutual funds, pension funds, and other beneficial owners. A comprehensive description of the U.S. market can be found in D'Avolio (2002), Kolasinski, Reed, and Ringgenberg (2013), and the recent Survey of Agent Securities Lending Activity by the Office of Financial Research, the Federal Reserve System, and staff from the SEC, summarized in Baklanova, Caglio, Keane, and Porter (2016).

Borrowing fees are typically not quoted directly but are derived from quoted rebate rates. For stock loans, the borrowers usually provide cash collateral to the lenders, who, in turn, pay interest (the rebate rate) on the held cash collateral. The borrowing fee is the difference between the market short-term interest rate and the rebate rate paid on the cash collateral. A high borrowing fee is observed when securities are difficult to borrow, which makes them special. A part of the fee paid by the borrower compensates lending agents and prime brokers for their services, although the predominant portion is retained by the beneficial owners. Specifically, approximately 80% of the securities lending income of investment companies in the United States accrues back to fund investors (Johnson and Weitzner (2023)).

3 Model with Benchmarking and Securities Lending

To illustrate the main mechanism, I develop a simple and tractable model of asset prices and borrowing fees in the presence of benchmarking. The model builds upon Brennan (1993) and Banerjee and Graveline (2013), introducing a market for asset lending to an economy with fund managers benchmarked to a market index. The distinguishing feature of the model is that fund managers' holdings contribute to the lending supply available to short-sellers. The goal of the model is to characterize the relationship between benchmarking, asset prices, and borrowing fees.

3.1 Model setup

There are two dates, $t = \{0, 1\}$. The financial market consists of a riskless asset with an exogenous interest rate normalized to zero and unlimited net supply (for example, a storage technology) and one risky asset paying a cash flow $\bar{D}$ at $t = 1$, with $\bar{D} \sim N(\mu, \sigma)$. I focus on a one-asset case for brevity, and the intuition in an economy with multiple risky assets is similar (see Internet Appendix C). The shares of the risky asset are in fixed supply, which I denote by $\bar{\theta} > 0$. Let p denote the price of the risky asset. There exists a benchmark index, which is a portfolio of ω shares of the risky asset.

There are three types of investors: direct investors, fund managers, and hedgers. All investors have a constant absolute risk aversion (CARA) utility function over terminal wealth (or compensation), $U(W) = -\exp^{-\gamma W}$, where γ is the coefficient of absolute risk aversion. They trade at $t = 0$ and collect payoffs at $t = 1$.

Direct investors, whose mass in the population is λ_D, manage their own portfolios. The terminal wealth of a direct investor is given by

$$W^D = W_0^D + \theta_D(\bar{D} - p),$$

where θ_D denotes the number of shares held by the direct investor and W_0^D is the investor's initial wealth. The direct investor chooses holdings θ_D to maximize expected utility $U(W^D)$.

Fund managers, with a mass λ_M, allocate funds on behalf of fund investors in exchange for compensation. Each fund manager is evaluated relative to the benchmark and chooses a portfolio of θ_M shares to maximize expected utility from compensation $U(w)$. Furthermore, fund managers are permitted to engage in securities lending to earn the fee of Δ per share, with an exogenous (scalar) limit $l \in (0, 1]$ on the fraction of the risky asset in their portfolio that they can lend out.[17]

Fund managers' compensation w incorporates three payouts. The first one linearly depends on the absolute performance of the fund, the second is based on the performance of the fund relative to the benchmark index, and the third is independent of performance (for example, a fixed salary).[18] Specifically,

$$\begin{aligned} w =& aR + b(R - B) + c, \quad a \geq 0,\, b > 0 \\ R \equiv& \theta_M(l\Delta + \bar{D} - p) \quad \text{and} \quad B \equiv \omega(\bar{D} - p), \end{aligned} \tag{1}$$

where R is the performance of the fund's portfolio and B is the performance of the benchmark index. The parameters a and b are the contract's sensitivities to absolute and relative performance, respectively, and c is the fixed payout size. This specification nests compensation of a passive fund manager, for whom b has to be very high to disincentivize any deviation from the benchmark. Because the fund's performance monotonically increases in securities lending, managers lend out their risky holdings up to the limit l.

Hedgers–the third type of investors–are endowed with $e\bar{D}$ units of consumption at $t = 1$ so that they engage in short-selling at $t = 0$ for hedging purposes. This is similar to how Banerjee and Graveline (2013) model short-selling. Each hedger chooses a portfolio θ_H to maximize expected

[17] There are various microfoundations for this parameter, which I discuss in Section 5.3.

[18] Ma, Tang, and Gómez (2019) and Evans, Gómez, Ma, and Tang (2023) analyze compensation of fund managers in the U.S. mutual fund industry and provide evidence supporting the specification I use here. Kashyap, Kovrijnykh, Li, and Pavlova (2023) derive such compensation as part of an optimal contract.

utility $U(W^H)$. Their terminal wealth is given by

$$W^H = W_0^H + e\bar{D} + \theta_H(\bar{D} - p + \mathbf{\Delta 1}_{\theta_H<0}),$$

where θ_H denotes the number of shares held by the hedger and W_0^H is the hedger's initial wealth. Δ is the fee that the hedger pays on the short position, that is when θ_H is negative. Hedgers in my model are necessary to generate a certain level of shorting demand independent of benchmarking. In general, hedging has long been recognized as a rationale for selling short (McDonald and Baron (1973)). One can think of these hedgers as investors endowed with equity risk, such as those with risky labor income, displacement risk (Gârleanu, Kogan, and Panageas (2012)), or convertible debt (Agarwal, Fung, Loon, and Naik (2011)). I denote hedgers' mass in the population as λ_H.

3.2 Portfolio choice

In this section, I describe the optimal portfolio choice of each investor type. All proofs for this section are in Internet Appendix B.1.

The portfolio demand of the direct investors is the standard mean-variance portfolio,

$$\theta_D = \frac{1}{\gamma\sigma}\left(\mu - p\right). \tag{2}$$

I focus on the case when the expected returns, $\mu - p$, are always positive so that the direct investors do not take part in the securities lending market, either as borrowers or lenders.

In contrast, fund managers do not face the same risk-return trade-off as direct investors, because of their compensation contracts and because they are allowed to lend securities. The portfolio demand of a fund manager is given by

$$\theta_M = \frac{1}{\gamma\sigma(a+b)}\left(\mu - p\right) + \frac{b}{a+b}\omega + \frac{1}{\gamma\sigma(a+b)}l\Delta. \tag{3}$$

Hence, fund managers split their risky asset holdings across three portfolios: the mean-variance portfolio (the first term in (3)), the benchmark portfolio (the second term), and the return-augmenting portfolio (the last term). The middle portfolio arises because the compensation structure makes the managers hedge against underperforming their benchmarks. The last term in (3) arises because managers hold more assets on which they can earn higher borrowing fees.[19]

[19] I could instead assume that fund managers receive a windfall gain when their fund family or lending agent lends out the stock. In that case, the portfolio demand of fund managers for a special asset would be the same as their demand for a general collateral asset (see Internet Appendix B.2.2). This assumption has implications for the supply schedule in the lending market, which I discuss in detail in Section 3.4.

Finally, a hedger's portfolio demand is

$$\theta_H = \frac{1}{\gamma\sigma}\left(\mu - p + \Delta\right) - e. \tag{4}$$

I focus on the case when the endowment e is so large that θ_H is negative. A hedger's shorting demand, $-\theta_H$, increases in asset price and decreases in the borrowing fee.

3.3 Equilibrium asset price and borrowing fee

Both the asset market and the securities lending market clear at the same time. The asset market clearing condition is

$$\lambda_D\theta_D + \lambda_M\theta_M + \lambda_H\theta_H = \bar{\theta}, \tag{5}$$

and the lending market clearing condition is

$$l\lambda_M\theta_M + \lambda_H\theta_H \geq 0. \tag{6}$$

If the price of the asset is such that the lending supply of this asset, $l\lambda^M\theta_M$, is larger than the shorting demand for it, $-\lambda_H\theta_H$, the latter condition is slack and the equilibrium borrowing fee is zero.[20] If instead the shorting demand is higher than the lending supply, there will be a positive fee to borrow the asset. The fee increases the utility of fund managers, so they will lend the maximum possible amount (up to the limit l). At the same time, the fee will bring the demand of hedgers down. The equilibrium fee will be such that the condition (6) binds.

Below, I present solutions for both an economy with the asset on special (for which condition (6) is binding) and an economy with a general collateral asset (for which condition (6) is slack). All derivations are in Internet Appendix B.2.

3.3.1 Asset on special

The market clearing conditions together with the investors' optimal portfolio demands define the equilibrium of the model. The expression for the equilibrium asset price is

$$p = \mu + \gamma\sigma\bar{B}(B_e e - B_\theta\bar{\theta} + B_\omega\omega_\lambda), \tag{7}$$

[20]In reality, multiplier l in the lending market condition is also affected by the share of funds that are permitted to lend. Internet Appendix A.1 shows that in the recent data, this share is above 70% for active and 98% for passive funds.

where B_e, B_θ, B_ω, and $\bar{B}$ are nonnegative scalars because $l \in (0, 1]$,[21]

$$\begin{aligned}
B_e &= l(1-l)\lambda_H \frac{\lambda_M}{a+b}, \\
B_\theta &= l^2 \frac{\lambda_M}{a+b} + \lambda_H, \\
B_\omega &= (1-l)\lambda_H, \\
\bar{B} &= \frac{1}{\frac{\lambda_M}{a+b}(l^2\lambda_D + (1-l)^2\lambda_H) + \lambda_D\lambda_H}, \\
\text{and } \omega_\lambda &\equiv \frac{b}{a+b}\lambda_M \omega.
\end{aligned}$$

Term ω_λ above represents BMI because it reflects the cumulative demand of fund managers induced by the relative performance component in their compensation (1). It also motivates the measure I use in the empirical part of the paper.[22]

Equation (7) highlights that benchmarking is a source of price pressure, or overvaluation, in my model (induced through the term $B_\omega \omega_\lambda$). It implies that if an asset's BMI ω_λ increases, for example, due to an addition to a market index, its price goes up (known as the index effect).

The equilibrium price also increases in the endowment of hedgers, $B_e e$. This is an equilibrium effect, which arises because the price increases in the fee that the manager can earn when lending the asset to hedgers. Higher hedging demand e makes lending more attractive, so the managers hold more of the asset, pushing the price up.[23] This is in contrast to the case with slack in the securities lending market: When the equilibrium fee is zero, the price unambiguously decreases in the endowment of hedgers, as I show in Section 3.3.2.

The equilibrium borrowing fee is

$$\Delta = \gamma\sigma\bar{B}\left(C_e e - C_\theta\bar{\theta} + C_\omega\omega_\lambda\right), \tag{8}$$

[21] Because I am focusing on the case with positive expected returns, that is, $\mu - p > 0$, the scalars have to satisfy $B_\theta\bar{\theta} - B_e e - B_\omega\omega_\lambda > 0$.

[22] ω_λ is an equivalent of the BMI introduced in Pavlova and Sikorskaya (2023), although here it is based on one benchmark index rather than multiple indexes. Extending to the case of multiple benchmark indexes does not change the key results in this paper.

[23] In line with that, Johnson and Weitzner (2023) show that some active mutual fund managers overweight assets with high borrowing fees. Furthermore, lending revenue accruing to price can be traced to the model in Duffie (1996).

where C_e, C_θ, and C_ω are scalars,

$$
\begin{aligned}
C_e =& \lambda_H \left((1-l) \frac{\lambda_M}{a+b} + \lambda_D \right), \\
C_\theta =& l \frac{\lambda_M}{a+b} + \lambda_H, \\
C_\omega =& (1-l)\lambda_H - l\lambda_D.
\end{aligned}
$$

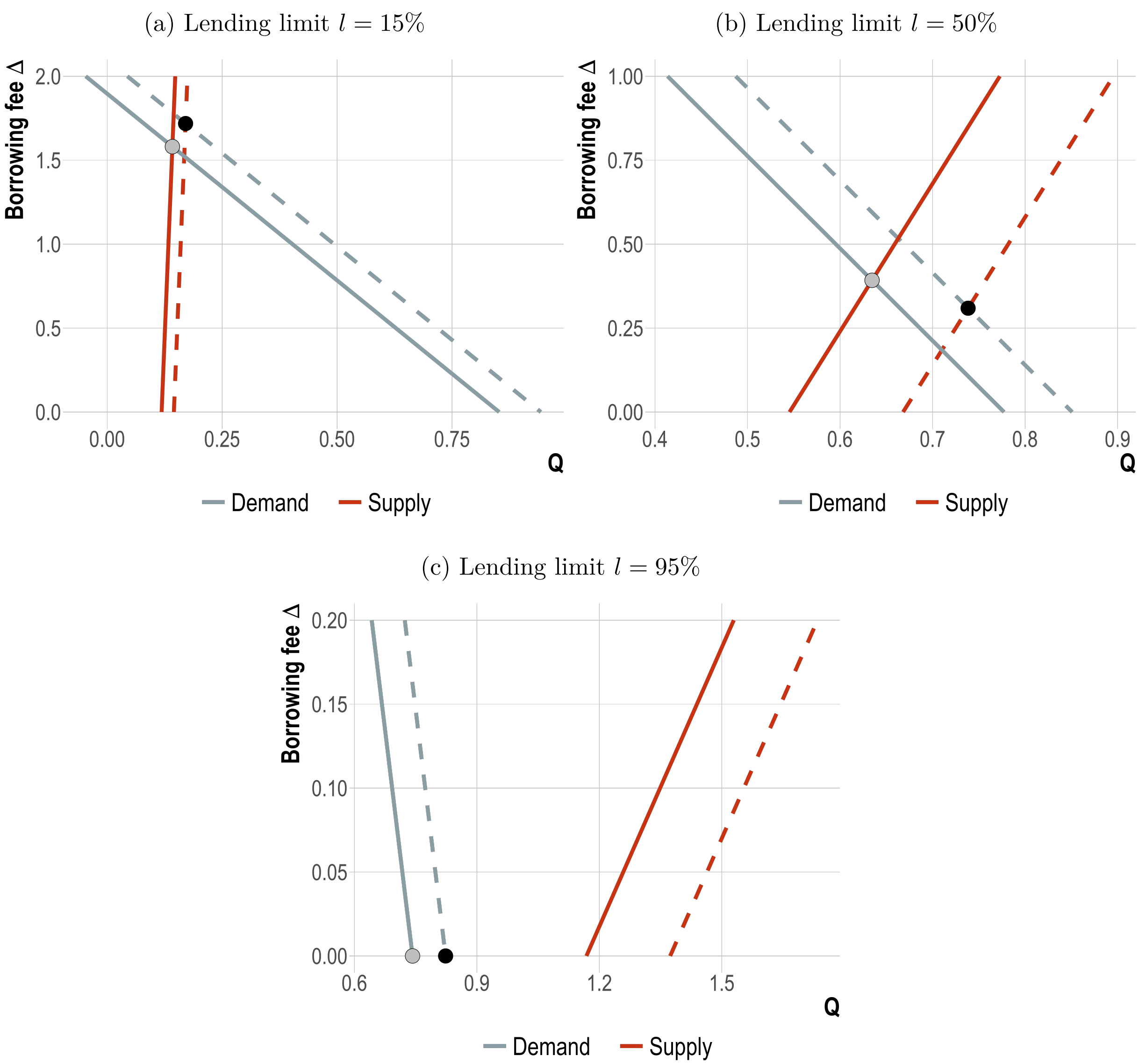
Because $l \in (0,1]$ and $\bar{B} > 0$, the equilibrium borrowing fee unambiguously increases in the size of the endowment of hedgers, e, and decreases in asset supply, $\bar{\theta}$. In contrast, the effect of the asset's BMI ω_λ depends on the sign of C_ω. If the population masses of hedgers and direct investors satisfy the following condition,

$$\frac{\lambda_H}{\lambda_D + \lambda_H} < l, \tag{9}$$

then $C_\omega < 0$ and the equilibrium borrowing fee decreases in BMI ω_λ. This condition compares the share of hedgers relative to direct investors with the lending limit l. When the limit is lenient enough, the supply effect of benchmarking dominates in the lending market. This model prediction is novel because the literature typically assumes that all long investors can lend, or in my model, $\lambda_D = 0$. Such an assumption is restrictive because not all (even institutional) investors have access to lending in the data (as shown in Internet Appendix A.1). Furthermore, in Internet Appendix D, I show that the relationship between benchmarking and borrowing fees is still ambiguous if direct investors are allowed to lend with a limit different from l. Finally, the trade-off between the demand and supply effects of benchmarking prevails even if the limit l is endogenously chosen by agents. In Appendices E and F, I solve extensions of the model with costly lending by fund managers and costly search by hedgers, respectively, and show that, although less tractable, such models deliver the same key results.

I provide a numerical illustration for the role of condition (9) in Figure 1. Panel (a) depicts the shift in the lending market equilibrium due to an increase in the BMI when $C_\omega > 0$ (setting $l = 15\%$). In this case, the equilibrium borrowing fee is higher with a larger BMI, the demand shift being larger than the supply shift. Panel (b) illustrates how the fee changes when $C_\omega < 0$ (setting $l = 50\%$). In this case, the fee is lower when BMI is higher because the supply shift is larger.

Figure 1: Demand and supply in the lending market



This figure plots demand and supply curves in the lending market. Panel (a) depicts the case when $l = 15\%$ ($C_\omega > 0$), panel (b) when $l = 50\%$ ($C_\omega < 0$), and panel (c) when $l = 95\%$ (general collateral asset). Solid lines correspond to an off-benchmark asset ($\omega_\lambda = 0$), while dashed lines correspond to an identical asset that belongs to the benchmark index. The black (gray) dot marks the equilibrium for the (off-)benchmark asset. The curves represent the partial equilibrium quantity demanded or supplied Q for each level of the borrowing fee Δ (and the corresponding equilibrium price). Internet Appendix B.4 details all parameter values.

3.3.2 General collateral asset

For a general collateral asset, lending market condition (6) is slack at the asset price which satisfies the spot market clearing (5). So the lending fee is zero and the equilibrium asset price is

$$p = \mu + \frac{1}{\frac{\lambda_M}{(a+b)} + \lambda_D + \lambda_H} \gamma\sigma(\omega_\lambda - \lambda_H e - \bar{\theta}). \tag{10}$$

Notice that, as for the asset on special, the price increases in BMI ω_λ (index effect) and decreases in supply $\bar{\theta}$. However, hedgers' endowment shocks e now reduce the price, because they increase shorting demand without triggering additional purchases from fund managers.

Panel (c) of Figure 1 illustrates the lending market for a general collateral asset, in which supply is always larger than demand and both are positively related to BMI.

3.3.3 Price sensitivity to benchmarking

In an economy with both benchmarking and securities lending, asset pricing effects of benchmarking are co-determined with the outcomes in the lending market of a special asset. Hence, the price sensitivity to benchmarking depends on whether the demand or supply effect of benchmarking dominates. Furthermore, a general collateral asset and a special asset have different sensitivities of price to benchmarking.

If the supply effect of benchmarking dominates, that is, if condition (9) holds, the price sensitivity of a special asset to benchmarking is lower than that of a general collateral asset. In other words, if benchmarking-induced purchases reduce the borrowing fee, more of the benchmarking price pressure will be counteracted by the hedgers' increased shorting. In the limiting case when fund managers lend out any new purchase of a benchmark asset ($l = 1$), benchmarking does not affect asset prices. See B_ω becoming zero in (7) and further details in Internet Appendix B.3. On the other hand, if the demand effect of benchmarking dominates, it will become even costlier to sell the asset short and the index effect will be larger. I formally compare price sensitivities with respect to benchmarking in Internet Appendix B.5, and Figure B1 provides the comparative statics for equilibrium price and borrowing fee.

3.4 Demand and supply in the lending market

My model features a downward-sloping shorting demand and an upward-sloping lending supply for special assets.[24] Demand is defined by the shorting needs of hedgers, whereas supply is

[24] Empirically, Kolasinski, Reed, and Ringgenberg (2013) find that the supply curve is mostly flat and has a positive slope for very high levels of specialness. The positive slope in my model comes from the

sourced from the fund managers' holdings up to the limit l,

$$Q^d = -\lambda_H \theta_H \quad \text{and} \quad Q^s = l\lambda_M \theta_M. \tag{11}$$

Only lending supply directly depends on BMI, while both shorting demand and lending supply are indirectly affected through equilibrium price and borrowing fee. In Internet Appendix B.6, I present the total derivatives of the demand and supply in the lending market with respect to BMI ω_λ. I find that both demand and supply always increase with ω_λ for both a special asset and a general collateral asset.

3.5 When do short-selling constraints bind?

The model explains how benchmarking contributes to short-selling constraints. From (8), there will be a strictly positive fee to borrow the asset if and only if

$$C_e e - C_\theta \bar{\theta} + C_\omega \omega_\lambda > 0. \tag{12}$$

That is, an asset for which (12) holds will be special. Notice that an asset is more likely to be on special when it has a lower supply $\bar{\theta}$ or when hedgers are more endowed with it (higher e). Naturally, an asset with a higher BMI ω_λ is less likely to be on special if $C_\omega < 0$, or if (9) holds, that is, if the supply effect of benchmarking dominates.

I can also rewrite (12) as a linear condition on l,

$$l < \lambda_H \frac{\left(\frac{\lambda_M}{a+b} + \lambda_D\right) e - \bar{\theta} + \omega_\lambda}{\frac{\lambda_M}{a+b}(\lambda_H e + \bar{\theta}) + (\lambda_D + \lambda_H)\omega_\lambda}.$$

Naturally, in an economy with a tighter limit on lending, any asset is more likely to be special.

3.6 Summary of model predictions

To summarize, I develop a model that features benchmarked fund managers who can lend their holdings to hedgers. It allows me to derive closed-form expressions for equilibrium asset prices

return-augmenting portfolio of fund managers, or the third term in their demand (3). Alternatively, I could assume that fund managers receive a windfall gain from their fund family or lending agent. In that case, their demand would not depend on the borrowing fee and the aggregate supply curve would be flat. To get a positive slope, one could define the lending limit as a nondecreasing function of borrowing fee (similar to the theoretical framework in Blocher, Reed, and Van Wesep (2013)), while the implications of benchmarking for the equilibrium borrowing fee would be qualitatively the same. The model in this paper provides a more tractable solution.

and borrowing fees in the presence of both benchmarking and securities lending. The model implies the following relationships. If an asset's BMI increases (for example, due to inclusion into a market index), my model predicts that

a) lending inventory (supply) should increase;

b) asset price should increase;

c) shorting demand should increase;

d) if the asset is on special, its borrowing fee should increase if the limit on fund manager lending is relatively tight and decrease if the limit is lenient;

e) if the asset is not on special, its borrowing fee should not change;

f) if we observe that the borrowing fee increases for the asset on special, its price increase should be higher than that for a general collateral asset.

In the following sections, I use a quasi-natural experiment to test the predictions of my model. I also evaluate the assumption of limited lending using novel regulatory data.

4 Data and Summary Statistics

4.1 Data sources

I use data on stock borrowing and lending activity from the S&P Global Securities Finance Equities Buyside Analytics Premium Data Feed (also known as Markit Securities Finance Buyside Analytics Premium Data Feed). The dataset includes daily stock-level data on borrowing activity, such as borrow-side loan fees, the quantity on loan, the available lendable supply, and other data. S&P obtains the information from loan market participants, who together account for over 90% of the market.[25] The daily data are available from July 2006.

My U.S. equity sample is an annual panel of stocks that were the Russell 3000 constituents in 2006-2018. To build the stock-level BMI measure, I use historical benchmark weights, primary prospectus benchmarks from historical fund prospectuses, and fund assets from the Center for Research in Securities Prices (CRSP) Survivor-Bias-Free U.S. Mutual Fund Database. The collection procedure for fund benchmarks is described in Section A.2.4 in the Internet Appendix. Historical benchmark weights are from FTSE Russell, Morningstar, and CRSP. Details on specific indexes

[25] See https://www.spglobal.com/marketintelligence/en/mi/products/securities-finance.html.

are reported in Section A.2.2 in the Internet Appendix. Importantly, Russell index data come from FTSE Russell directly. It includes proprietary total market values (capitalization) as of the rank day in May and provisional constituent lists available before the reconstitution day in June for the Russell 3000E index. U.S. stock data are from CRSP and Compustat and are described in Section A.2.1 of the Internet Appendix. Details on funds data are in Internet Appendix A.2.3.

I also collect information on funds securities lending from N-PORT and N-CEN filings. N-PORT reports are novel quarterly filings that replaced N-Q reports from the third quarter of 2019. Each filing includes the schedule of fund investments, the value of each holding on loan, and the value on loan with each borrower on the reporting date. The N-CEN annual reports are filed from 2019. They include high-level information such as whether the fund is permitted to lend and its net income from lending. I provide further details in Internet Appendix A.2.6.

4.2 Key summary statistics

Table 1 describes the key data samples used in this paper. It reveals that a typical general collateral stock next to the Russell cutoff has 28% of its shares in lending inventory and close to 5% loaned to short-sellers. On average, borrowing such a stock costs 39 bps per annum. Panel II of the table shows that 5% of stocks next to the Russell cutoff are special. They are costly to borrow, with an average borrowing fee of 5.6%. Special stocks have over 17% of their shares on loan, on average, which implies utilization of lending inventory of over 75%. Therefore, both samples are similar to those studied in the earlier literature, for example, in Saffi and Sigurdsson (2011). I provide detailed definitions and descriptive statistics for all variables in Internet Appendix A.3. Throughout my analysis, all variables are winsorized at 0.5% and 99.5% (or at 99% if taking only positive values).

5 Russell Reconstitution

In this section, I use the changes in the amount of capital benchmarked against stocks around the Russell index reconstitutions to test the predictions of my model in the U.S. equity market.

5.1 Russell reconstitution, benchmarking, and lending supply

The Russell indexes undergo annual reconstitution in June. All eligible stocks are ranked based on their market capitalization values, and the stocks above the so-called Russell cutoff are

Table 1: Key sample summary statistics

Variable	No. obs.	Mean	Median	St. dev.	p1	p99
Panel A: General collateral stocks						
ΔBMI, % MV	13,047	0.09	-0.04	2.56	-9.03	9.46
Δ Lending inventory, % shares	13,047	-0.03	0.07	1.88	-6.09	5.25
Δ Shorting demand, % shares	13,047	0.21	0.06	1.86	-5.20	6.41
Δ Borrowing fee, %	13,047	0.01	0.00	0.21	-0.15	0.25
Stock return, %	13,047	-0.85	-0.60	9.18	-26.10	23.45
BMI in May, % MV	13,047	22.10	23.19	6.19	4.97	33.31
Lending inventory in May, % shares	13,047	28.46	28.81	8.57	6.34	48.71
Shorting demand in May, % shares	13,047	5.06	3.23	5.38	0.06	24.09
Borrowing fee in May, %	13,047	0.39	0.38	0.09	0.25	0.79
Active utilization in May, %	13,047	15.54	10.57	15.07	0.20	64.18
Market value, USD million	13,047	3,485.75	2,471.14	2,899.54	526.99	13,512.05
Panel B: Special stocks						
ΔBMI, % MV	638	0.96	0.24	3.50	-6.37	12.19
Δ Lending inventory, % shares	638	0.32	0.21	2.74	-7.54	8.22
Δ Shorting demand, % shares	638	-0.35	-0.29	3.10	-7.57	7.44
Δ Borrowing fee, %	638	0.19	-0.21	4.09	-10.48	16.15
Stock return, %	638	-0.50	-0.27	13.80	-36.93	34.25
BMI in May, % MV	638	18.46	18.88	7.28	2.67	31.53
Lending inventory in May, % shares	638	17.84	17.02	8.96	1.85	42.49
Shorting demand in May, % shares	638	17.06	15.74	8.88	1.75	41.36
Borrowing fee in May, %	638	5.61	3.12	6.26	1.02	31.82
Active utilization in May, %	638	75.75	80.02	17.29	31.41	98.64
Market value, USD million	638	2,187.51	1,670.28	1,589.00	499.47	7,984.77

This table reports the summary statistics for the key samples analyzed in the paper. Statistics for general collateral stocks are presented in panel A and those for special stocks are presented in panel B. All stocks have to be within 500 ranks around the Russell cutoff in 2007–2018, with changes in lending market variables computed as differences between July and May. Stock return is as of June. A stock is considered special if its average fee in May is above 1% and a general collateral stock otherwise. ΔBMI is the change in BMI (amount of capital benchmarked against a stock relative to its market value), as defined in Section 5.1. Lending inventory is active lendable quantity and shorting demand is short quantity on loan, both scaled by shares outstanding. Active utilization is short quantity on loan as a fraction of active lendable quantity. Borrowing fee is Markit's indicative fee. See further details in Internet Appendix A.3.

assigned to the Russell 1000 index on the reconstitution day in June. This ranking is based on a fixed date in May, so any shock to a stock near the Russell cutoff can send it to one side or the other. The mechanical nature of this process makes the assignment of stocks to indexes next to the cutoff as good as random (Chang, Hong, and Liskovich (2015)).[26]

When a stock crosses the Russell cutoff, it enters a benchmark index of a different group of funds so the amount of assets benchmarked to that stock changes. Following Pavlova and Sikorskaya

[26] I discuss this in more detail and also explain how my approach avoids common research design issues with the Russell cutoff in Section A.5 of the Internet Appendix.

(2023), I compute the total benchmarking intensity (BMI) for stock i in month t as

$$BMI_{it} = \frac{\sum_{j=1}^{J} \lambda_{jt}\omega_{ijt}}{MV_{it}}, \tag{13}$$

where λ_{jt} is the assets under management (AUM) of mutual funds and ETFs benchmarked to index j in month t, ω_{ijt} is the weight of stock i in index j in month t, and MV_{it} is the market capitalization of stock i in month t. In constructing BMI, I rely on data for the 34 most tracked U.S. equity indexes, coming from S&P Dow Jones, CRSP, and FTSE Russell index providers, as explained in Section 4.

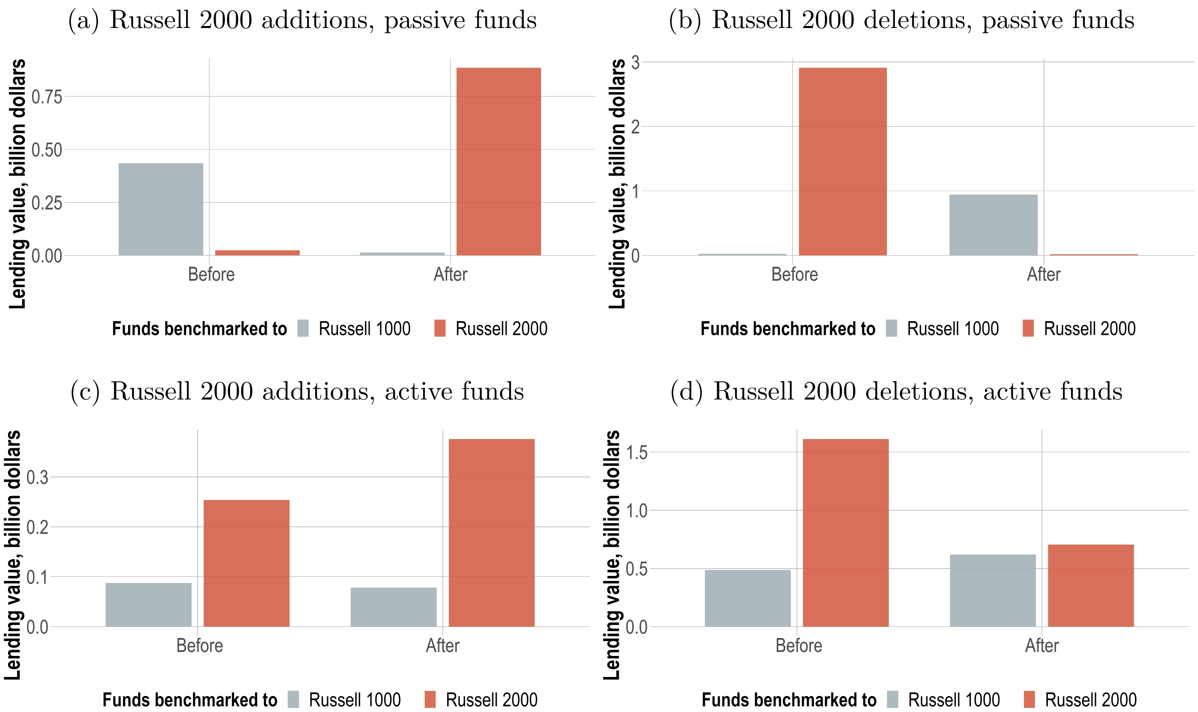
BMI has a large discontinuity around the Russell cutoff, due to stock membership in all nine Russell indexes that share this cutoff. These indexes include the Russell 1000 and the Russell Midcap to the left of the cutoff and the Russell 2000 to the right of it (blend, value, and growth in each case). On average, a stock moving from the Russell 1000 index to the Russell 2000 experiences a sizeable increase in BMI of 8.6 percentage points. Internet Appendix A.6 illustrates the discontinuity and discusses changes in BMI around the cutoff in more detail.

I use BMI rather than only the index membership in the main analysis for two reasons. First, it allows me to measure the strength of the pass-through to lending inventory and supply, which is an economically interesting figure. Specifically, this pass-through is related to the limit on lending in my model, see equation (11). Second, BMI offers more variation and hence higher precision of estimates in my regression analyses, which counteracts the small sample issues with having too few special stocks near the Russell cutoff. Nevertheless, I show in Internet Appendix A.9 that using the index membership dummy yields qualitatively the same results.

As long as the mechanical nature of Russell reconstitutions makes index membership exogenous, the change in BMI during the Russell reconstitution is not related to a given stock's fundamentals and can be used as a shock to the amount of capital benchmarked against the stock. The Russell reconstitution thus offers a quasi-experimental setup to study the effects of benchmarking on asset spot and lending markets.

Academic literature has documented discontinuities in mutual fund and ETF ownership around the Russell cutoff (see an overview in Glossner (2021)). Given that funds make their holdings available for lending, the increase in fund ownership is expected to increase the supply of shares in the lending market. I use funds' regulatory filings from 2020-2022 to illustrate that funds increase lending of stocks added to their benchmarks and reduce lending of stocks excluded from their benchmarks. Figure 2 shows that aggregate lending follows changes in funds' benchmarks. For example, there is a noticeable increase in lending by passive funds benchmarked to the Russell

Figure 2: Aggregate fund lending of the Russell 2000 index additions and deletions



This figure plots the aggregate fund lending of the Russell 2000 additions and deletions before (March–May) and after (July–September) the Russell reconstitutions of 2020–2022, according to funds' N-PORT filings. Only funds with identified benchmarks and types (active or passive) are included. Russell 1000 group includes funds benchmarked to the Russell 1000 and Russell Midcap indexes (blend, value, or growth). Russell 2000 group includes funds benchmarked to the Russell 2000 indexes (blend, value, or growth). Further details are provided in Internet Appendix A.7.

2000 of stocks added to the index (panel (a)). Similarly, active funds benchmarked to the Russell 2000 lend more of stocks added to the index (panel (c)). Internet Appendix A.7 shows that these patterns are significant at a stock level and provides further details of this analysis.

Therefore, lending and borrowing of a stock are likely to be positively related to the amount of capital benchmarked against the stock, as my model predicts. I formally test model predictions in the next section.

5.2 Benchmarking effects on spot and lending markets

The model in Section 3 predicts that an increase in BMI leads to increases in asset price, lending inventory, and shorting demand, whereas the prediction for the borrowing fee depends on the lending limit. In this section, I test these theoretical predictions using the change in BMI around the Russell reconstitution.

5.2.1 Regression specifications

To understand the effects of benchmarking on spot and lending market outcomes, I estimate the following specifications:

$$\Delta Y_{it} = \alpha \Delta BMI_{it} + \delta' \bar{X}_{it} + \mu_{st} + \varepsilon_{it}, \tag{14}$$

$$\Delta Y_{it} = \beta_1 \Delta BMI_{it} \times D(special)_{it} + \beta_2 \Delta BMI_{it} \times D(not\,special)_{it} + \zeta' \bar{X}_{it} + \nu_{st} + \epsilon_{it}. \tag{15}$$

The dependent variable, ΔY_{it}, is the change in the stock's lending inventory (active lendable quantity of shares), short quantity on loan (Markit's measure of short interest), borrowing fee, or the stock price. The changes in lending market variables are computed as the difference in means of daily observations for stock i between May and July of year t. Change in price is the return of stock i in June of year t (because June is the month when most of the price pressure due to the Russell reconstitution occurs, see the discussion in Chang, Hong, and Liskovich (2015)). ΔBMI_{it} is the difference between the BMI of stock i in May and June of year t (defined in (13)), which effectively compares the pre- and post-reconstitution levels of BMI.

Specification (15) introduces interactions between ΔBMI_{it} and $D(special)_{it}$ to allow the effect of BMI to be different for stocks on special and general collateral stocks, in line with my model. In all baseline analyses, I classify stock i as special, or $D(special)_{it} = 1$, if its average borrowing fee exceeds 1% before the reconstitution month (specifically, in May of year t), and zero otherwise (following D'Avolio (2002) and Aggarwal, Saffi, and Sturgess (2015)). As I discuss in Section 5.2.6, the results are qualitatively the same if specialness is defined using percentiles of the fee distribution (in relative terms) or using Markit's proprietary scores, which are widely disseminated to practitioners, and if it is measured in March or April of year t.

In both specifications above, $\bar{X}_{it}$ is a vector of controls ensuring exogeneity of ΔBMI. $logMV_{it}$ is the logarithm of total market value, the ranking variable as of May provided by Russell. $BandingControls_{it}$ include dummies for being in the band and being in the Russell 2000 as well as their interaction in May of year t. $Float_{it}$ is the Russell float factor, a proprietary liquidity measure affecting index weight. Conditional on $logMV_{it}$, $BandingControls_{it}$ and $Float_{it}$ in May, the change in BMI due to the Russell reconstitution is exogenous. With these controls, I broadly follow Appel, Gormley, and Keim (2019) (with further discussion in Section 5.2.6). Other controls in vector $\bar{X}$ include a five-year monthly rolling β^{CRSP} computed using CRSP total market value-weighted index and a one-year monthly rolling average bid-ask percentage spread. I supplement the controls with these variables to account for any stale information in the float factor, as discussed in Internet Appendix A.6. Finally, μ_{st} and ν_{st} are year by $D(special)$ fixed effects, which allow for

Table 2: Response of spot and lending variables to changes in benchmarking intensity (BMI)

	Δ Lending inventory, % shares	Δ Quantity on loan, % shares	Δ Borrowing fee, %	Stock return, %
	(1)	(2)	(3)	(4)
Panel A: No interactions				
ΔBMI, % MV	0.175***	0.136***	0.013**	0.122***
	(18.67)	(14.51)	(2.29)	(2.98)
Observations	13,685	13,685	13,685	13,685
Adjusted R-squared	0.144	0.089	0.078	0.202
Panel B: With specialness interactions				
ΔBMI, % MV × D(not special)	0.179***	0.129***	-0.004	0.105***
	(18.99)	(14.01)	(-1.26)	(2.59)
ΔBMI, % MV × D(special)	0.126***	0.213***	0.206***	0.306*
	(3.43)	(5.64)	(3.97)	(1.72)
Observations	13,685	13,685	13,685	13,685
Adjusted R-squared	0.144	0.090	0.106	0.202
$\beta_1 - \beta_2$	-0.053	0.083**	0.210***	0.201
	(-1.43)	(2.23)	(4.09)	(1.11)

This table reports the estimates of specification (14) (panel A) and specification (15) (panel B) in the panel of stocks within 500 ranks around the Russell cutoff in 2007–2018. The last row reports the t-test for estimation results in panel B. Changes in lending market variables are computed as differences between July and May; stock return is measured in June; see further details in Internet Appendix A.3. A stock is considered special, or $D(special) = 1$, if its fee in May is above 1%. All regressions include controls and D(special) by year fixed effects. t-statistics based on standard errors clustered by stock are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

differences in trends for special and general collateral stocks.

5.2.2 Results for the lending inventory and quantity on loan

Estimation results are presented in Table 2. Column (1) shows that a change in a stock's BMI is indeed strongly positively related to the change in the lendable inventory of its shares. On average, a 1 pp increase in BMI is associated with an 18 bps increase in the lending inventory. This is consistent with the Russell case studies discussed in Section 5.1 and corroborates the assumption of my model that benchmarked funds supply their holdings for lending.

Column (2) of Table 2 documents the effect of a change in BMI on the quantity on loan (short interest). Consistent with the prediction of my model, quantity on loan significantly increases, for both general collateral and special stocks. The magnitude of the increase is economically significant and similar to that of the change in inventory, at 13 bps for general collateral stocks and 21 bps for special stocks per 1 pp increase in BMI. Results in column (2) are in line with Pavlova and

Sikorskaya (2023), who show that BMI increases short interest in the full sample of stocks around the Russell cutoff.[27]

5.2.3 Results for the borrowing fee

Column (3) of Table 2 sheds light on the ex-ante ambiguous relationship between benchmarking intensity and borrowing fees. I find that the borrowing fee of special stocks increases in response to the rise in BMI, which implies that the demand effect of benchmarking dominates in Russell reconstitutions. The increase is economically significant, with the fee rising by 21 bps for a 1 pp increase in BMI. This implies that special additions to the Russell 2000 see their borrowing fees increase by 1.5 pp (their average BMI change is 7.4 pp).[28] This corresponds to an increase of over 25% relative to the level in May.

Importantly, column (3) of Table 2 shows that there is no change in the borrowing fee for general collateral stocks. In the language of my model, the lending market constraint is slack because the lending supply is abundant. Consistent with that, general collateral stocks have 28% of their shares in lending inventory, on average, and only 5% of their shares are on loan to short-sellers, as shown by the descriptive statistics in Table 1.

These results shed new light on the role of institutional ownership in the formation of short-selling constraints. The literature has typically associated institutional ownership with a larger lending supply and lower borrowing fees. For example, Prado, Saffi, and Sturgess (2016) document that a one-standard-deviation increase in institutional ownership (equal to 30 pp in their sample) is associated with a decrease in fees of 5.6 bps, on average, for general collateral and special stocks in 2006-2010. Estimates in column (3) of Table 2 imply that a one-standard-deviation increase in BMI leads to a 3.2 bps (72.5 bps) increase in fees in the pooled (special) sample. For more comparability, in Section 5.2.5, I study the implied changes in institutional ownership around the Russell cutoff. I estimate that a 1 pp increase in institutional ownership leads to a 77 bps increase in fees for special stocks. In sum, I find that despite increasing the lending supply, an inflow of institutional capital leads to higher borrowing fees.

I plot the average daily estimates of regression (14), separately for special and not special

[27] Results of this subsection are also generally consistent with the findings of a contemporaneous study of lending supply and demand around Russell reconstitutions in Beschwitz, Honkanen, and Schmidt (2022). They document an increase in lending inventory and quantity on loan for stocks added to the Russell 2000 index. However, this paper does not study special stocks and hence does not find that index membership triggers changes in their borrowing fees, which is the key result of my paper and is tightly connected with the model in Section 3.

[28] In Internet Appendix A.9, I get the same magnitude when estimating equation (15) using an index membership dummy rather than the change in BMI.

stocks, in Internet Appendix A.11. Consistent with inelastic buying (and lending) by benchmarked fund managers, lending supply sharply increases at reconstitution (considering the settlement of T+3 prevalent in my sample). Similarly, quantity on loan sees the largest increase then too. Yet, it takes the borrowing fees of special stocks around one month to get to the level corresponding to the estimate in Table 2. In fact, the borrowing fee variable provided by Markit is a value-weighted average across all outstanding loans so the new equilibrium fee level will get incorporated into this variable only after loan contracts are renewed. Finally, Internet Appendix A.11 confirms that none of these variables exhibits an imbalance before the reconstitution month.

The model in Section 3 also predicts that benchmarking may make an asset special if the demand effect dominates. In Internet Appendix A.14, I study switches from a general collateral to a special status and show that a stock with a larger increase in BMI is more likely to remain special after the reconstitution. However, this effect is economically small and not statistically significant, potentially due to the small number of switches in my sample period.

5.2.4 Results for the stock price

Consistent with my model's prediction for the stock price, Table 2 confirms that price pressure is the highest for stocks experiencing the largest increase in BMI, all else being equal. As per column (4) of Table 2, a 1 pp increase in BMI leads to a 12 bps higher return in June. This is not a new result, as there is a vast body of literature documenting the index effect. What is novel, however, is that the index effect is stronger for special stocks, with the magnitude of the coefficient on ΔBMI increasing threefold for these stocks (although not significantly in this specification). In my model that occurs when the demand effect of benchmarking dominates, so it is in line with the result in column (3).

Estimates in column (4) of Table 2 suggest that the price elasticity of demand for special stocks is lower than that of general collateral stocks. Because α in specification (14) is the sensitivity of the change in price to the change in quantity, the average estimate of the price elasticity of demand in my sample is -1/0.12 = -8.3. Panel B of Table 2 reveals that the elasticity estimate for special stocks is -1/0.31 = -3.3 and -1/0.11 = -9.5 for general collateral stocks.[29] The difference in these

[29] My elasticity estimates are larger in magnitude than those in the literature (e.g., -1 in Koijen and Yogo (2019)), yet they should be viewed as upper bounds for two reasons. First, the change in BMI assigns the same importance to active and passive funds while the model predicts that passive funds should have a larger weight (I discuss sensitivity with respect to that in Internet Appendix 5.2.5). Second, I assume that all rebalancing occurs in June and none of it is anticipated. If some of the price pressure occurs in May or July, the true price impact coefficient should be larger than that reported in column (4) of Table 2. Assuming a 50% weight on active AUM and a 50% anticipatory price pressure yields the elasticity estimates of -1.2 and -2.8 for special and general collateral stocks, respectively.

estimates is consistent with prior literature linking the size of index effect to arbitrage risk (for example, Wurgler and Zhuravskaya (2002) and Petajisto (2009)).

5.2.5 Pass-through from BMI to lending supply

Results thus far suggest that the pass-through from BMI to lending supply is rather weak. In this section, I argue that this reflects both the insufficient response of inventory and its limited utilization. Finally, I use changes in BMI as an instrument for changes in institutional ownership around the Russell cutoff to show that the pass-through from ownership to supply is also limited.

My estimates in column (1) of Table 2 imply that one dollar of new benchmarked capital translates into only 18 cents of new lending inventory. This coefficient is estimated quite precisely and stable across specifications, as verified in Internet Appendices A.10 and A.13. However, the estimated pass-through is likely a lower bound for the true pass-through because of how BMI is constructed. When computing BMI, I assign equal weights to active and passive funds, while the true weight on active funds should reflect the strength of the relative performance component in their compensation ($b/(a+b)$ in the model). If I assume a lower weight on active funds, the estimate of the pass-through increases. Table 3 reports the sensitivity of the pass-through estimate to how active funds' assets are weighted in BMI. The estimated pass-through increases as the weight on active funds is reduced. Assuming that active funds do not contribute to BMI (and the lending inventory) at all, the pass-through of passive BMI is 59%.[30] Therefore, the estimates in Tables 2 and 3 suggest that the true level of the pass-through from BMI to lending inventory lies in the range of 18% and 59%.

Furthermore, the response of lending supply to BMI is also weakened by the fact that only a fraction of lending inventory typically gets utilized; this is known as utilization of inventory. In my model, utilization corresponds to the lending limit (see Section 3.4). Stocks next to the Russell cutoff have pre-reconstitution utilization levels of 16% and 76% for general collateral and special stocks, respectively. Moreover, utilization increases by only around 0.3 percentage points in response to a 1 pp increase in BMI, as shown in Internet Appendix A.15.

To account for the potential differences between the ownership changes predicted by BMI and the actual changes in institutional ownership, I use changes in BMI as an instrument for changes in institutional ownership following Pavlova and Sikorskaya (2023). ΔBMI remains a valid instrument in my application because it affects all dependent variables only through changes

[30] This assumption is not realistic as the case studies in Internet Appendix A.7 show a large contribution of active funds to lending around Russell reconstitutions and the aggregate N-PORT data suggests almost equal contribution in recent years.

Table 3: Response of lending inventory to changes in BMI for different levels of active funds' contribution

	Δ Lending inventory, % shares					
	(1)	(2)	(3)	(4)	(5)	(6)
ΔBMI, % (0% active)	0.591***					
	(11.75)					
ΔBMI, % (20% active)		0.452***				
		(15.81)				
ΔBMI, % (40% active)			0.329***			
			(17.34)			
ΔBMI, % (60% active)				0.254***		
				(18.07)		
ΔBMI, % (80% active)					0.205***	
					(18.48)	
ΔBMI, % (only active)						0.208***
						(19.77)
Observations	13,685	13,685	13,685	13,685	13,685	13,685
Adjusted R-squared	0.123	0.137	0.142	0.144	0.144	0.146

This table reports the estimates of specification (14) for alternative definitions of BMI in the panel of stocks within 500 ranks around the Russell cutoff in 2007–2018. Changes in lending inventory are computed as differences between July and May; see details in Internet Appendix A.3. All regressions include controls and D(special) by year fixed effects. t-statistics based on standard errors clustered by stock are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

in ownership. In particular, I estimate the following two-stage least squares regression:

$$\Delta IO_{it} = \kappa \Delta BMI_{it} + \delta' \bar{X}_{it} + \mu_{st} + \varepsilon_{it}, \tag{16}$$

$$\Delta Y_{it} = \alpha \widehat{\Delta IO}_{it} + \zeta' \bar{X}_{it} + \nu_{st} + \epsilon_{it}. \tag{17}$$

ΔIO_{it} is the change in institutional ownership of stock i implied by the quarterly 13F filings from March to June of year t, computed relative to the stock's market value.[31] The rest of the specification is the same as in the baseline test; see equation (14).

Table 4 reports the estimates. The first-stage estimation results confirm that ΔBMI is a strong instrument for ΔIO, with an F-statistic of 117.1. Second-stage results show that the pass-through from institutional ownership to lending inventory is at 67% (42% for special stocks). Finally, I find that a 1 pp increase in institutional ownership of special stocks leads to a 77 bps increase in their borrowing fees.

[31] To compute institutional ownership ratios, I follow the code of Luis Palacios, Rabih Moussawi, and Denys Glushkov, which is publically available on WRDS. I run the code on Thomson Reuters s34 regenerated data that avoids errors identified in 2010–2016. See https://wrds-www.wharton.upenn.edu/documents/952/S12_and_S34_Regenerated_Data_2010-2016.pdf.

Table 4: Response of lending variables to changes in institutional ownership (IO) instrumented by changes in BMI

	Δ Lending inventory, % shares			Δ Quantity on loan, % shares	Δ Borrowing fee, %	Stock return, %	Δ Lending inventory, % shares	Δ Quantity on loan, % shares	Δ Borrowing fee, %	Stock return, %
	OLS			2SLS			2SLS			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Panel A: Second-stage estimates										
ΔIO, %	0.088***	0.803***	0.673***	0.523***	0.049**	0.466***				
	(14.77)	(8.69)	(10.82)	(10.01)	(2.15)	(2.87)				
ΔIO, % $\times$ D(not special)							0.695***	0.500***	-0.013	0.415***
							(19.11)	(14.05)	(-0.95)	(2.65)
ΔIO, % $\times$ D(special)							0.416***	0.787***	0.770***	1.055*
							(3.44)	(6.16)	(4.42)	(1.69)
Panel B: First-stage estimates										
ΔBMI, %			0.259***							
			(10.82)							
D(in Russell 2000 in June)		2.747***								
		(9.31)								
Observations	13,691	13,691	13,691	13,691	13,691	13,691	13,691	13,691	13,691	13,691
F-Stat. (excl. instruments)		86.7	117.1							

This table reports the estimates of specification (16) (panel A) and specification (17) (panel B) in the panel of stocks within 500 ranks around the Russell cutoff in 2007–2018. Column (1) reports an OLS estimate of the coefficient of lending inventory on the change in institutional ownership. Columns (2) and (3) report 2SLS estimates with Russell 2000 membership dummy and ΔBMI used as instruments, respectively. Columns (4)–(6) report 2SLS estimates for other dependent variables, for which I do not report first-stage estimates because they are the same as in column (3). In columns (7)–(10), I first compute values of IO predicted with ΔBMI, then use these predicted values, interacted with specialness, in the second stage. I do not adjust standard errors to account for the prediction step. A stock is considered special, or $D(special) = 1$, if its average fee in May is above 1%. Changes in lending market variables are computed as differences between July and May; stock return is measured in June; see further details in Appendix A.3. All regressions include controls and D(special) by year fixed effects. t-statistics based on standard errors clustered by stock are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

5.2.6 Robustness and further discussion

This section addresses potential concerns about the research design, assumptions, and interpretation of the results.

First, my results are robust to a number of permutations in the research design. In the baseline analysis, I use a local linear regression approach; that is, the samples are restricted to the neighborhood of the cutoff (rectangular kernel). My baseline bandwidth is 500 stocks around the cutoff, which allows for sufficient variation in special stocks; and Table A9 in the Internet Appendix shows that my findings are robust to changing the bandwidth to 200, 300 or 750 stocks. Furthermore, due to the small number of special stocks, I do not include the interactions of control variables with specialness in the baseline specification. Table A8 in the Internet Appendix demonstrates that the results are robust to adding such interactions and to including fewer controls. I cluster standard errors by stock, yet my conclusions are not affected if I double-cluster standard errors by stock and year instead. Finally, the results are robust to including stock fixed effects and using alternative definitions of specialness, as shown in Internet Appendix Table A7.

Second, the main threat to using changes in BMI in stock-level regressions is that index membership is potentially endogenous. However, there is a large body of literature that uses membership in the Russell 2000 index as an instrument for institutional ownership in a similar setting. This literature argues that, after controlling for factors that determine index inclusion, such as the ranking variable that Russell uses for index assignment at the end of May, the index membership is exogenous. For the same purpose, Appel, Gormley, and Keim (2019) advocate including banding controls to account for the specifics of the Russell methodology after 2007. Appel, Gormley, and Keim (2021), Heath, Macciocchi, Michaely, and Ringgenberg (2021) and Wei and Young (2021) discuss potential issues with the construction of the sample and controls, which I largely avoid by using the proprietary Russell ranking variable and Russell 3000E index files. I provide further details in Section A.5 of the Internet Appendix. Furthermore, Internet Appendix A.6 shows that stock liquidity could be a potential source of endogeneity of ΔBMI due to stocks' float factors entering the expression for BMI. To address that concern, I control for the Russell proprietary float factor as of May and include the bid-ask spread to account for potential staleness in the float factor. Finally, Internet Appendix A.12 confirms that the main results go through if I exclude stocks that move across the Russell cutoff. The remaining stocks experience (smaller) changes in BMIs because their index weights get revised as *other* stocks are moving across the cutoff. Therefore, such variation is even less likely related to the fundamentals.[32]

[32] I thank Antonio Coppola and Matteo Maggiori for pointing this out. A similar identification approach is used by Aghaee Shahrbabaki (2022) for the S&P 500 index.

A potential concern with the Russell reconstitution setting is that it has been used many times in economic research, and hence a multiple testing problem may arise. Nevertheless, the relevant t-statistics in Table 2 are well above the 5% critical value that accounts for multiple testing, suggested in the literature specifically for the Russell reconstitution.[33]

Third, it may not be immediately clear from the empirical results that a change in BMI leads to a shift in lending supply. Given the observed increase in borrowing fees and quantity on loan for special stocks, a shift in demand must have occurred. However, the positive coefficient in column (1) of Table 2 may be due to both the shift in the supply curve and the movement along the supply curve. I argue that it is the former for two reasons. First, lending inventory is slow-moving and unlikely responsive to fees at the horizon of my test. The advertised inventory represents the total potential number of shares available for lending, not the number of shares available at current fee levels, as pointed out by Saffi and Sigurdsson (2011) and others.[34] Second, Internet Appendix A.13 formally shows that my reduced-form estimates imply a stronger pass-through to shorting demand than to lending supply. By exploiting an instrument for demand for special stocks suggested by the literature, I identify a positive shift in inventory and supply curves due to BMI and confirm that my estimate of the pass-through is not sensitive to the simultaneity of supply and demand. Moreover, I find that the sensitivity of supply to fees around the Russell reconstitutions is weak, which might be due to both the short horizon of my test and the empirical evidence for the prevailingly flat supply curve discussed in footnote 24. Therefore, a change in BMI indeed leads to a shift in lending supply.

Furthermore, it is also plausible that special stocks with increases in their BMIs (predominantly additions to the Russell 2000) have experienced some form of distress that made them special in the first place, drove addition to the index and brought about higher borrowing fees. I verify that results are virtually the same if I exclude stocks that are likely to be in distress, as measured by Altman's Z-score (Altman (1968)) below 3 or a drastic decrease in market value rank in the previous year (a drop of 500 ranks). Additions to the Russell 2000 also have similar pre-reconstitution proprietary Russell value ratios and Compustat-based book-to-market ratios, and my results are

[33]In particular, Heath, Ringgenberg, Samadi, and Werner (2023) recorded 17 outcomes studied around the Russell reconstitutions, which implies a t-statistic of 2.91 using the multiple-testing correction from Romano and Wolf (2005) and Romano and Wolf (2016). This number is reported on their website `https://www.reusingnaturalexperiments.com/database` (as of September 2023). Assuming 30 outcome variables studied, the 5% critical value for t-statistic should be 3.07.

[34]This is Markit's description of how lending inventory is constructed: "The lending pools are generally aggregated from underlying asset owners who have their assets in custody with the lending agents. The pool is not dependent on fee, it is more dependent on which instruments asset owners have a long-term positive view, as they are more likely to lend out an instrument they have a long-term positive view on." See further discussion and suggestive evidence in Baklanova, Caglio, Keane, and Porter (2016).

robust to controlling for them.

An underlying assumption in my analysis is that special and general collateral stocks are different across a dimension orthogonal to BMI, which is driving shorting demand. In the model, it is represented by the size of hedgers' endowment e. A large part of the literature takes disagreement–for example, measured by the dispersion of analyst forecasts (Diether, Malloy, and Scherbina (2002))–as the key driver of short-selling and stock specialness. Given the mechanical nature of the Russell reconstitution, disagreement should not be related to changes in BMI. I validate this assumption in Internet Appendix A.16 and show that my estimates are virtually unaffected if concurrent changes in disagreement are included as controls.

Finally, contemporaneous research has argued that market participants perceive borrowing from passive funds as less risky (Palia and Sokolinski (2024) and Beschwitz, Honkanen, and Schmidt (2022)). This could be due to, for example, the less frequent recall of previously lent shares by lenders with longer investment horizons. Through this channel, the equilibrium shorting demand and borrowing fee could also increase with BMI as long as it reflects a more stable lending supply.

I test for this channel using several borrowing risk measures (following Engelberg, Reed, and Ringgenberg (2018) and Muravyev, Pearson, and Pollet (2022b)) and find no reduction in these measures for special stocks in my sample. Specifically, I check how the borrowing fee volatility, utilization volatility, number of failures to deliver, and the option-implied fee risk premium change with BMI around the Russell cutoff. I observe no change in fee risk premium and failures to deliver while fee volatility *increases* in some specifications. Tables A15 and A16 in the Internet Appendix report these results. They also document that the borrowing fees implied by option prices increase with the same magnitude as Markit's fees, further validating my measure of borrowing costs. Overall, BMI does not seem to increase shorting demand by reducing borrowing risk in my sample.

5.2.7 External validity

With increasing size of the passive fund industry and decreasing tracking errors of active funds (Stambaugh (2014)), benchmarks should have an increasing influence on lending supply. Indeed, even further away from the Russell cutoff, funds mostly lend stocks that are inside their benchmark indexes. Internet Appendix A.8 illustrates that funds benchmarked to the largest Russell indexes primarily lend stocks within their benchmarks. For example, within-benchmark stocks account for almost 99% of loan values of funds benchmarked to the Russell 1000 index. Similarly, above 83% of the loan value of Russell 2000 funds comes from stocks within this index. The value-weighted average share of loan values that comes from such within-benchmark lending is over 86% in my sample period.

My results extend to other settings with mandate-driven rebalancing, such as central bank purchases. In fact, the literature has argued that lending of bonds from a central bank's balance sheet affects quantitative easing effectiveness (e.g., Pelizzon, Subrahmanyam, Tomio, and Uno (2024), Roh (2022), and Jappelli, Subrahmanyam, and Pelizzon (2023)), which is similar to how lending of institutions affects the role of investment mandates for asset prices. To gather further evidence outside of the Russell experiment, I study purchases of ETFs by the Bank of Japan (BoJ) in 2010–2022. I find that cross-sectional shocks to the size of the BoJ purchases lead to results very similar to those reported in the main text. Specifically, with an increase in the BoJ purchases, special stocks in Japan experience an increase in lending supply, shorting demand, and borrowing fees. This evidence from the BoJ purchases suggests that the demand effect of benchmarking is dominant for Japanese stocks as well. Details of this test, identification assumptions, and the results are provided in Internet Appendix G.

Finally, even though the number of special stocks in my main U.S. sample is limited, it is an important group of securities. An increasing number of studies are linking asset pricing anomalies to special stocks (Chen, Hong, and Stein (2002), Geczy, Musto, and Reed (2002), Stambaugh, Yu, and Yuan (2012), Drechsler and Drechsler (2016), and Muravyev, Pearson, and Pollet (2022a)). Even though historically around 10% of U.S. stocks have been considered special at a given point in time, over 80% of stocks become special at some point of their lifespan, and Daniel, Klos, and Rottke (2024) show that in recent years the share of stocks on special has grown closer to 30%. In other geographies, special stocks typically represent even a larger share of the market, for example, a third of the Japanese market, as shown in Internet Appendix G.

5.3 What drives limited lending?

The previous section shows that borrowing fees increase with BMI. In the model, it is the lending limit on fund managers' holdings that is driving a wedge between the demand and supply effect of benchmarking. The dominant demand effect of benchmarking and the weak pass-through from BMI to lending inventory suggest that managers underprovide their holdings for lending.

Consistent with that, in this section, I uncover explicit limits on lending set by investment companies in the United States and document suggestive evidence for funds' binding lending supply in the recent Russell reconstitutions. I also discuss other potential drivers of the limited pass-through from benchmarking to lending supply.

5.3.1 Evidence on explicit lending limits from regulatory filings

The recent modernization of fund regulatory reporting in the United States has provided more granular data on lending. I use N-PORT and N-CEN filings, available for the Russell reconstitutions from 2020, to shed light on explicit lending limits.

One of the well-known limits on lending is that regulators in the United States impose a total portfolio-level lending limit of 1/3, which is often quoted in the literature. Because collateral may be counted as part of the total assets, this usually means that funds are allowed to lend up to 50% of their net assets. However, in the data, this limit does not bind. Internet Appendix A.1 combines N-PORT and N-CEN filings to show that the value on loan represents only 1% of investment company assets (on average and conditional on lending). Furthermore, Figure A2 in the Internet Appendix graphically demonstrates that the percentage of fund net assets on loan (for all funds that lend) is significantly below the regulatory limit.

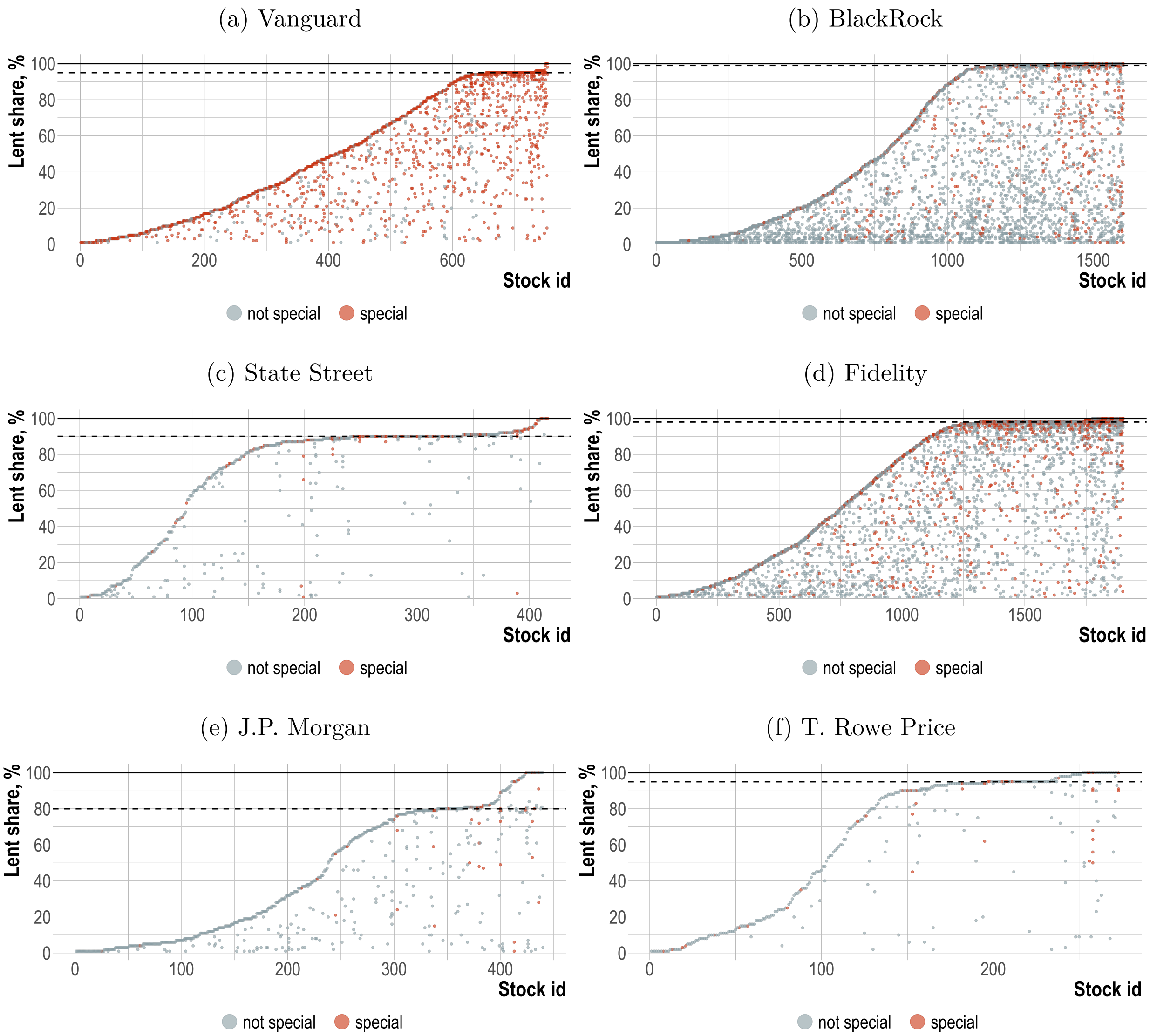
Funds also set limits on lending at the position level, driven by their investment and lending policies. Figure 3 plots how much of each holding is on loan (lent share) for several prominent investment companies in the United States. Because lending is affected by demand, the lent shares can be anywhere between 0% and 100%. However, the bunching of lent shares reveals that investment managers impose position-level limits on securities lending.[35] For example, Vanguard funds seem to have an effective limit of 95%, whereas State Street funds limit their lending to 90% of position values.[36] Passive funds of Fidelity show a limit of around 97.5%. A notable exception is BlackRock, which has the most lenient limit, at 99%, if any. Active fund managers also impose limits. For example, the plots for J.P. Morgan and T. Rowe Price in panels (e) and (f) reveal fuzzy limits at 80% and 95%, respectively.

If the limited lending by funds is important in driving the demand effect of benchmarking, we should observe that their lending inventory is exhausted during Russell reconstitutions and that larger lent shares are associated with higher borrowing fees. In Internet Appendix A.7, I use the N-PORT data on Russell 2000 additions and deletions in the 2020–2022 reconstitutions to demonstrate that both are supported by the data. First, I use regression analysis to explore whether the increase in a stock's borrowing fee is related to how much of that stock funds lend out. The results suggest that borrowing fees increase more when the lent shares are larger, and this

[35] Figure 3 also reveals that for any given stock, the share of holding on loan is almost always the same across funds within an investment company. This means that all funds get an allocation of lending proportional to how much they hold within their company, implying that the lending decisions are likely to be made at a company level. This is consistent with Honkanen (2024), which finds that allocation of lending across funds is proportional to their AUM.

[36] My conversations with representatives of State Street and Vanguard confirmed that these companies had limits at these levels.

Figure 3: Illustration of lent shares at position level for prominent investment managers in the United States



This figure plots the share of each holding that is on loan for funds managed by Vanguard, BlackRock, State Street, Fidelity, J.P. Morgan, and T. Rowe Price. The data are as of the report date in the second quarter of 2021 and rounded to percentage points. I include only domestic equity funds with a defined active or passive type, as described in Internet Appendix A.2.3. On the x-axis is a unique ID assigned for each stock on loan within each investment manager. Each dashed line corresponds to the sample mode of lent shares, computed using all lent shares above 1% within the corresponding company. Observations with a lent share above 100% are set to 100%.

relationship is present only for special stocks, which is consistent with the model. Second, the lent share histograms in Figure A6 in the Internet Appendix illustrate that many special stocks moving between indexes during the Russell reconstitutions are lent out at the levels of 90%–100% of how much funds hold. However, the same histograms also reveal that many funds do not lend these special stocks at all (lent share is 0%). This is puzzling in light of my model because funds seem to forgo income from lending these high-fee stocks. Therefore, the next section discusses factors that can drive limited lending apart from portfolio-level and position-level limits.

5.3.2 Further discussion of limited lending

In addition to the explicit lending limits discussed in the previous section, other factors, such as lending market participation costs, concentration of lenders, and search frictions, could contribute to the limited pass-through from BMI to lending supply. In this section, I discuss these factors in more detail and argue that they can unlikely fully explain the sparse lending of special stocks around the Russell reconstitutions documented in the previous section.

First, my results above abstract away from the costs of lending. Not all funds are even permitted to engage in securities lending, according to their investment policies. Anecdotally, industry practitioners cite reputation concerns, fiduciary duty, and small investment scale as drivers of a decision not to lend. Internet Appendix A.1 shows that according to the recent regulatory filings of domestic equity funds, around 99% of passive funds and 73–86% of active funds are permitted to lend. Of those, around 99% of passive funds and 84–94% of active funds participate in lending activities. Having decided to lend, funds face the costs of running a lending program (whether in-house, through a custodian, or a third-party lending agent). Therefore, the observed limited lending may reflect such cost-benefit trade-offs. In Internet Appendix E, I introduce costly lending into the model in Section 3. I find that even if lenders can set the lending limit endogenously, benchmarking has an ambiguous effect on the borrowing fee.

Additionally, the literature has demonstrated that lender concentration can reduce lending supply (Prado, Saffi, and Sturgess (2016) and Chen, Kaniel, and Opp (2022)). Internet Appendix A.15 documents that the concentration of loan values across lenders, as computed by Markit, decreases for general collateral stocks and does not change for special stocks in response to an increase in BMI. Furthermore, I find that special stocks in my sample exhibit a relatively low lender concentration of 19% (out of 100%). Similarly, there is a small decrease in inventory concentration (or the distribution of the quantity of lendable shares across potential lenders rather than the distribution of the actual quantity of loan), and its pre-reconstitution level for special stocks is also 19%. Hence, changes in lender concentration alone cannot account for my findings, and yet, it is plausible that its level could contribute to the limited pass-through from new benchmarked capital to lending supply.

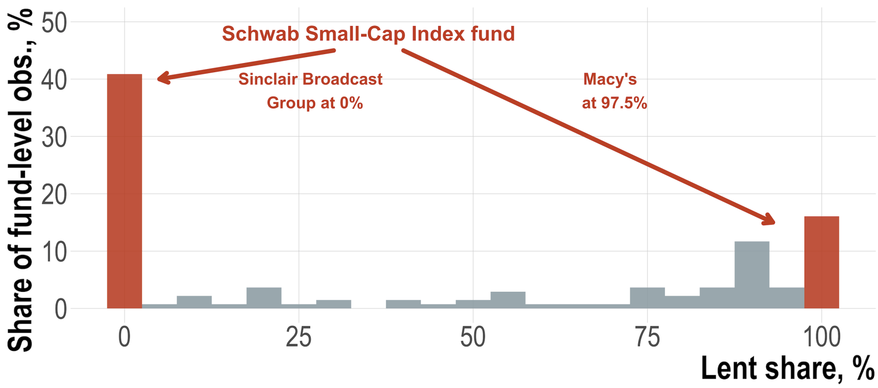
Finally, since most lending transactions happen over the counter, search frictions may contribute to the incomplete utilization of inventory (Duffie, Gârleanu, and Pedersen (2002)). These frictions are evident in the active involvement of specialist lending agents and prime brokers, documented loan fee dispersion (see Kolasinski, Reed, and Ringgenberg (2013) and Chague, De-Losso, Genaro, and Giovannetti (2017)), as well as in the ongoing efforts of regulators to enhance transparency in the securities lending markets (U.S. Securities and Exchange Commission (2021)). These frictions should be alleviated with an increase in BMI, as benchmarked owners are widely known to supply their holdings for lending. Nevertheless, Internet Appendix F augments the model in Section 3 with costly search by borrowers (similar to Banerjee and Graveline (2014)). I find that even when short-sellers optimally choose the lending limit (search intensity), benchmarking may increase or decrease the equilibrium borrowing fee, consistent with the baseline model.

Lending costs, lender concentration, and search costs are unlikely to fully explain limited lending in the data. To illustrate that, Figure 4 plots a histogram of lent shares in special stocks added to the Russell 2000 index in 2020-2022, based on the holdings of benchmarked funds in the quarter after reconstitution. Over 40% of these stocks are not lent out, and even such prominent lenders as Vanguard and Schwab do not lend some special stocks (see panels (a) and (b)). For those stocks that are lent, funds mostly lend more than 75% of what they hold in these stocks. Moreover, the same special stock may be fully lent by some funds but not by others (e.g., TIAA-CREF's lending of Sinclair Broadcast in panel (c)).

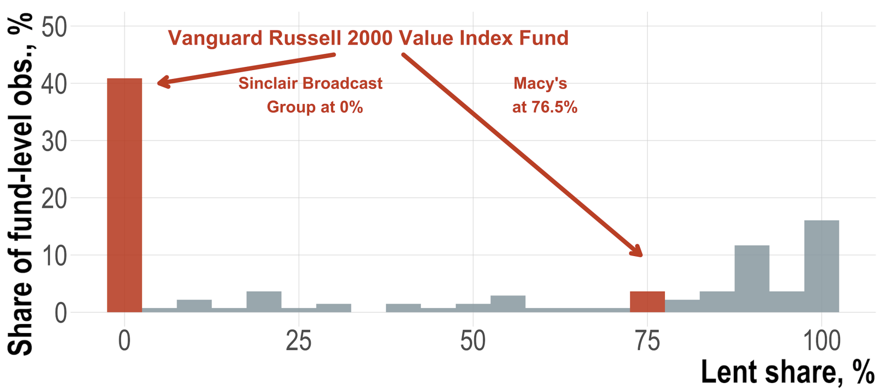
These lending patterns suggest that funds may specialize in lending only a subset of stocks. To formalize this, in Table A18 in the Internet Appendix reports conditional correlation coefficients between lent shares and some basic stock characteristics. It shows that fund-by-stock fixed effects account for over half of the variation in the extensive margin (whether a fund lends a special stock) and 40% of the variation in the intensive margin (how much is lent). In contrast, stock characteristics explain only about 3% of the variation in lending on both margins. This strong influence of fund-by-stock fixed effects indicates specialization in the securities lending market, consistent with findings in other N-PORT studies (e.g., Dong and Zhu (2022)).

Figure 4: Lending in special stocks added to the Russell 2000 index in 2020-2022 by benchmarked funds

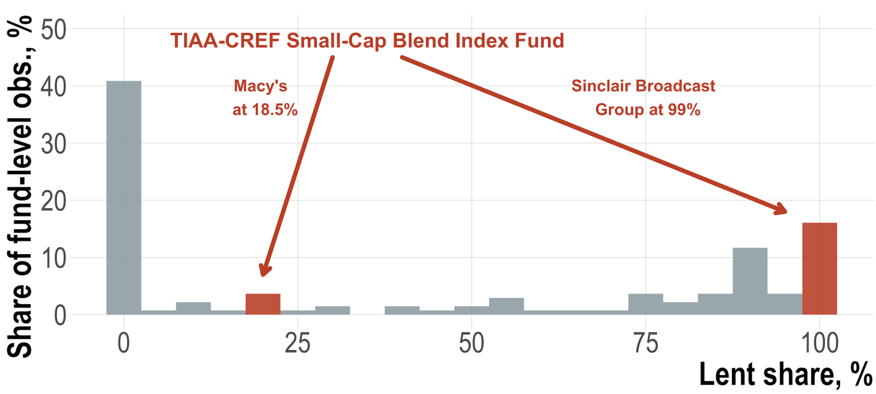
(a) Schwab Small-Cap Index Fund



(b) Vanguard Russell 2000 Value Index Fund



(c) TIAA-CREF Small-Cap Blend Index Fund



This figure plots a histogram of lent shares in special stocks added to the Russell 2000 index in 2020-2022 of active and passive funds benchmarked to the Russell 2000 index (blend, value, or growth). Each panel highlights lending of two stocks by a specific index fund, all captured in the third quarter of 2020. Observations with a lent share above 100% are set to 100%.

6 Concluding Remarks

Short-selling plays a crucial role in price discovery within financial markets. At the same time, the cost of short-selling is determined in the securities lending and borrowing market, where institutional investors act as key lenders.

In this paper, I exploit variation in institutional mandates to provide new insights into how institutions influence the formation of short-selling constraints. I propose a simple model with benchmarked fund managers who can also lend their holdings to short-sellers. In this model, benchmarking has an ambiguous effect on the equilibrium borrowing fee (the price of selling an asset short). An asset included in a benchmark index will generally have a larger lending supply but also attract greater shorting demand because its price is inflated relative to an asset outside of the index. By exploiting plausibly exogenous variation in how much capital is benchmarked against stocks, I find that borrowing fees tend to increase with benchmarking-induced purchases. This is consistent with the dominant demand effect, or overvaluation effect, of benchmarking. In the model, the demand effect of benchmarking dominates if fund managers undersupply their holdings for lending due to lending limits. Using the evidence from novel regulatory filings of investment companies in the United States, I discuss several drivers of such lending limits in the data.

I find that the weak pass-through of benchmarked capital to lending supply contributes to the asset pricing effects of investment mandates. To facilitate price discovery, it may be beneficial to address supply-side frictions, such as those stemming from market participation or lending costs, lender concentration, and search costs. This paper abstracts away from strategic actions or active rebalancing in response to shorting demand that may also limit lending (for example, Greppmair, Jank, Saffi, and Sturgess (2020) and Honkanen (2024)). Nevertheless, formulating an optimal policy action depends on which friction is key and requires further research. The new data collection effort announced by the SEC is likely to facilitate inquiry in this direction.[37]

The magnitude of the index effect has been decreasing over time, particularly for the S&P 500 index reconstitutions, as documented by Bennett, Stulz, and Wang (2020), Aghaee Shahrbabaki (2022), and Greenwood and Sammon (2022). The model in this paper implies that relaxing limits on lending counteracts benchmarking price pressures. Evans, Ferreira, and Prado (2017) document a strong increase in funds' participation in lending in 1996-2008 and my analysis of the regulatory filings for 2020-2022 confirms this trend. Therefore, the dynamics in the index effect may be affected by the lending policies of benchmarked fund managers becoming more accommodating over time.

My findings may have implications for the design of unconventional monetary policies.

[37] See the SEC Chair Gary Gensler's statement from October 13, 2023 at https://www.sec.gov/news/statement/gensler-statement-short-sale-101323.

Recent literature on bond quantitative easing has shown that central bank purchases can depress the repo rates through the so-called scarcity channel (D'Amico, Fan, and Kitsul (2018), Arrata, Nguyen, Rahmouni-Rousseau, and Vari (2020), and Corradin and Maddaloni (2020)). Pelizzon, Subrahmanyam, Tomio, and Uno (2024) demonstrate that the introduction of lending of bonds from the central bank's portfolio mitigates scarcity effects. My findings for equity markets emphasize the potential role of lending limits in influencing the effectiveness of quantitative easing, an aspect not previously considered in the literature. Therefore, by adjusting the lending program and its lending limits,[38] central banks may transition more smoothly into a tightening regime, prior to unwinding their holdings. I see it as a promising avenue for future research.

The intuition in this paper can be applied to any investment mandate. Although my model features benchmarking, adding a preference for certain assets directly into a lender's utility function would yield very similar results. This could include a preference for safe assets (Krishnamurthy and Vissing-Jorgensen (2012)), ESG assets (Pástor, Stambaugh, and Taylor (2021)) or correspond to any type of taste (Fama and French (2007)). My results suggest that by introducing lending limits specific to ESG assets, regulators may achieve stronger effects on the cost of capital at the same level of investment. Understanding this requires more research into the lending policies of investment companies and a careful analysis of distributional effects because the primary beneficiaries of securities lending revenues are fund investors.

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[38] The banks in the European system do not disclose their limits, whereas the Federal Reserve has an issue-level lending cap on bonds in its System Open Market Account (SOMA) portfolio. This limit has been relaxed from 45% in 1999 to 90% in 2007 (`https://www.newyorkfed.org/markets/sec_faq`).

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A Internet Appendix: Additional U.S. Evidence

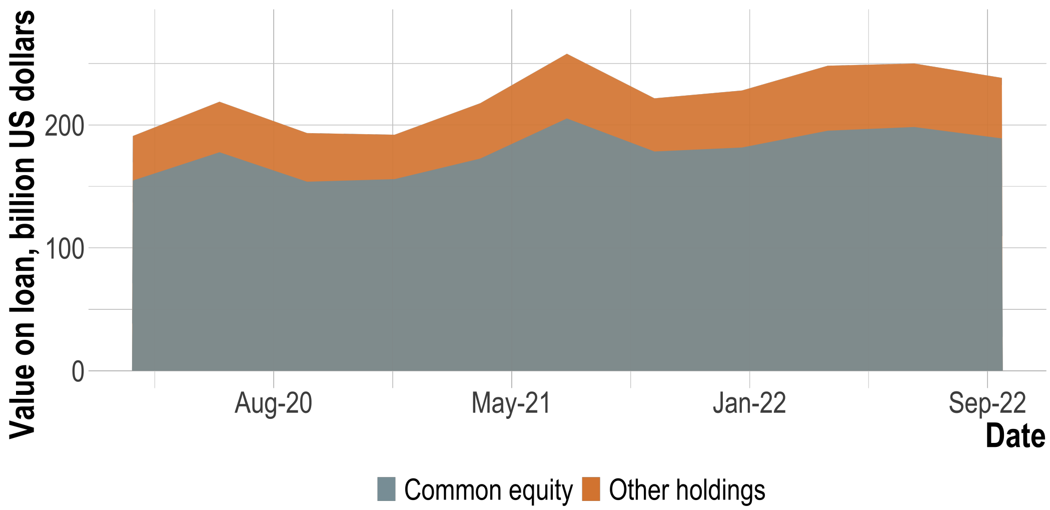
A.1 Aggregate insights into the lending activity of U.S. investment companies from regulatory filings

This section provides aggregate descriptive statistics using N-PORT and N-CEN filings. The parsing of both types of filings is described in Appendix A.2.6.

A.1.1 Aggregate value on loan

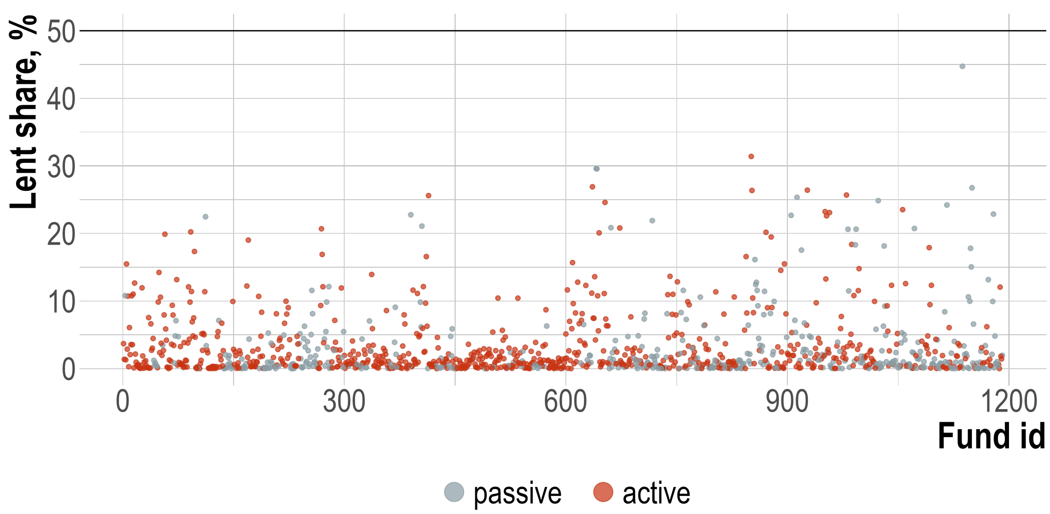
The aggregate quarterly value on loan between Q1 2020 and Q3 2022 is plotted in Figure A1. Lending of common equity holdings contributes 80% or more to the aggregate value on loan in each quarter.

Figure A1: Aggregate value on loan as reported in N-PORT filings



This figure plots the aggregate value on loan as reported in N-PORT filings for all investment companies in the United States. Common equity value is the total of loan values with the asset category 'EC' and the 'Long' payoff profile.

Figure A2: Fund-level value on loan as reported in N-PORT filings



This figure plots the value on loan relative to fund net assets as reported in N-PORT filings for all investment companies in the United States in the second quarter of 2021. Only funds permitted to lend securities by their investment policies are included. The horizontal line marks the regulatory limit of 50%.

A.1.2 Aggregate lending descriptive statistics

Table A1 reports descriptive statistics on the lending activity of investment companies in the United States.

Table A1: Key descriptive statistics on securities lending by year

	Net assets, $ billion	Value on loan, $ billion	Securities lending income, $ billion	Share of funds permitted to lend, %	Share of funds lending, %	Share of fund assets on loan, %
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Domestic equity index mutual funds and ETFs						
2019	3,886.88	51.38	0.69	98.52	97.29	1.32
2020	4,375.83	55.46	0.75	98.74	98.08	1.27
2021	5,595.14	51.83	0.69	99.07	98.20	0.93
Panel B: Domestic equity active mutual funds						
2019	5,003.81	53.15	0.41	72.83	61.42	1.06
2020	5,258.05	47.96	0.42	86.01	72.39	0.91
2021	6,223.62	46.74	0.30	85.02	80.32	0.75
Panel C: All funds of U.S. investment companies						
2019	21,884.28	218.96	2.61	70.17	62.99	1.00
2020	23,517.93	212.93	2.54	77.36	68.69	0.91
2021	27,990.66	217.00	2.25	77.55	73.73	0.78

This table reports descriptive statistics on lending activity of domestic equity funds of U.S. investment companies according to their annual N-CEN filings in 2019–2021. Fund observation is attributed to a given year when the report date is within that year. Net assets are the total of average monthly net assets. Value on loan is the average value of lent out securities. Share of assets on loan is computed as a fund-level ratio of average value of securities on loan to the average monthly net assets. Shares in columns (4)–(6) are asset-weighted averages across funds in a given year. Share in column (6) is conditional on lending. In panels A and B, I include only funds with a defined type as described in Appendix A.2.3. Panel C reports statistics for all funds submitting N-CEN forms.

A.2 Data

A.2.1 U.S. stock data

U.S. stock data come from standard sources. I take daily returns, prices, adjustment factors, bid and ask prices, and historical stock identifiers from CRSP. Returns are adjusted for delisting, following Shumway (1997). Market, risk-free rate, and factor returns are from Ken French's database.[39] These data are merged with S&P securities lending data using CUSIP and date. All fundamental accounting data, such as book values, come from Compustat. I use a CRSP-Compustat linking table and take into account release dates to ensure that the variables are available to the public by the Russell rank date in May.

A.2.2 Historical benchmark weights data

I obtain benchmark weights data from the following sources. All the constituent weights for 22 Russell benchmark indexes are from the FTSE Russell (London Stock Exchange Group). The Russell indexes include (all total return in USD): Russell 1000, 2000, 2500, 3000, 3000E, Top 200, Midcap, Small Cap Completeness (blend), and their growth and value counterparts. Constituent weights for the S&P 500 TR USD and S&P MidCap 400 TR USD are from Morningstar and are available from September 1989 and September 2001, respectively, to October 2015. I construct constituent weights for S&P 500 after October 2015 manually from constituent lists and prices available through CRSP. I generate the S&P 400 weights from holdings of index funds (Dreyfus and iShares).[40] The constituent weights for the CRSP U.S. indexes are from Morningstar and are available from 2012. These indexes include (all total return in USD): Total Market, Large Cap, Mid Cap, Small Cap (blend), and their growth and value counterparts.

A.2.3 U.S. funds data

U.S. fund data are from the CRSP Survivor-Bias-Free U.S. Mutual Fund Database. In particular, I use fund total net assets, fund returns, and investment style information.

Active and Passive Domestic Equity Funds. I follow the major steps of the procedure described in Doshi, Elkamhi, and Simutin (2015) to select active domestic equity funds and modify it to identify passive funds. In particular, I use *crsp_obj_cd* (CRSP objective code) to identify 'equity', 'domestic', 'cap-based or style' and exclude 'hedged' and 'short' and remove those funds that changed their objectives. I also keep only funds with 'ioc' variable in Thomson

[39] See https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

[40] Because the S&P 400 index is relatively small, these weights do not contribute much to the analysis.

Reuters S12 file (investment objective) not in (1,5,6,7). Active funds are identified as those without $Index\_fund\_flag$ or with 'B' (index-based funds) and without et_flag. I also exclude funds that have a range of words in their names, as per the list below.

1. Generic and index provider names: index, indx, ' idx ', s&p, ' sp ' (with spaces), nasdaq, msci, crsp, ftse, barclays, ' dj ', ' dow ', jones, russell, ' nyse ', wilshire, 400, 500, 600, 1000, 1500, 2000, 2500, 3000, 5000

2. Passive management names: ishares, spdr, trackers, holdrs, powershares, streettracks, ' dfa ', 'program', etf, exchange traded, exchange-traded

3. Target fund names: target, retirement, pension, 2005, 2010, 2015, 2020, 2025, 2030, 2035, 2040, 2045, 2050, 2055, 2060, 2065, 2070, 2075.

Similarly, the sample of passive funds consists of index funds and ETFs available on CRSP. Index funds are those with $index\_fund\_flag$ equal to D or E and those that include any of the following words in their name:

1. Generic and index provider names: index, indx, ' idx ', s&p, ' sp ' (with spaces), nasdaq, msci, crsp, ftse, barclays, ' dj ', ' dow ', jones, russell, ' nyse ', wilshire, 400, 500, 600, 1000, 1500, 2000, 2500, 3000, 5000

2. Passive management names: ishares, 'dfa', 'program'.

ETFs are identified as funds that have et_flag or have one of the following words in their name:

1. Passive management names: spdr, trackers, holdrs, powershares, streettracks, etf, exchange traded, exchange-traded.

Furthermore, I exclude all leverage and inverse funds by identifying the following in their names: leverage, inverse, 2x, 1.5x, 1.25x, 2.5x, 3x, 4x. Finally, I clean the resulting sample of funds with share classes of different types as per the rule: (a) Put ETF share classes of index funds as ETFs. (b) When missing the flag for otherwise index funds and *portno* is the same, set to index. (c) If *cl_grp* is different, exclude.

A.2.4 Construction of the historical fund benchmark data

I manually assemble a dataset of historical mutual funds and ETF benchmarks from the following sources:

1. Snapshot of benchmarks (*primary_prospectus_benchmark* field) from Morningstar as of September 2018.

2. Database of historical fund prospectuses available on the website of the U.S. Securities and Exchange Commission (SEC).[41]

3. SEC Mutual Fund Prospectus Risk/Return Summary datasets (MFRR).[42] Benchmarks are mentioned in the annual return summary published in prospectuses.

I use the *crsp_fundno*-CIK mapping from CRSP (table *crsp_cik_map*) to link central index key (CIK), that is, a SEC identifier, back to *crsp_fundno*. To link CRSP and Morningstar, I slightly extend the procedure in the Data Appendix to Pastor, Stambaugh, and Taylor (2015). For funds that did not get merged by ticker or CUSIP, I compare monthly total net assets and monthly return for each pair of funds between CRSP and Morningstar. In particular, I repeat *Step 2* of the procedure at 80^{th} percentile and manually remove non-unique matches or matches of share classes within the same master fund. I add matched funds to the merged sample.

A.2.5 Scraping the EDGAR and building text-based series

Reporting of manager compensation contracts was required by SEC Rule S7-12-04[43] beginning in October of 2004. The filings that include information on fund benchmark and manager compensation are N-1A/485 (registration statement including a prospectus), 497K (summary prospectus), 497 (fund definitive materials), and 497J (certification of no change in definitive materials). I access the filings using package 'edgarWebR' available in R.[44] For each CIK in *crsp_cik_map*, I retrieve a list of all historical filings (485 and 497/497K/497J forms) and parse them into raw text format. Having obtained the filings for each CIK and each filing date, I re-organize the dataset into a panel: quarterly text files for each fund. To do so, I assign observations with a 497J form a 'no-change' tag. Moreover, after looking at the text data, I assign a 'no-change' tag to 497 forms with no reference to benchmark or manager compensation.

Before extracting the data, each of the filings is tokenized and de-capitalized, punctuation and certain stop words are removed. All these steps are done using the NLTK module in Python. After that, I classify all 485 and 497K documents as prospectuses, and I look into the content of 497 filings to classify them into prospectuses or statements of additional information (SAI).

[41] The SEC's fund search page: https://www.sec.gov/edgar/searchedgar/mutualsearch.html

[42] The MFRR page: https://www.sec.gov/dera/data/mutual-fund-prospectus-risk-return-summary-data-sets.

[43] Available at https://www.sec.gov/rules/final/33-8458.htm.

[44] Description is available at https://cran.r-project.org/web/packages/edgarWebR/index.html.

Typically, funds specify the type of the document in the header, I therefore search for the exact match ('prospectus' or 'statement of additional information') in the first 100 characters of the filing.

Fund families may choose to submit one prospectus for many funds. Within one prospectus document, many funds can share the same section or each fund can have a separate section. I therefore extract the fund-relevant part of the prospectus whenever possible (typically in the second case only). To do so, I search for the fund name and the fund ticker in the text. Most commonly, the relevant section begins with a ticker/name and has it repeated on each page throughout the section. I then extract the part of the text with the highest density of tickers/fund names.

When extracting benchmarks from the (isolated) text, I use a set of rules that helps the algorithm to pick up the benchmark correctly. The main rules include:

- Search for a benchmark series name from the list (already decapitalized): {*s&p, russell, crsp, msci, dj, dow jones, nasdaq, ftse, schwab, barclays, wilshire, bridgeway, guggenheim, calvert, kaizen, lipper, redwood, w.e. donoghue, essential treuters, barra, ice bofaml, bbgbarc, cboe*}.[45] If a benchmark from the list is found, I retrieve the subsequent 40 characters to extract the full benchmark name. I match the full names using the list from Morningstar (e.g., *russell 1000 value tr usd*).

- If several matches are established, I record the number of matches and each benchmark name (with subsequent characters, as above).

- I also search for words from the list (*context words*): {*index, benchmark, reference, performance, relative, return, measure, evaluate, assess, calculate*}. I use these words in two ways. First, if a benchmark name match is established, I check if any of these *context words* is present within 100 characters around the name. Second, if no match is established, I record pairwise distance in letters between benchmark names and *context words* and return the pair with minimum distance. This second approach is based on the string format of the text and required if the match was not established due to imprecision in tokenization.

I manually clean the extracted data to remove typos and map it to full benchmark names. In the resulting sample of fund benchmarks by quarter, I manually verify all funds that were matched with several benchmarks or that had a benchmark change. Subsequently, I validate a random sample of funds through manual analysis of the prospectus text. I also compare the benchmarks as of September 2018 with a snapshot I obtained from the Morningstar database and manually resolve

[45] This list has been compiled using the Morningstar benchmark snapshot for mutual funds and ETFs. It is survivorship-bias free. According to Morningstar, the first three benchmark series take close to 90% of the market and the first seven – close to 100%.

any mismatch. Finally, I compare a time series I get with a series available for a small sample of funds in MFRR.

A.2.6 U.S. funds securities lending data

Using R package 'edgarWebR', I download the full history of N-PORT, N-PORT/A, N-CEN, and N-CEN/A filings for each unique CIK (central index key, SEC fund company identifying number) in the $crsp\_fundno$-CIK mapping from CRSP (table *crsp_cik_map*). My sample includes reports filed up to March 1, 2023. N-PORT filings are quarterly (holdings schedule), and N-CEN filings are annual. If there are amended filings for the same report date (N-PORT/A and N-CEN/A), I use the last available filing. The filings are machine-readable so I simply extract the relevant data, as follows.

1. Fields from N-PORT and N-PORT/A filings
    - Filing information: CIK, series ID, series name, report date, filing date
    - Fund information: series ID, total assets, and net assets
    - Fund borrower information: series ID, borrower name, borrower legal entity identifier (LEI), and borrower aggregate loan value
    - Fund holdings: series ID, investment name, CUSIP, ISIN, ticker, number of shares, value of shares in USD, weight in portfolio, long or short position indicator, asset category, investment country, indicator whether any amount of this investment represents reinvestment of cash collateral received for loaned securities, whether any portion of this investment is treated as a fund asset and received for loaned securities (i.e., a non-cash collateral), whether any portion of this investment is on loan by the fund, and loan value.
2. Fields from N-CEN and N-CEN/A filings
    - Filing information: CIK, series ID, series name, report date, filing date
    - Fund information: series ID, fund type (ETF, inverse, fund of funds, etc.), monthly average net assets, whether the fund is permitted to lend, whether the fund lent, average value of securities on loan, net income from securities lending
    - Fund lending agent information: series ID, agent name, agent legal entity identifier (LEI), and whether lending agent is affiliated with the investment company

In my sample, the number of unique funds (series ID level) in N-PORT data is 13,267, and the number of funds that have a merged type from CRSP is 2,988 (including 2,261 active and 727 passive funds). The latter sample includes only domestic equity funds identified as described in Section A.2.3.

A.3 Variable definitions and descriptive statistics

Table A2: Key variable definitions and descriptive statistics

Variable	Definition	Units	Source (field)	Mean	Median	St. dev.	p1	p99
Panel A: U.S. data (sample around the Russell cutoff)								
ΔBMI	Change in BMI as defined in equation (13) from May to June	% MV	FTSE Russell, Morningstar, CRSP, CRSP MFDB, SEC	0.13	-0.03	2.62	-8.90	9.79
Δ Lending inventory	Difference between the average daily active inventory (ActiveLendableQuantity) as a share of shares outstanding (SHROUT*1000) in July and May.	% shares	Markit (ActiveLendableQuantity) and CRSP (SHROUT)	-0.01	0.07	1.93	-6.13	5.57
Δ Quantity on loan	Difference between the average daily short quantity on loan (ShortLoanQuantity) as a share of shares outstanding (SHROUT*1000) in July and May.	% shares	Markit (ShortLoanQuantity) and CRSP (SHROUT)	0.19	0.05	1.94	-5.66	6.54
Δ Borrowing fee	Difference between the average daily borrowing fee (IndicativeFee) in July and May.	%	Markit (IndicativeFee)	0.02	0.00	0.91	-1.41	1.84
Stock return	Stock return in June, adjusted for delisting, not annualized.	%	CRSP	-0.83	-0.59	9.44	-26.75	24.78
Lending inventory in May	Average daily active inventory (ActiveLendableQuantity) in May	% shares	Markit (ActiveLendableQuantity)	27.97	28.44	8.88	5.52	48.54
Quantity on loan in May	Average daily short quantity on loan (ShortLoanQuantity) in May	% shares	Markit (ShortLoanQuantity)	5.62	3.49	6.14	0.06	27.82
Borrowing fee in May	Average daily borrowing fee (IndicativeFee) in May	%	Markit (IndicativeFee)	0.63	0.38	1.74	0.25	8.14
D(special)	1 if IndicativeFee in May >1%, 0 otherwise	Boolean		0.05	0.00	0.21	0.00	1.00
Markit score in May	Average Markit's Daily Cost of Borrow Score in May, where 1 is cheapest and 10 is most expensive	1-10		1.12	1.00	0.66	1.00	4.83
(Total) Market value	Proprietary log market value (ranking variable).	Million dollars	FTSE Russell	3,425.3	2,404.1	2,865.0	526.9	13,487.6
Float	Proprietary float factor (fraction of shares floated)	Fraction	FTSE Russell	0.11	0.00	0.19	0.00	0.78
β^{CRSP}	CAPM beta as of May, 5-year monthly rolling, computed using CRSP total market value-weighted index		CRSP	1.28	1.20	0.63	0.19	3.38
Bid-ask spread	1-year monthly rolling average bid-ask percentage spread	%	CRSP	0.13	0.10	0.13	0.02	0.53
Band	1 if stock is in the Russell band in May	Boolean		0.29	0.00	0.46	0.00	1.00
D(in Russell 2000)	1 if stock is in the Russell 2000 index in May	Boolean		0.51	1.00	0.50	0.00	1.00
M/B	Market-to-book ratio (EV/Assets - Total, or EV/AT)	Fraction	Compustat	2.05	1.57	1.57	0.85	8.39
Value ratio	Fraction of stock shares assigned to value indices	Fraction	FTSE Russell	0.50	0.49	0.45	0.00	1.00
Panel B: U.S. data (N-PORT sample)								
Change in fee	The fee after the reconstitution of year t minus the fee before the reconstitution, as of fund report dates.	%	Markit (IndicativeFee)	0.11	0.00	2.22	-1.19	0.96
Change in fee (aggregated)	The fee after the reconstitution of year t minus the fee before the reconstitution, as of fund report dates, average across all funds.	%	Markit (IndicativeFee)	0.10	0.00	1.82	-3.20	1.04
LentShare	Share of fund holding on loan, or loanVal/ValUSD, after the Russell reconstitution (not conditional on lending).	%	SEC	7.52	0.00	23.93	0.00	100.00
LentShare (aggregated)	Share of fund holding on loan, or loanVal/ValUSD, averaged across funds after the Russell reconstitution (not conditional on lending).	%	SEC	6.69	2.46	10.57	0.00	57.69
D(special)	1 if IndicativeFee in the three months before the reconstitution >1%, 0 otherwise, as of fund report dates.	Boolean		0.03	0.00	0.17	0.00	1.00
Change in quantity on loan	The shorting demand after the reconstitution of year t minus the fee before the reconstitution, as of fund report dates.	% shares	Markit (ShortLoanQuantity)	-0.56	-0.36	4.30	-18.71	10.17
Change in quantity on loan (aggregated)	The shorting demand after the reconstitution of year t minus the fee before the reconstitution, as of fund report dates, average across all funds.	% shares	Markit (ShortLoanQuantity)	-0.65	-0.56	3.95	-9.38	9.40

A.4 Details on "Active" Inventory and Utilisation in Markit data

Throughout the paper, I use Markit's "active" lendable quantity as a measure of lending inventory. All results are qualitatively the same if I use the total lendable quantity instead, yet the active field should better reflect the level of inventory available to market participants. Below are the details from Markit's data FAQ.

Figure A3: Markit's calculation of active fields

What are the "Active" Fields?

Active fields look at the depth of the stock borrow market with more sophistication - drawing on uniquely granular inventory files that are received each day from all major global custodians and large institutional asset managers.

Securities Finance collects inventory from the securities lending market however, there is sometimes a difference between the total amount that could be borrowed from this pool and the actual amount on offer (i.e. where securities are held in too small parcels or have been restricted by the beneficial owner – see below for the full methodology). It is important to understand what is "actively" available in the market. Securities Finance have developed a methodology for calculating this active availability using its unique market knowledge and understanding of market conventions.

What is the methodology used to calculate active inventory?

1. If a stock has a Markit Securities Finance proprietary benchmark fee of less than 100bp then all inventory will be considered active.
2. If a given fund has inventory in a stock but has no current trades, then all inventory of that stock in that fund will be considered inactive.
3. If a given fund has trades in a stock but none of them started within the last 30 calendar days, then only the quantity/value that is currently out on loan will be considered active.
4. If the fund has trades in a stock and some of them start within the last 30 days, and there is less than £500,000 inventory that is NOT currently out on loan, only the quantity/value that is currently out on loan will be considered active.
5. If the fund has trades in a stock, and some of them start within the last 30 days, and there is more than £500,000 inventory that is NOT currently out on loan, then all lendable will be considered active.

Excerpt from S&P's (Markit's) Global Securities Finance Equities Buyside Analytics Data Feed FAQ (2022).

A.5 Russell Reconstitution

Russell indexes undergo a reconstitution at the end of June each year. The reconstitution is a two-step process: assigning a stock to an index and determining the weight of the stock in that index. The first step is solely based on the ranking of all eligible securities by their total market capitalization on the rank day in May. For most of the years in my sample, the rank day falls on the last trading day in May and the reconstitution day falls on the last Friday of June.[46] Russell uses its broadest Russell 3000E index as the universe of eligible securities together with newly admitted stocks. The details on the methodology are provided in the official and publicly available guide.[47]

[46] Exceptions are the rank days 05/27/2016, 05/12/2017, and 05/11/2018 and the reconstitution days 06/22/2007 and 06/23/17.

[47] See https://research.ftserussell.com/products/downloads/Russell-US-indexes.pdf.

Ranks are computed based on the proprietary measure of the total market capitalization of eligible securities. In the second step of the reconstitution, each stock in the index is assigned a weight based on its float-adjusted market capitalization in June. To define the adjustment, Russell uses proprietary float factors, which I infer from total and float-adjusted market capitalization.

FTSE Russell has shared with me their proprietary market capitalization measure, Russell 3000E constituent lists as well as the preliminary constituent lists from June. These proprietary data allow me to replicate the index assignment rule very closely.[48] Finally, by restricting my analysis to stocks that are next to the Russell cutoff in May rather than in June, I avoid selection in sample construction, which is discussed in detail in Wei and Young (2021).

Because of the availability of securities lending data, I include Russell reconstitutions starting from 2007, when FTSE Russell introduced a "banding" policy. According to this policy, a stock is assigned to the Russell 2000 index, if and only if:

- it was in the Russell 2000 in the previous year and its total market value rank in May falls between the left cutoff $(1000 - c_1)$ and 3000,
- it was in the Russell 1000 and its total market value rank in May falls between the right cutoff $(1000 + c_2)$ and 3000.

The band, that is, the range of ranks between $(1000 - c_1)$ and $(1000 + c_2)$, is based on a mechanical rule, but it changes each year with the distribution of firm sizes around the cutoff. Specifically, it is a 5% band around the cumulated market cap of the stock ranked 1000 in the Russell 3000E universe on the rank date. Because the assignment is based on ranks, firms cannot manipulate it. This suggests that within a window around the left and the right cutoff in each year, whether a stock ranks above or below the cutoff – and therefore switches indexes or stays – is as good as randomly assigned.

[48] Around 40 bps of observations are incorrectly assigned even when using the proprietary data (including 10 special stocks). The presence of measurement error in the running variable may pose a challenge to treatment effect identification, which is discussed in the context of the Russell reconstitution by Wei and Young (2021), Appel, Gormley, and Keim (2021), and Heath, Macciocchi, Michaely, and Ringgenberg (2021). Therefore, to alleviate the concern that my findings are affected by this error, I implement a "doughnut trimming" design suggested by the literature. In particular, Dong and Kolesár (2023) point out that when misclassification happens right next to the cutoff (which is the case in my data), this approach yields an estimate with a causal interpretation. When trimming 10–30 observations right next to the cutoff, I observe virtually identical estimates. Finally, my results are unchanged if I use ranks based on public data, constructed following Ben-David, Franzoni, and Moussawi (2019).

A.6 What drives variation in BMI?

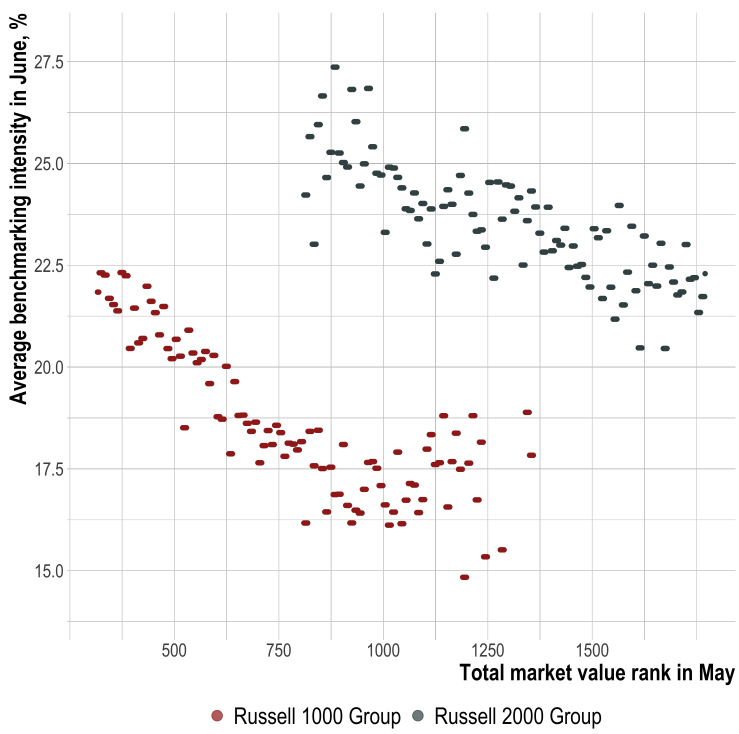
Figure A4 plots the average values of BMIs around the Russell cutoffs immediately after the reconstitution. The figure reveals the sizeable discontinuity at both left and right cutoffs. There is a 5%–8% gap in BMIs for stocks within the Russell band. See Section A.5 for the details on the band and how cutoffs are defined.

Changes in a stock's BMI are driven by the stock's membership in benchmark indexes, assets benchmarked to these indexes, and index total market values. To see that, use a definition of a stock weight in any value-weighted index j,

$$\omega_{ijt} = \frac{MV_{it}\mathbf{1}_{ijt}}{\sum_{k=1}^{N} MV_{kt}\mathbf{1}_{kjt}} = \frac{MV_{it}\mathbf{1}_{ijt}}{\text{IndexMV}_{jt}}, \tag{18}$$

where the index membership dummy $\mathbf{1}_{ijt}$ is equal to one if stock i belongs to index j at time t and IndexMV_{jt} is the total market cap of all stocks in index j at time t, and rewrite BMI defined in

Figure A4: BMI after the Russell reconstitution



This figure plots the average BMI of stocks to the left and to the right of the Russell cutoff in the reconstitutions of 2007–2018. Russell 1000 group includes funds benchmarked to the Russell 1000 and Russell Midcap indexes (blend, value, or growth). Russell 2000 group includes funds benchmarked to the Russell 2000 indexes (blend, value, or growth).

(13) as

$$BMI_{it} = \sum_{j=1}^{J} \frac{\lambda_{jt}\mathbf{1}_{ijt}}{\sum_{k=1}^{N} MV_{kt}\mathbf{1}_{kjt}} = \sum_{j=1}^{J} \frac{\lambda_{jt}\mathbf{1}_{ijt}}{\text{IndexMV}_{jt}}. \tag{19}$$

There are two potential caveats. First, some index providers use the float-adjusted market cap rather than the total market cap. That is, strictly speaking, (19) should be

$$BMI_{it} = \sum_{j=1}^{J} \frac{\lambda_{jt}FF_{ijt}\mathbf{1}_{ijt}}{\sum_{k=1}^{N} MV_{kt}FF_{kjt}\mathbf{1}_{kjt}},$$

where FF_{ijt} denotes the float factor of stock i in index j at time t (the float factors are often index-specific and therefore proprietary). Because the float factor reflects stock liquidity, it could be a potential source of endogeneity. Russell primarily uses companies' SEC filings to compute their free float. In my regression analysis, I use the free float factors, implied by the data provided by Russell, as one of the control variables and supplement it with bid-ask spread to account for any stale information in the float factor. The second caveat concerns value and growth indexes. They typically include only a fraction of the market value of the stock that they deem related to value or growth style (this classification is based on index providers' proprietary classification algorithms). In my sample, this split of shares between Russell value and growth indexes does not strongly affect changes in BMI around the Russell cutoff. Furthermore, additions to the Russell 2000 have similar pre-reconstitution proprietary value ratios and Compustat-based market-to-book ratios, and my results are robust to controlling for them.

A.7 Case studies on funds' lending around the Russell reconstitutions

In this section, I illustrate changes in the lending supply of stocks whose index membership changed in the Russell reconstitutions of 2020–2022. My sample is limited to these years because the loan value data by fund comes from N-PORT filings, available from the last quarter of 2019. I identify additions and deletions with the official FTSE Russell index composition files and arrive at a sample of 212 stocks, for 211 of which I have data in N-PORT.

First, I confirm that the aggregate holdings of funds follow changes in their benchmarks. For example, Figure A5 (a) illustrates that stocks added to the Russell 2000 experience an increase in holdings by passive funds benchmarked to the index. Similarly, panel (c) shows that the aggregate holdings of active funds benchmarked to the Russell 2000 also increase. As funds lend what they own, Figure 2 in the main text confirms that aggregate lending is a mirror image of aggregate ownership.

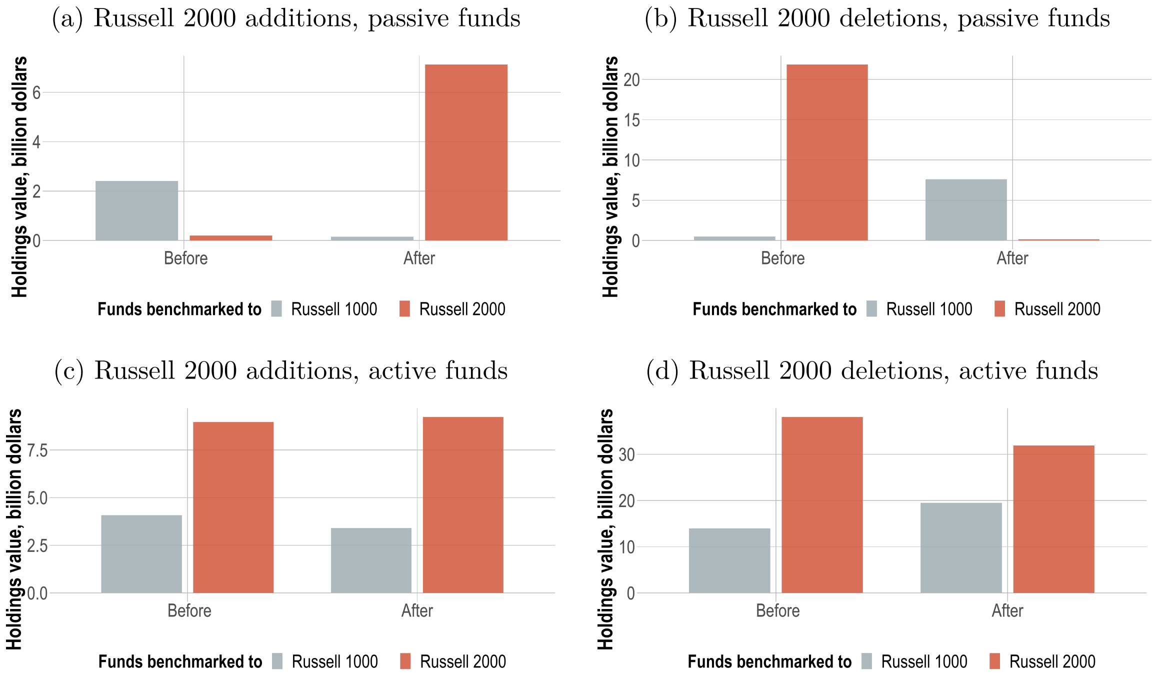
Figure A5: Aggregate fund holdings of the Russell 2000 index additions and deletions

(a) Russell 2000 additions, passive funds

(b) Russell 2000 deletions, passive funds

(c) Russell 2000 additions, active funds

(d) Russell 2000 deletions, active funds



This figure plots the aggregate fund holdings of the Russell 2000 additions and deletions before (March–May) and after (July–September) the reconstitutions of 2020–2022, according to their N-PORT filings. Only funds with an identified benchmarks and types are included. Russell 1000 group includes Russell Midcap funds.

These aggregate changes in ownership and lending are also detectable at a stock level. Table A3 reports changes in the ownership of funds with different benchmarks and changes in their contribution to the total amount on loan for additions and deletions to the Russell 2000 index. In general, additions see an increase in the ownership of domestic equity funds of around 1% and a similar-sized increase in their lending share. Deletions see a decrease in domestic equity fund ownership of 6% and a decrease of 5% in their lending share. The table shows that these changes are driven not only by passive funds. Active funds also change their holding and lending mostly in line with their benchmarks. For example, for an average stock deleted from the Russell 2000 index, passive funds benchmarked to Russell 2000 decrease their share in lending by 3.2%, and active funds benchmarked to Russell 2000 decrease their share in lending by 1.7%.

Next, I study the lending behavior of funds benchmarked to the indexes around the Russell cutoff immediately after the reconstitution. In particular, I examine what fraction of additions' and deletions' position value is on loan (lent share). As Figure A6 illustrates, the majority of stocks that moved indexes in the Russell reconstitutions are not on loan (panels (a) and (b)). However, conditional on lending, most of them have lent shares close to 100% (panels (c) and (d)). Panels (e) and (f) show the same patterns within special stocks. Many of them are not on loan, and conditional on lending, lent shares are close to 100%. However, it is puzzling why funds do not lend out many special stocks, albeit the model predicts that they should.

Finally, I find that there is a positive cross-sectional relationship between the change in the borrowing fee around the Russell reconstitution and the average lending share after the reconstitution. To study this relationship, I estimate the following regression:

$$\begin{aligned} Change\,in\,Fee_{ijt} = &\beta_1 LentShare_{ijt} \times D(special)_{ijt} + \beta_2 LentShare_{ijt} \times D(not\,special)_{ijt} \\ &+ \nu_{sjt} + \epsilon_{ijt}. \end{aligned} \tag{20}$$

The dependent variable, $Change\,in\,Fee_{ijt}$, is the change in the stock i's borrowing fee, computed as the Markit's fee after the reconstitution of year t minus the fee before the reconstitution, as observed on the report dates of fund j.[49] $LentShare_{ijt}$ is the share of holdings in stock i on loan computed for fund j after the reconstitution of year t. $D(special)_{ijt} = 1$ if the average fee before the reconstitution is above 1%, and zero otherwise. Similarly, $D(not\,special)_{ijt} = 1$ if the average fee before the reconstitution is up to 1%, and zero otherwise. ν_{sjt} are specialness by year fixed effects. I also consider a version of specification (20) in which all variables are simple averages across funds.

Table A4 reports the estimation results. Columns (1) and (2) suggest that borrowing fees increase more when the lent shares are larger, and this relationship is present for special stocks only. A 1 percentage point increase in lent share is associated with a 4 bps increase in borrowing fee

[49] Because funds have different report dates, I use observations three months around the reconstitution to account for all quarterly N-PORT reports. For any given fund, I effectively include one observation before and one observation after the reconstitution.

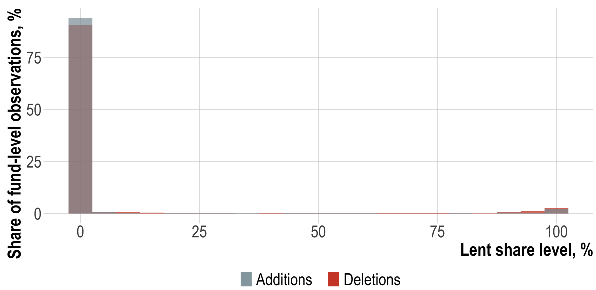
Table A3: Stock-level fund holding and lending of the Russell 2000 index additions and deletions

	Group of funds													
	Additions to Russell 2000							Deletions from Russell 2000						
	Total N-PORT	Russell 1000		Russell Midcap		Russell 2000		Total N-PORT	Russell 1000		Russell Midcap		Russell 2000	
		Active	Passive	Active	Passive	Active	Passive		Active	Passive	Active	Passive	Active	Passive
Panel A: Fund ownership relative to stock market value, %														
Mean	1.04	-1.20	-1.35	-0.10	-1.15	0.10	4.47	-6.09	0.20	1.14	-0.16	1.39	-0.95	-6.01
t-stat	(7.24)	(-11.4)	(-66.6)	(-9.78)	(-56.24)	(5.8)	(73.54)	(-44.43)	(19.07)	(30.57)	(-6.69)	(52.61)	(-24.89)	(-83.03)
Panel B: Fund lending relative to the total value on loan, %														
Mean	1.09	-0.16	-0.33	-0.12	-0.37	-0.23	2.27	-4.94	0.02	0.43	0.27	0.52	-1.69	-3.16
t-stat	(18.21)	(-32.54)	(-178.09)	(-14.26)	(-176.16)	(-15.68)	(194.99)	(-77.06)	(1.58)	(268.4)	(26.39)	(266.59)	(-73.29)	(-313.65)

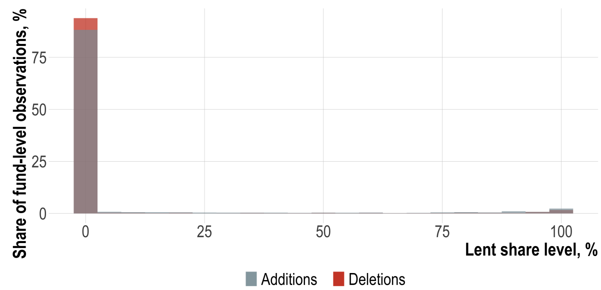
This table compares the average ownership (panel A) and lending share (panel B) of each group of funds from before the Russell reconstitution (March–May) to after (July–September) in 2020–2022. The sample includes 126 additions to the Russell 2000 and 85 deletions from it. "Total N-PORT" column includes only domestic equity funds identified, as described in Section A.2.3.

Figure A6: Lent share frequency for the Russell 2000 additions and deletions

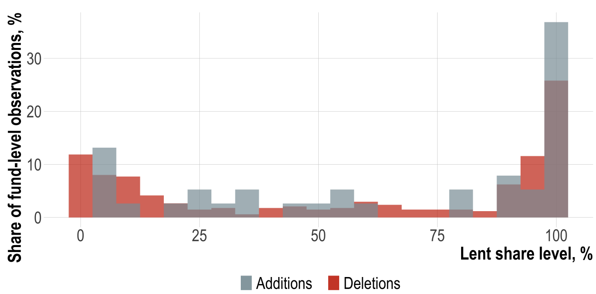
(a) Russell 1000 funds



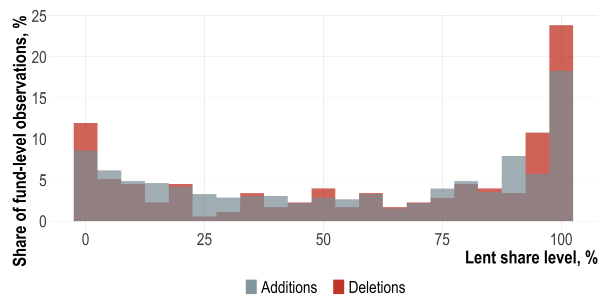
(b) Russell 2000 funds



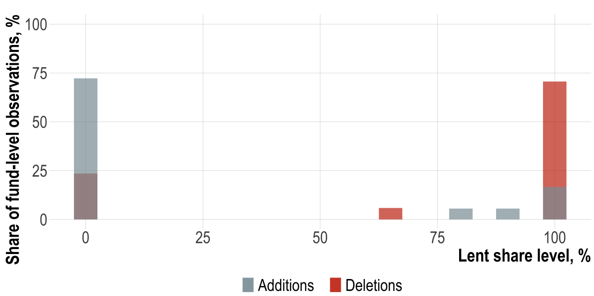
(c) Russell 1000 funds (conditional)



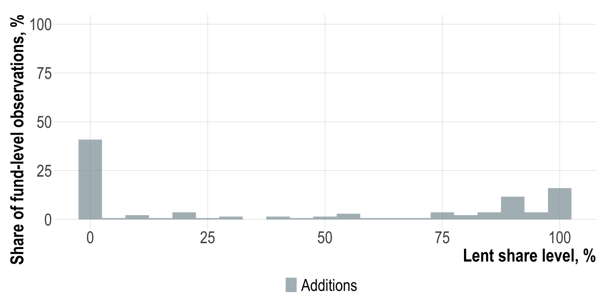
(d) Russell 2000 funds (conditional)



(e) Russell 1000 funds (special stocks)



(f) Russell 2000 funds (special stocks)



This figure plots the frequency shares of the fund-level lent share for the Russell 2000 additions and deletions. Panels (a) and (b) include data on all stocks, panels (c) and (d) plot shares conditional on lending (within observations with lent share above 0), and panels (e) and (f) plot shares for special stocks only (average fee of above 1% before the reconstitution). Panels (a), (c), and (e) include data of funds benchmarked to the Russell 1000 or Russell Midcap indexes (blend, value, or growth) and panels (b), (d), and (f) include data of funds benchmarked to the Russell 2000 indexes (blend, value, or growth). The data are as of the report date within three months after the respective reconstitution month (that is, the first available quarterly filing per fund). I include only domestic equity funds with a defined active or passive type, as described in Appendix A.2.3. Binwidth is 5%. Observations with lent share above 100% are set to 100%.

Table A4: Relationship between the change in fees and lent shares in the Russell reconstitutions

	Change in fee, %						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Lent share, %	0.005**						
	(1.99)						
Lent share × D(not special)		0.002	0.002	0.002*	0.005*	0.002	0.001
		(1.43)	(1.45)	(1.96)	(1.90)	(0.12)	(0.04)
Lent share × D(special)		0.039**	0.027**	0.031**	0.031	0.147***	0.135***
		(2.12)	(2.22)	(2.21)	(1.59)	(10.10)	(6.21)
Change in demand × D(not special)			0.010*	0.009	0.020	-0.010	0.020
			(1.71)	(1.41)	(1.39)	(-0.16)	(0.15)
Change in demand × D(special)			0.307***	0.298***	0.302***	0.296***	0.265***
			(5.88)	(5.94)	(7.18)	(4.85)	(3.29)
Observations	10,060	10,060	10,060	9,892	3,852	189	108
Adjusted R-squared	0.210	0.221	0.331	0.312	0.204	0.376	0.435
FE	Special x Year	Special x Year	Special x Year	Special x Year and Fund	Special x Year and Fund	Special x Year	Special x Year
Cluster	Stock	Stock	Stock	Stock	Stock	N	N
Sample	All	All	All	All	Russell 2000 additions	All	Russell 2000 additions

This table reports the estimates of specification (20) in the panel of fund holdings of the Russell 2000 additions and deletions in 2020–2022. In columns (1)–(5), the observations are organized in a stock-fund-year panel, whereas in columns (6)–(7) I use a stock-year panel of data averaged across funds. Lent share is the share of holdings in a given stock on loan. A stock is considered special, or $D(special) = 1$, if its fee on the report date is above 1%. Changes are computed between the report date after the reconstitution and the report date before the reconstitution. See details in Appendix A.3. t-statistics based on standard errors with indicated clusters are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

on special stocks around the Russell reconstitution. Because both fees and lent shares are affected by shorting demand, one might be concerned that the relationship is due to the fee reacting to an increase in demand. To alleviate this concern, I control for the change in shorting demand (total value on loan) in column (3) and find that, even though the fee is highly sensitive to changes in demand for special stocks, the coefficient on the lent share is virtually unaffected. Columns (4) and (5) add fund fixed effects to remove unobserved heterogeneity with respect to lent shares across funds. In column (5), I further restrict the sample to the Russell 2000 additions and find that the coefficient is not affected (although it is not statistically significant, perhaps because of the reduction in sample size). Finally, to show that the results are not driven by the repeated observations at a fund level or sparse report timings, in columns (6) and (7) I use the lent shares averaged across all funds in the sample. For such aggregate regressions, the borrowing fee increases by around 15 bps in response to a 1 percentage point increase in the lent share of special stocks.

A.8 Funds' lending across the largest Russell indexes

In this section, I report the average values of funds' lending of stocks inside and outside their benchmark indexes in 2020–2022. My sample is limited to these years because the loan value data by fund comes from N-PORT filings, available from the last quarter of 2019. I also only have the official FTSE Russell index composition files for this period of time and hence only consider the key Russell benchmark indexes.

Table A5: Share of value on loan coming from within-benchmark lending and not

Benchmark index	**Mean value on loan, billion US dollars**	**% within-benchmark**	**% not within-benchmark**
Russell 1000	1,665.3	98.6	1.4
Russell 1000 Growth	2,467.2	92.3	7.7
Russell 1000 Value	1,366.3	75.3	24.7
Russell 2000	746.7	83.7	16.3
Russell 2000 Growth	351.5	65.9	34.1
Russell 2000 Value	219.5	67.5	32.5
Russell Midcap	522	81.1	18.9
Russell Midcap Growth	553.5	64.8	35.2
Russell Midcap Value	275.1	81.8	18.2

This table reports the average monthly loan values of stocks in major Russell benchmark indexes in 2020–2022 as well as the share of that value that comes from funds benchmarked to a given index and not. Loan values are from N-PORT filings of funds with any of the nine indexes identified as a benchmark.

A.9 U.S. regressions with index membership dummy

Table A6: Response of spot and lending variables to the Russell index membership

	Δ Lending inventory, % shares	Δ Quantity on loan, % shares	Δ Borrowing fee, %	Stock return, %
	(1)	(2)	(3)	(4)
Panel A: No interactions				
D(in Russell 2000)	2.101***	2.029***	0.285*	1.354*
	(12.52)	(12.37)	(1.93)	(1.83)
Observations	9,659	9,659	9,659	9,659
Adjusted R-squared	0.175	0.129	0.163	0.240
Panel B: With specialness interactions				
D(in Russell 2000) $\times$ D(not special)	2.154***	2.045***	0.178	1.178
	(12.92)	(12.41)	(1.33)	(1.60)
D(in Russell 2000) $\times$ D(special)	1.501***	1.855***	1.486***	3.341**
	(5.00)	(5.44)	(3.56)	(2.41)
Observations	9,659	9,659	9,659	9,659
Adjusted R-squared	0.176	0.129	0.178	0.241
$\beta_1 - \beta_2$	-0.653**	-0.189	1.308***	2.163*
	(-2.55)	(-0.60)	(3.60)	(1.82)

This table reports the estimates of specification (14) (panel A) and specification (15) (panel B) in the panel of stocks within 300 ranks around the Russell cutoff in 2007–2018. I use Russell 2000 index membership dummy instead of ΔBMI as the main independent variable (similar to Appel, Gormley, and Keim (2019)). The last raw reports the t-test for estimation results in panel B. Changes in lending market variables are computed as differences between July and May; stock return is measured in June; see further details in Appendix A.3. A stock is considered special, or $D(special) = 1$, if its fee in May is above 1%. All regressions include controls, stock and D(special) by year fixed effects. t-statistics based on standard errors clustered by stock are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

A.10 Alternative specifications for U.S. regressions

A.10.1 Alternative definitions of specialness

Table A7: Response of lending variables to changes in BMI

	Δ Lending inventory, % shares	Δ Quantity on loan, % shares	Δ Borrowing fee, %	Stock return, %
	(1)	(2)	(3)	(4)
Panel A: Top tercile				
ΔBMI, % × D(not special)	0.185***	0.129***	-0.006*	0.097**
	(18.47)	(14.07)	(-1.94)	(2.37)
ΔBMI, % × D(special)	0.138***	0.166***	0.079***	0.204*
	(6.61)	(6.73)	(3.53)	(1.92)
Observations	13,685	13,685	13,685	13,685
Adjusted R-squared	0.143	0.088	0.042	0.203
Panel B: Top quintile				
ΔBMI, % × D(not special)	0.176***	0.128***	-0.004	0.115***
	(18.30)	(13.83)	(-1.39)	(2.78)
ΔBMI, % × D(special)	0.168***	0.195***	0.134***	0.175
	(5.82)	(6.19)	(3.51)	(1.18)
Observations	13,685	13,685	13,685	13,685
Adjusted R-squared	0.143	0.088	0.069	0.201
Panel C: Top decile				
ΔBMI, % × D(not special)	0.176***	0.132***	-0.001	0.117***
	(18.49)	(14.04)	(-0.33)	(2.81)
ΔBMI, % × D(special)	0.159***	0.211***	0.288***	0.240
	(3.81)	(4.62)	(3.64)	(0.99)
Observations	13,685	13,685	13,685	13,685
Adjusted R-squared	0.144	0.087	0.138	0.200
Panel D: Markit score above 1				
ΔBMI, % × D(not special)	0.178***	0.127***	-0.004	0.107***
	(18.60)	(13.76)	(-1.37)	(2.59)
ΔBMI, % × D(special)	0.147***	0.212***	0.159***	0.247*
	(4.61)	(6.38)	(3.83)	(1.65)
Observations	13,685	13,685	13,685	13,685
Adjusted R-squared	0.144	0.090	0.088	0.202

This table reports the estimates of specification (15) in the panel of stocks within 500 ranks around the Russell cutoff in 2007–2018. Changes in lending market variables are computed as differences between July and May; stock return is measured in June; see further details in Appendix A.3. A stock is considered special, or $D(special) = 1$, if its fee in May is in the top tercile (panel A), top quintile (panel B), or top decile (panel C) of fee distribution in that year (across all Russell 3000 constituents). In panel D, I use Markit's proprietary Daily Cost of Borrow Score, averaged over May, to classify stocks as special. All regressions include controls and D(special) by year fixed effects. t-statistics based on standard errors clustered by stock are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

A.10.2 Alternative controls

Table A8: Response of lending variables to changes in BMI

	Δ Lending inventory, % shares	Δ Quantity on loan, % shares	Δ Borrowing fee, %	Stock return, %
	(1)	(2)	(3)	(4)
Panel A: Removing liquidity controls				
ΔBMI, % × D(not special)	0.179***	0.129***	-0.003	0.080*
	(19.03)	(14.07)	(-1.12)	(1.96)
ΔBMI, % × D(special)	0.126***	0.213***	0.207***	0.275
	(3.45)	(5.55)	(3.97)	(1.50)
Observations	13,685	13,685	13,685	13,685
Adjusted R-squared	0.144	0.088	0.105	0.194
Panel B: Adding interactions of controls with stock specialness				
ΔBMI, % × D(not special)	0.177***	0.133***	-0.000	0.102**
	(18.75)	(14.29)	(-0.28)	(2.53)
ΔBMI, % × D(special)	0.135***	0.172***	0.184**	0.369
	(3.13)	(3.73)	(2.58)	(1.61)
Observations	13,685	13,685	13,685	13,685
Adjusted R-squared	0.145	0.091	0.120	0.203

This table reports the estimates of changes in specification (15) in the panel of stocks within 500 ranks around the Russell cutoff in 2007–2018. Specification in panel A removes β^{CAPM} and the bid-ask spread. Panel B includes baseline controls and their interactions with D(special). Both panels include D(special) by year fixed effects. Changes in lending market variables are computed as differences between July and May; stock return is measured in June; see further details in Appendix A.3. A stock is considered special, or $D(special) = 1$, if its average fee in May is above 1%. t-statistics based on standard errors clustered by stock are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

A.10.3 Alternative band widths

Table A9: Response of lending variables to changes in BMI

	Δ Lending inventory, % shares	Δ Quantity on loan, % shares	Δ Borrowing fee, %	Stock return, %
	(1)	(2)	(3)	(4)
Panel A: Band width of 200				
ΔBMI, % × D(not special)	0.202***	0.136***	-0.005	0.217***
	(16.06)	(11.30)	(-1.27)	(4.37)
ΔBMI, % × D(special)	0.167***	0.240***	0.204***	0.180
	(3.55)	(5.36)	(2.71)	(0.91)
Observations	7,766	7,766	7,766	7,766
Adjusted R-squared	0.174	0.111	0.097	0.209
Panel B: Band width of 300				
ΔBMI, % × D(not special)	0.179***	0.135***	-0.008*	0.098*
	(14.02)	(11.48)	(-1.66)	(1.89)
ΔBMI, % × D(special)	0.134***	0.256***	0.244***	0.349*
	(3.00)	(6.29)	(3.64)	(1.79)
Observations	9,659	9,659	9,659	9,659
Adjusted R-squared	0.191	0.136	0.195	0.241
Panel C: Band width of 750				
ΔBMI, % × D(not special)	0.177***	0.126***	-0.001	0.068**
	(23.23)	(16.95)	(-0.58)	(2.05)
ΔBMI, % × D(special)	0.150***	0.215***	0.157***	0.216
	(4.69)	(6.37)	(3.38)	(1.35)
Observations	18,781	18,781	18,781	18,781
Adjusted R-squared	0.137	0.077	0.085	0.194

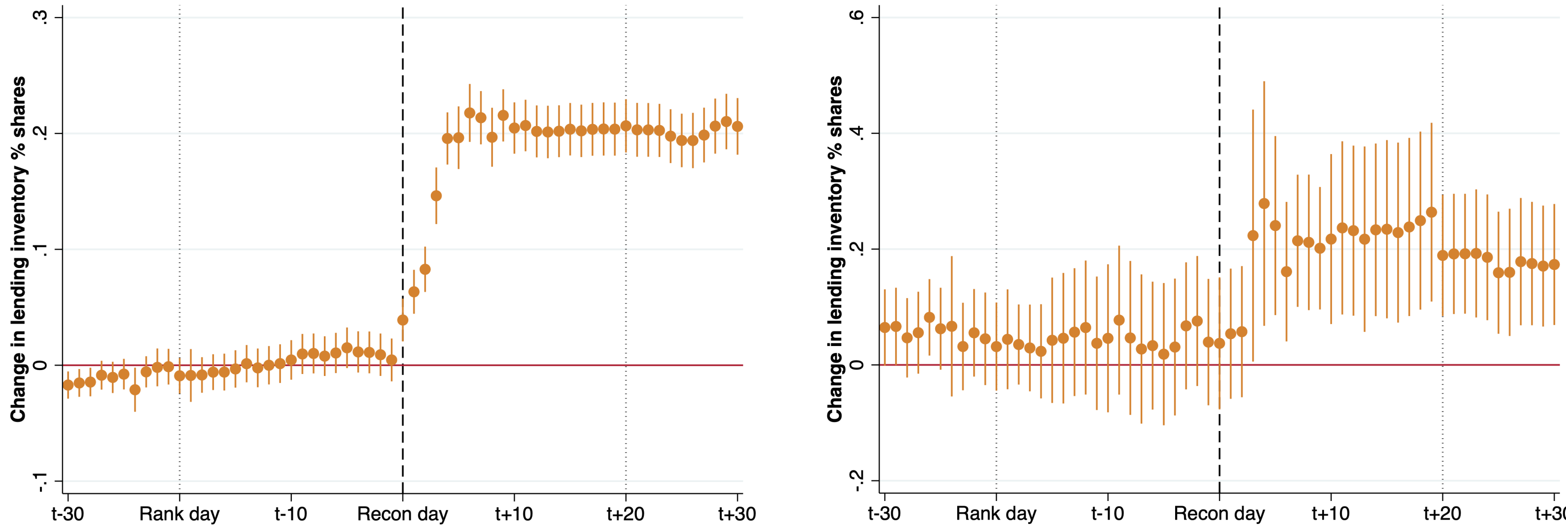
This table reports the estimates of specification (15) in the panel of stocks within 200 (panel A), 300 (panel B), or 750 (panel C) ranks around the Russell cutoff in 2007–2018. Changes in lending market variables are computed as differences between July and May; stock return is measured in June; see further details in Appendix A.3. A stock is considered special, or $D(special) = 1$, if its fee in May is above 1%. All regressions include controls and D(special) by year fixed effects. t-statistics based on standard errors clustered by stock are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

A.11 Daily changes in lending market variables

Figure A7: Daily estimates of changes in lending market variables on ΔBMI

(a) Lending inventory, not special

(b) Lending inventory, special



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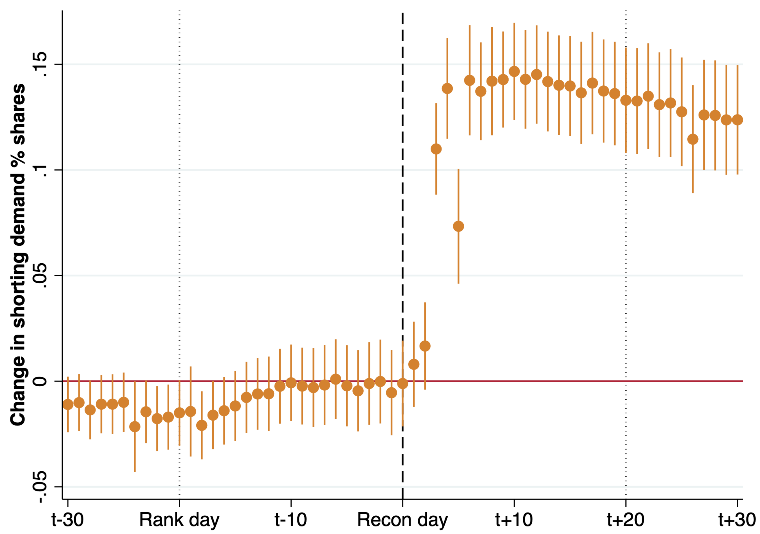
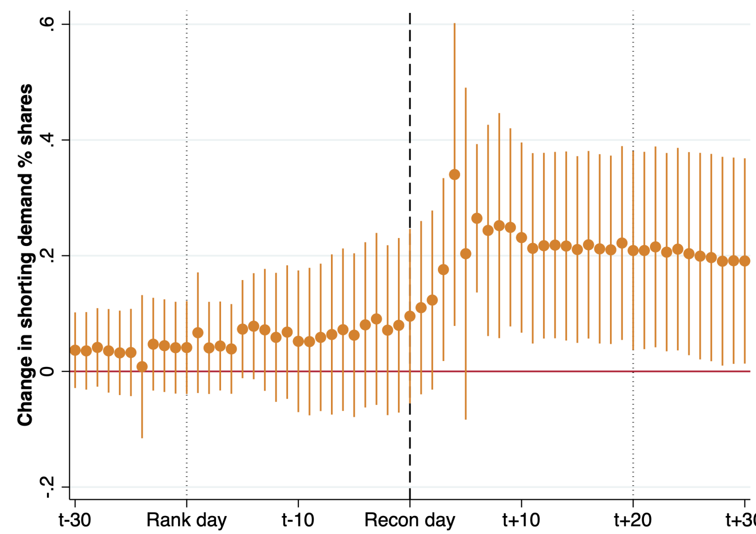
(c) Quantity on loan, not special



(d) Quantity on loan, special



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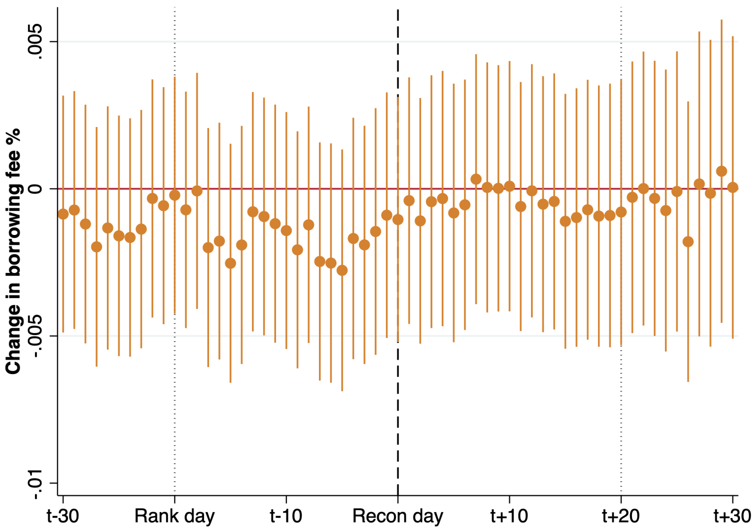
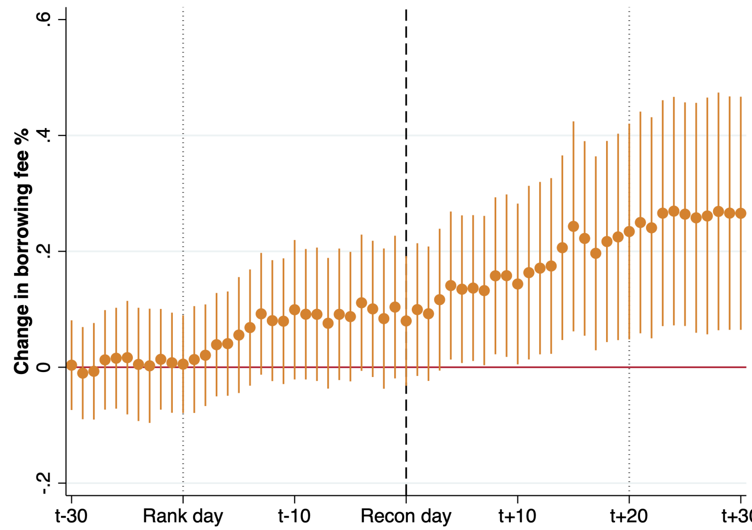
(e) Borrowing fee, not special



(f) Borrowing fee, special



This figure plots the daily estimates of the loading on ΔBMI and the corresponding 95% confidence intervals from regression (14), estimated separately for special (panels (b), (d), (f)) and not special stocks (panels (a), (c), (e)). The estimation window covers all trading days from mid-May to mid-August each year. Changes in variables are computed relative to the value at the end of April each year and demeaned at a stock level. The reconstitution day (recon day) is the actual historical reconstitution date, and the rank day is assumed to be on the last trading day in May.

A.12 Baseline results in the sample of stocks not switching indexes

Table A10: Response of spot and lending variables to changes in BMI in a sample of stocks that did not move indexes

	Δ Lending inventory, % shares	Δ Quantity on loan, % shares	Δ Borrowing fee, %	Stock return, %
	(1)	(2)	(3)	(4)
ΔBMI, % × D(not special)	0.135***	0.076***	-0.005***	0.217***
	(10.89)	(6.30)	(-3.01)	(4.25)
ΔBMI, % × D(special)	0.112*	0.158**	0.178**	0.429*
	(1.85)	(2.45)	(2.40)	(1.69)
Observations	13,098	13,098	13,098	13,098
Adjusted R-squared	0.104	0.053	0.091	0.208
$\beta_1 - \beta_2$	-0.022	0.082**	0.183**	0.212
	(-0.38)	(1.26)	(2.45)	(0.82)

This table reports the estimates of specification (15) in the panel of stocks within 500 ranks around the Russell cutoff in 2007-2018 excluding stocks that moved across the cutoff in a given year. The last raw reports the t-test for estimation results in panel B. Changes in lending market variables are computed as differences between May of year t and May of year $t+1$ and otherwise consistent with the main text. A stock is considered special, or $D(special) = 1$, if its fee in May is above 1%. All regressions include controls and D(special) by year fixed effects. t-statistics based on standard errors clustered by stock are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

A.13 More evidence on the shift in supply

If supply in the lending market moves in response to changes in borrowing fees, the findings in the main text may represent a movement along the supply curve rather than a shift in the supply curve. In this section, I show that it is not the case for Russell reconstitutions. First, I argue that under the assumption of downward-sloping shorting demand and upward-sloping supply, my estimates imply that BMI shifts demand more than it shifts supply. Then, I use an instrumental variable for shorting demand suggested by the literature to identify the lending supply and lending inventory curve parameters. Overall, results in this section confirm that BMI leads to a shift in both lending supply and shorting demand.

A.13.1 Identification without an instrument for demand (as in the main text)

The model in Section 3 can be written as the following system of structural equations for the lending market:

$$Q^{supply} = b_0 + b_1\Delta + b_2 w + v, \tag{21}$$

$$Q^{demand} = a_0 + a_1\Delta + a_2 w + u, \tag{22}$$

where w denotes BMI.

By equating them the supply and demand equations, I get a reduced-form equation for the borrowing fee Δ. Then I plug it into the supply equation to get a reduced-form representation for the quantity on loan Q.

$$\begin{aligned}\Delta =& \frac{b_2 - a_2}{a_1 - b_1} w + \frac{b_0 - a_0}{a_1 - b_1} + \frac{v - u}{a_1 - b_1} \\ =& \pi_{\Delta,w} w + \pi_{\Delta,0} + \epsilon, \end{aligned} \tag{23}$$

$$\begin{aligned} Q =& \frac{a_1 b_2 - a_2 b_1}{a_1 - b_1} w + \frac{b_0 a_1 - a_0 b_1}{a_1 - b_1} + \frac{a_1 v - b_1 u}{a_1 - b_1} \\ =& \pi_{Q,w} w + \pi_{Q,0} + \nu. \end{aligned} \tag{24}$$

Because these reduced-form equations provide 4 estimates, the system of structural equations above is not identified (it has 6 parameters).

In the main text, I estimate (23) and (24) in changes, which only influences interpretation of the constant terms. Therefore, I keep all equations in levels here for a better exposition. The corresponding reduced-form estimates are

$$\pi_{\Delta,w} > 0,$$

$$\pi_{Q,w} > 0.$$

They imply that either $b_2 > a_2$ and $a_1 > b_1$ or $b_2 < a_2$ and $a_1 < b_1$. Under the theoretical sign restrictions of $a_1 < 0$ and $b_1 > 0$ (downward-sloping shorting demand and upward-sloping lending supply), $a_1 - b_1 < 0$, so empirical estimates imply that $b_2 < a_2$ (pass-through from BMI to demand is stronger).

In sum, even though the structural parameters are not strictly identified, the reduced-form estimates together with theoretical sign restrictions suggest that an increase in BMI shifts shorting demand more than it shifts lending supply.

A.13.2 Identification with a demand shift

In order to identify the shift in lending supply around Russell reconstitutions and to support my assumptions for lending inventory, I use an exogenous demand shifter. Specifically, I follow Kolasinski, Reed, and Ringgenberg (2013), who use discretionary accruals, among other variables, as an instrument for shorting demand. Due to the slow-moving nature of lending inventory, it is unlikely that short-term shorting signals such as high discretionary accruals affect lending supply, although they strongly predict shorting demand. Furthermore, several papers find that institutions do not tilt their portfolios to anomalies (see Lewellen (2011) and Edelen, Ince, and Kadlec (2016)), so these signals unlikely affect lending inventory even in the long term.

First, I estimate the following 2SLS regression for special stocks:

$$\begin{aligned} Change\,in\,fee_{it} &= \gamma Accruals_{it} + \kappa \Delta BMI_{it} + \delta' \bar{X}_{it} + \mu_{st} + \varepsilon_{it}, \\ \Delta Y_{it} &= \alpha \widehat{Change\,in}\,fee_{it} + \beta \Delta BMI_{it} + \zeta' \bar{X}_{it} + \nu_{st} + \epsilon_{it}. \end{aligned}$$

$Accruals_{it}$ are computed for stock i in May of year t, in line with Sloan (1996). I use both the change in inventory (active lendable shares) and the shorting quantity variable (short quantity on loan) as the dependent variable ΔY_{it}. The rest of the specification is the same as in the baseline test, described near equation (14).

Results are reported in Table A11. Columns (1) and (4) report the estimates of the coefficient on change in BMI β without including $Change\,in\,fee$ to show that the estimates are virtually the same as in the main text (because the specification here is estimated in the subsample of special stocks as opposed to using interactions). Columns (2) and (5) include $Change\,in\,fee$ and report OLS estimates. The OLS estimate for the quantity on loan is significant and positive, consistent with the prevailing demand shocks in my sample. The OLS estimate for inventory is insignificantly negative. Finally, columns (3) and (6) report 2SLS estimates with $Change\,in\,fee$ around the Russell reconstitution instrumented by $Accruals$. The first-stage estimates in panel B highlight that $Accruals$ is a strong instrument for the change in borrowing fee, with the effective F-statistic above 27. For quantity on loan, the second-stage estimate for the change in fee is positive but close to zero and insignificant. This implies a rather unresponsive supply at least at the two-month horizon of my tests.[50] Importantly, the coefficients on ΔBMI are almost the same as the baseline estimates. Finally, inventory appears not sensitive to fees, consistent with the discussion in Section 5.2.6.

Next, I discuss what structural parameters these estimates identify. With a demand shifter,

[50] I get $\hat{\alpha} \approx 0.3$ if I use one-year changes while the loading of inventory on fees remains close to zero.

Table A11: Sensitivity of coefficient on BMI to simultaneity in lending supply and shorting demand

	Change in quantity on loan, %			**Change in inventory, %**		
	Baseline	OLS	2SLS	Baseline	OLS	2SLS
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Second-stage estimates						
$Change\,in\,fee$, %		0.12**	0.04		-0.05	-0.01
		(3.26)	(0.34)		(-1.48)	(-0.08)
ΔBMI, %	0.17***	0.15***	0.16***	0.13***	0.14***	0.13***
	(3.51)	(3.07)	(2.94)	(3.00)	(3.16)	(2.69)
Panel B: First-stage estimates						
$Accruals$			1.75***			1.75***
			(5.21)			(5.21)
F-Stat (excl. instruments)			27.10			27.10
Observations	613	613	613	613	613	613

This table reports the estimates of specification described in Section A.13 in the panel of special stocks within 500 ranks around the Russell cutoff in 2007–2018. Panel A reports the second-stage and OLS estimates, whereas panel B reports the first-stage estimates. Changes in lending market variables are computed as differences between July and May, see details in Appendix A.3. A stock is considered special, or $D(special) = 1$, if its fee in May is above 1%. All regressions include controls and year fixed effects. t-statistics based on standard errors clustered by stock are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

structural equations for the lending market are as follows,

$$\begin{aligned} Q^{supply} &= b_0 + b_1\Delta + b_2 w + v, \\ Q^{demand} &= a_0 + a_1\Delta + a_2 w + a_3 A + u, \\ Inv &= c_0 + c_1\Delta + c_2 w + e, \end{aligned}$$

where A is accruals. The corresponding reduced-form equations are

$$\begin{aligned} \Delta =& \frac{b_2 - a_2}{a_1 - b_1} w - \frac{a_3}{a_1 - b_1} A + \frac{b_0 - a_0}{a_1 - b_1} + \frac{v - u}{a_1 - b_1} \\ =& \pi_{\Delta,w} w + \pi_{\Delta,A} A + \pi_{\Delta,0} + \epsilon, \qquad (25) \\ Q =& \frac{a_1 b_2 - a_2 b_1}{a_1 - b_1} w - \frac{b_1 a_3}{a_1 - b_1} A + \frac{b_0 a_1 - a_0 b_1}{a_1 - b_1} + \frac{a_1 v - b_1 u}{a_1 - b_1} \\ =& \pi_{Q,w} w + \pi_{Q,A} A + \pi_{Q,0} + \nu, \qquad (26) \\ Inv =& \left(\frac{c_1 b_2 - c_1 a_2}{a_1 - b_1} + c_2\right) w - \frac{c_1 a_3}{a_1 - b_1} A + \left(\frac{c_1 b_0 - c_1 a_0}{a_1 - b_1} + c_0\right) + \left(\frac{c_1 v - c_1 u}{a_1 - b_1} + e\right) \\ =& \pi_{Inv,w} w + \pi_{Inv,A} A + \pi_{Inv,0} + \xi, \qquad (27) \end{aligned}$$

These allow to me identify the supply and inventory equations. However, because I have 9 reduced-form estimates and 10 structural parameters, the parameters of the demand equation are not identified.

I estimate (25) – (27) equation by equation on a sample of special stocks around the Russell cutoff and get the estimates below (robust t-statistics in parentheses):[51]

$$
\begin{aligned}
\pi_{Q,w} =& 0.171(3.50),\\
\pi_{Q,A} =& 0.065(0.33),\\
\pi_{\Delta,w} =& 0.188(2.52),\\
\pi_{\Delta,A} =& 1.749(5.21),\\
\pi_{Inv,w} =& 0.131(3.00),\\
\pi_{Inv,A} =& -0.012(-0.08).
\end{aligned}
$$

Using these reduced-form estimates, I can recover the structural parameters of supply and inventory equations:

$$
\begin{aligned}
b_1 &= 0.037, \quad & b_2 &= 0.164,\\
c_1 &= -0.007, \quad & c_2 &= 0.133.
\end{aligned}
$$

Therefore, I find that the pass-through from BMI to both inventory and supply is positive ($b_2 > 0$ and $c_2 > 0$). The sensitivity of supply to fee is weakly positive, and it is virtually zero for inventory. Together with the sign restrictions from the previous section, these estimates imply that the pass-through from BMI to shorting demand is positive and above $b_2 = 0.164$.

A.14 Switches in specialness and BMI

In this section, I analyze changes in stock specialness around Russell reconstitutions. I document transition probabilities at one-month and one-year horizons and show how changes in specialness are related to changes in BMI.

Table A12 documents that the specialness of stocks in my sample is quite persistent. A total of 87% of stocks next to the Russell cutoff that are special in May (prior to the reconstitution) remain special in July (after the reconstitution). At a one-year horizon, 54% of stocks remain special. These probabilities are similar in the full sample of Russell 3000 constituents, at 89% and 66% in July and May of the following year, respectively.

[51] I omit all constants because I estimate (25) – (27) in changes, so I cannot recover b_0 and c_0.

Table A12: Short- and long-term transition probabilities in specialness

	D(not special in July)	D(special in July)	D(not special in May next year)	D(special in May next year)
Panel A: Stocks around the Russell cutoff				
D(not special in May)	99%	1%	97%	3%
D(special in May)	13%	87%	46%	54%
Panel B: Full sample				
D(not special in May)	97%	3%	95%	5%
D(special in May)	11%	89%	34%	66%

This table reports specialness transition probabilities in the panel of stocks within 500 ranks around the Russell cutoff (panel A) and for all Russell 3000 constituents (panel B) in 2007–2018. A stock is considered special, or $D(special) = 1$, if its fee in May is above 1%.

Table A13 reports the estimates of a linear probability model of future stock specialness using specialness in May, change in BMI, and their interaction as main predictors. The exact specification is as follows:

$$
\begin{aligned}
D(special)_{it+h} = {} & \alpha D(special)_{it} + \beta \Delta BMI_{it} + \gamma \Delta BMI_{it} \times D(special)_{it} \\
& + \zeta' \bar{X}_{it} + \nu_t + \epsilon_{it+h},
\end{aligned} \tag{28}
$$

where $D(special)_{it+h} = 1$ if stock i has an average borrowing fee of over 1% in either July of year t or in May of year $t+1$, and all other variables are defined in Section 5.2.

Table A13 confirms that stock specialness is highly persistent even conditional on controls and year fixed effects. If a stock is special in May, it has a 85% higher chance of being special in July of the same year and 49% higher chance of being special in May of the next year. Furthermore, Table A13 shows that a change in BMI has limited predictive power for future specialness. Immediately after the reconstitution, a special stock is more likely to remain special if its BMI has increased; however, the economic magnitude is very small (at 60 bps larger probability for each 1 percentage point increase in BMI). At a one-year horizon, this estimate is 80 bps yet still statistically insignificant.

Table A13: Specialness and changes in BMI

	D(special in July)	D(special in May next year)
	(1)	(2)
D(special)	0.849***	0.489***
	(58.16)	(20.10)
ΔBMI, %	-0.000	-0.001
	(-0.70)	(-0.72)
ΔBMI, % $\times$ D(special)	0.006	0.008
	(1.60)	(1.37)
Observations	13,692	12,171
Adjusted R-squared	0.735	0.267

This table reports the estimates of specification (28) in the panel of stocks within 500 ranks around the Russell cutoff in 2007–2018. A stock is considered special, or $D(special) = 1$, if its average fee in May is above 1%. All regressions include controls and year fixed effects. t-statistics based on standard errors clustered by stock are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

A.15 Response of other lending features to BMI

In this section, in order to provide further support for the mechanism in my model, I analyze how changes in other lending market variables are related to changes in BMI around Russell reconstitutions. Specifically, I show that special stocks do not experience economically significant changes in utilization, loan tenure, or concentration of borrower, lender, or inventory shares. Furthermore, I document increases in option-implied borrowing fees of the same size as those reported in the main text and find no evidence of changes in fee risk premia or riskiness of short-selling.

Table A14 reports the estimates of specifications (14) and (15) for additional dependent variables, namely, active utilization, active utilization (short), Markit score, tenure, lender concentration, borrower concentration, and inventory concentration. Active utilization is quantity on loan relative to active lendable quantity (active inventory). Active utilization (short) is short quantity on loan relative to active lendable quantity. Markit score is Markit's proprietary Daily Cost of Borrow Score which measures how expensive it is to borrow a stock, based on the wholesale segment (agent lenders lending to intermediaries, e.g. prime brokers). Tenure is the loan-size-weighted average number of days from the start date to present for all transactions. Lender and borrower concentration levels are computed by Markit and represent Herfindahl-Hirschman indexes for the lender

Table A14: Response of additional lending variables to changes in BMI

	Change in						
	active utilization, %	active utilization (short), %	loan tenure, days	Markit score	lender concentration, %	borrower concentration, %	inventory concentration, %
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: No interactions							
ΔBMI, % MV	0.287***	0.337***	-0.531***	0.350**	-0.275***	-0.270***	-0.012*
	(8.42)	(8.86)	(-4.13)	(2.21)	(-5.46)	(-5.22)	(-1.83)
Observations	13,685	13,371	13,685	13,684	7,963	7,963	13,692
Adjusted R-squared	0.078	0.090	0.023	0.101	0.019	0.006	0.083
Panel B: With specialness interactions							
ΔBMI, % MV × D(not special)	0.274***	0.328***	-0.558***	-0.151	-0.298***	-0.285***	-0.007
	(8.98)	(9.31)	(-4.14)	(-1.61)	(-5.63)	(-5.24)	(-1.26)
ΔBMI, % MV × D(special)	0.436**	0.512*	-0.220	6.063***	-0.005	-0.097*	-0.063**
	(2.22)	(1.73)	(-0.56)	(4.29)	(-0.10)	(-1.69)	(-2.11)
Observations	13,685	13,371	13,685	13,684	7,963	7,963	13,692
Adjusted R-squared	0.078	0.091	0.023	0.126	0.019	0.006	0.083
$\beta_1 - \beta_2$	0.162	0.185	0.338	6.214***	0.293***	0.188***	-0.056*
	(0.83)	(0.63)	(0.81)	(4.45)	(4.58)	(2.90)	(-1.91)

This table reports the estimates of specification (14) (panel A) and specification (15) (panel B) in the panel of stocks within 500 ranks around the Russell cutoff in 2007–2018. Lender and borrower concentration levels are available from 2012 onwards, resulting in a lower number of observations in columns (4) and (5). The last raw reports the t-test for estimation results in panel B. Changes in lending market variables are computed as differences between July and May, see details in Appendix A.3. A stock is considered special, or $D(special) = 1$, if its fee in May is above 1%. All regressions include controls and D(special) by year fixed effects. t-statistics based on standard errors clustered by stock are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

and borrower shares in the value on loan, respectively. Inventory concentration is also computed by Markit and represents a Herfindahl-Hirschman index for the lender share in lendable quantity. I use changes in level variables computed as in the main text, and results are very similar if I use differences in logarithms instead. In unreported tests, I also find that the economically small decrease in inventory concentration for special stocks documented here is due to the decrease in the share of the largest inventory holder and is not present in more recent data (from 2012 onwards).

Table A15 reports the estimates of specifications (14) and (15) for dependent variables related to borrowing fee risk, namely, changes in borrowing fee volatility and changes in borrowing fee risk premium implied by option prices (adjusted). I compute fee volatility as a sample variance of daily borrowing fees in a given month (annualized, in %) and compare its value in May (before the reconstitution) to several months after the reconstitution – July, August, September, and October. I document that borrowing fee volatility for special stocks increases immediately after the reconstitution and tapers off with time. Therefore, the short-term increase in volatility must be driven not by an increase in the riskiness of short-selling but rather by the renegotiation of loans (consistent with fee dynamics discussed in Section 5.2 and Appendix A.11). I also show that

Table A15: Response of borrowing fee risk to changes in BMI

	Change in						
	borrowing fee, %	option-implied borrowing fee, %	option-implied fee risk premium, %	fee volatility (Jul-May), %	fee volatility (Aug-May), %	fee volatility (Sep-May), %	fee volatility (Oct-May), %
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: No interactions							
ΔBMI, %	0.010	0.003	-0.005	0.070**	0.011	0.007	-0.021
	(1.55)	(0.25)	(-0.53)	(2.27)	(0.64)	(0.35)	(-1.11)
Observations	7,684	7,684	7,684	13,689	13,687	13,678	13,625
Adjusted R-squared	0.103	0.049	0.034	0.055	0.026	0.053	0.077
Panel B: With specialness interactions							
ΔBMI, % × D(not special)	-0.004	-0.015	-0.010	-0.001	-0.022**	-0.017	-0.028**
	(-1.28)	(-1.64)	(-1.16)	(-0.06)	(-2.14)	(-1.17)	(-2.26)
ΔBMI, % × D(special)	0.188***	0.220***	0.058	0.882***	0.393**	0.281	0.065
	(2.80)	(2.94)	(0.94)	(2.74)	(2.25)	(1.56)	(0.40)
Observations	7,684	7,684	7,684	13,689	13,687	13,678	13,625
Adjusted R-squared	0.126	0.056	0.035	0.064	0.034	0.057	0.077
$\beta_1 - \beta_2$	0.192***	0.234***	0.068	0.883***	0.416**	0.298*	0.093
	(2.90)	(3.14)	(1.09)	(2.75)	(2.37)	(1.66)	(0.59)

This table reports the estimates of specification (14) (panel A) and specification (15) (panel B) in the panel of stocks within 500 ranks around the Russell cutoff. Columns (1)–(3) only include optionable stocks in 2007–2015 (as in Muravyev, Pearson, and Pollet (2022a)), while columns (4)–(7) use the baseline sample. The last raw reports the t-test for estimation results in panel B. Changes in variables in columns (1)–(3) are computed as differences between July and May. Changes in fee volatility are computed between May and July, August, September, and October in columns (4), (5), (6), and (7), respectively. A stock is considered special, or $D(special) = 1$, if its fee in May is above 1%. All regressions include controls and D(special) by year fixed effects. t-statistics based on standard errors clustered by stock are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

changes in option-implied borrowing fee (adjusted for early exercise) are very similar to those in Markit's borrowing fee used in the main text.[52]

Table A16 reports the estimates of specifications (14) and (15) for more dependent variables related to borrowing fee risk following Engelberg, Reed, and Ringgenberg (2018). Specifically, I investigate whether the changes in utilization volatility (often used as a measure of recall risk), lending inventory (active supply) volatility, quantity on loan (short interest) volatility, and failures to deliver are related to changes in BMI around the Russell reconstitutions. I find that for special stocks, none of these variables significantly decrease in BMI. Therefore, I find no evidence of a decrease in the borrowing risk in my setting.

[52]The computational details for the option-implied borrowing fee and borrowing fee risk premium are provided in Muravyev, Pearson, and Pollet (2022b) and Muravyev, Pearson, and Pollet (2018). I thank Dmitriy Muravyev for sharing the data.

Table A16: Response of further short-selling risk measures to changes in BMI

	Change in					
	utilization volatility, %	utilization (short) volatility, %	lending inventory volatility, %	quantity on loan volatility, %	number of failures to deliver, bps	new number of failures to deliver, bps
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: No interactions						
ΔBMI, %	-0.975**	-1.466**	-0.001	0.001	-0.004	-0.00
	(-2.17)	(-2.47)	(-1.28)	(1.13)	(-0.12)	(-0.60)
Observations	12,168	12,150	12,168	12,168	12,168	12,168
Adjusted R-squared	0.035	0.034	0.114	0.052	0.186	0.186
Panel B: With specialness interactions						
ΔBMI, % × D(not special)	-0.946**	-1.222**	-0.001**	0.000	-0.014	-0.004
	(-2.27)	(-2.28)	(-2.15)	(0.43)	(-0.56)	(-1.13)
ΔBMI, % × D(special)	-1.312	-4.290	0.004	0.006*	0.108	0.015
	(-0.48)	(-1.16)	(1.55)	(1.82)	(0.42)	(0.71)
Observations	12,168	12,150	12,168	12,168	12,168	12,168
Adjusted R-squared	0.035	0.034	0.115	0.053	0.186	0.186
$\beta_1 - \beta_2$	-0.366	-3.068	0.005**	0.005*	0.122	0.019
	(-0.13)	(-0.83)	(2.04)	(1.77)	(0.48)	(0.90)

This table reports the estimates of specification (14) (panel A) and specification (15) (panel B) in the panel of stocks within 500 ranks around the Russell cutoff. The last raw reports the t-test for estimation results in panel B. Changes in all variables are computed as differences between one year after the Russell reconstitution and one year before the reconstitution. Failures to deliver are taken from the U.S. SEC website (`https://www.sec.gov/data-research/sec-markets-data/fails-deliver-data`) and scaled by shares outstanding. New failures to deliver are computed as change in the number of failures to deliver relative to the previous observation.[a] A stock is considered special, or $D(special) = 1$, if its fee in May is above 1%. All regressions include controls and D(special) by year fixed effects. t-statistics based on standard errors clustered by stock are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

[a] This change technically cannot be interpreted as the number of new failures to deliver. I use it simply to capture potential jumps in the number of failures. See all caveats of the data at `https://www.sec.gov/data-research/sec-markets-data/fails-deliver-data`.

A.16 Disagreement and BMI

In this section, I show that changes in disagreement as measured by the dispersion in analyst forecasts are not driving the main results.

I define disagreement in line with the literature. Specifically, I use the standard deviation of EPS estimates scaled by the absolute value of the mean estimate (Diether, Malloy, and Scherbina (2002)). The change in dispersion is computed from the last available summary date prior to June to the first available date after June. I use the summary estimate table from I/B/E/S following the discussion of different vintage issues in WRDS.[53]

Table A17 shows that for September EPS forecasts, there is a weak negative relationship between the level of disagreement and BMI in May. Intuitively, stocks that belong to major benchmark indexes may exhibit less information asymmetry resulting in analysts disagreeing less about these stocks' prospects. Columns (2) and (3) further document no significant relationship between BMI and disagreement in changes, for the full sample of stocks and special stocks only. Nevertheless, to ensure that the contemporaneous changes in disagreement are not driving my findings, I add the change in disagreement interacted with specialness to the baseline regressions. Columns (4) to (7) show that the estimates are virtually unaffected.

Table A17: Disagreement and changes in BMI

	EPS dispersion in May	Δ EPS dispersion	Δ EPS dispersion	Δ Lending inventory, % shares	Δ Quantity on loan, % shares	Δ Borrowing fee, %	Stock return, %
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
BMI in May, %	-0.340*						
	(-1.69)						
ΔBMI, %		0.104	2.093				
		(0.61)	(1.63)				
ΔBMI, % × D(not special)				0.175***	0.119***	-0.003	0.098**
				(16.82)	(12.32)	(-1.01)	(2.27)
ΔBMI, % × D(special)				0.119***	0.216***	0.191***	0.341*
				(2.97)	(5.40)	(3.54)	(1.81)
ΔEPS dispersion × D(not special)				-0.001	0.000	0.000*	-0.016***
				(-1.40)	(0.38)	(1.70)	(-3.07)
ΔEPS dispersion × D(special)				-0.006***	0.001	0.004	-0.028**
				(-2.73)	(0.78)	(1.52)	(-2.05)
Observations	11,421	11,421	502	11,421	11,421	11,421	11,421
Adjusted R-squared	0.044	0.001	-0.011	0.150	0.093	0.124	0.208
$\beta_1 - \beta_2$				-0.056	0.096**	0.194***	0.242
				(-1.37)	(2.44)	(3.61)	(1.27)

This table reports the estimates of specification (15) with added Δ EPS dispersion controls in the panel of stocks within 500 ranks around the Russell cutoff in 2007–2018. Column (3) includes only special stocks. EPS dispersion is computed as standard deviation in September EPS forecasts scaled by the absolute value of the mean EPS forecast, as reported in the forecast summary table of I/B/E/S. Change in dispersion is computed as the difference between the last available summary date prior to June and the first available summary date after June. Changes in lending market variables are computed as differences between July and May; stock return is measured in June; see further details in Appendix A.3. A stock is considered special, or $D(special) = 1$, if its average fee in May is above 1%. The last raw reports the t-test for no difference in loading on ΔBMI for special and not special stocks. All regressions include controls and D(special) by year fixed effects. t-statistics based on standard errors clustered by stock are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

[53] See WRDS research guide to I/B/E/S: https://wrds-www.wharton.upenn.edu/pages/grid-items/ibes-wrds-101-introduction-and-research-guide/.

A.17 Stock fundamentals and lending shares

Table A18: Conditional correlation between fund-level stock lending share and stock characteristics

	Stock-level lending by funds						
	All stocks		Special stocks				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Extensive margin, D(Lent Share > 0)							
D(special)	0.407***	0.158***					
	(39.86)	(19.02)					
Size decile			0.033***	0.012***	0.016***	0.011***	0.012***
			(13.53)	(3.79)	(4.86)	(3.47)	(4.16)
Volatility, 1y rolling					7.060***	8.476***	5.127***
					(4.18)	(4.86)	(3.05)
Beta, 1y rolling					0.028***	0.015**	0.018***
					(4.26)	(2.53)	(3.11)
Bid-ask spread, 1y rolling						-12.752***	-13.419***
						(-17.08)	(-18.95)
Borrowing fee							0.923***
							(9.61)
Observations	4,778,953	4,675,790	263,414	222,925	210,223	208,069	208,069
Adjusted R-squared	0.108	0.508	0.021	0.533	0.541	0.542	0.546
Panel B: Intensive margin, Lent Share							
D(special)	0.163***	0.081***					
	(27.45)	(23.87)					
Size decile			0.024***	0.005**	0.005*	0.003	0.005*
			(12.09)	(2.10)	(1.90)	(1.36)	(2.02)
Beta, 1y rolling					0.013***	0.008*	0.010**
					(3.05)	(1.89)	(2.23)
Volatility, 1y rolling					5.945***	6.736***	4.227***
					(3.56)	(3.81)	(2.83)
Bid-ask spread, 1y rolling						-5.298***	-5.923***
						(-5.22)	(-5.92)
Borrowing fee							0.751***
							(13.87)
Observations	417,905	351,070	124,351	100,525	96,131	95,839	95,839
Adjusted R-squared	0.040	0.481	0.027	0.397	0.403	0.402	0.408
FE	N	Fund x Stock and Date	N	Fund x Stock and Date	Fund x Stock and Date	Fund x Stock and Date	Fund x Stock and Date

This table reports the estimates of regressing fund-level stock lending share on stock characteristics in the panel of fund holdings in 2020–2022. In columns (1)–(2), I use the full fund-stock-quarter panel of holdings, whereas in columns (3)–(7) I include only special stocks. Included fixed effects are specified in each column. Lent share is the share of holdings in a given stock on loan. A stock is considered special, or $D(special) = 1$, if its fee on the report date is above 1%. Size decile is computed daily over the sample of stocks in fund holdings. Volatility is one-year rolling sum of daily squared returns. Beta is the estimate of stock return sensitivity to CRSP value-weighted index return, computed over one year of daily data with a minimum of three trading months of data. Bid-ask spread is the one-year rolling average quoted bid-ask spread scaled by the close price. Borrowing fee is Markit's indicative fee used in the baseline analysis. All characteristics, except for size decile and beta, are winsorized daily at 99%. Beta is winsorized daily at 0.5% and 99.5%. t-statistics based on standard errors clustered by fund-stock and date are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

B Baseline model details and proofs

B.1 Portfolio choice

B.1.1 Solution to the direct investor's problem.

The direct investor chooses a portfolio θ_D to maximize his expected utility $U(W^D)$:

$$\max_{\theta_D} E_0[-\exp\{-\gamma W^D\}]. \tag{29}$$

To evaluate the expectation in (29), I need the following property. Suppose $Y \sim N(E[Y], Var[Y])$ is an $N \times 1$ random vector, α is a (constant) scalar and x is a constant vector. Then

$$Ee^{\alpha x' Y} = e^{\alpha x' E[Y] + \frac{\alpha^2}{2} x' Var[Y] x}. \tag{30}$$

Substituting in the terminal wealth $W^D = W_0^D + \theta_D(\bar{D} - p)$ and using property (30), I can equivalently represent the direct investor's problem as

$$\max_{\theta_D} \left[-\exp\{-\gamma[W_0^D + \theta_D(\mu - p) - \frac{\gamma}{2}\sigma\theta_D^2]\} \right].$$

The first order condition (FOC) with respect to θ_D yields the demand function (2):

$$\begin{aligned} -\gamma(\mu - p) + \gamma^2\sigma\theta_D =& 0, \\ \theta_D =& \frac{1}{\gamma\sigma}(\mu - p). \end{aligned}$$

B.1.2 Solution to the fund manager's problem

A fund manager chooses risky holdings θ_M to maximize his expected utility from compensation $U(w)$. The optimization problem of the fund manager is

$$\max_{\theta_M} E_0[-\exp\{-\gamma(aR + b(R - B) + c)\}],$$

or equivalently,

$$\max_{\theta_M} E_0[-\exp\{-\gamma((a+b)\theta_M(l\Delta + \bar{D} - p) - b\omega(\bar{D} - p))\}].$$

Again using property (30), I can write the fund manager's problem as

$$\max_{\theta_M} \left[-\exp\{-\gamma \left((a+b)\theta_M(l\Delta + \mu - p) - b\omega(\mu - p) - \frac{\gamma}{2}\sigma((a+b)\theta_M - b\omega)^2 \right)\} \right].$$

The FOC with respect to θ_M yields the demand function (3):

$$\begin{aligned}-\gamma(a+b)(l\Delta+\mu-p)+\gamma^2(a+b)\sigma((a+b)\theta_M-b\omega) =&0,\\ (a+b)\theta_M-b\omega =&\frac{1}{\gamma\sigma}(l\Delta+\mu-p),\\ \theta_M =&\frac{1}{\gamma\sigma(a+b)}(l\Delta+\mu-p)+\frac{b}{a+b}\omega.\end{aligned}$$

B.1.3 Solution to the hedger's problem

The hedger chooses risky holdings θ_H to maximize his expected utility $U(W^H)$. After substituting in $W^H = W_0^H + e\bar{D} + \theta_H(\bar{D} - p + \Delta\mathbf{1}_{\theta_H<0})$, I can write the hedger's problem as

$$\max_{\theta_H} E_0[-\exp\{-\gamma(W_0^H + e\bar{D} + \theta_H(\bar{D} - p + \Delta\mathbf{1}_{\theta_H<0}))\}]. \tag{31}$$

As discussed in the main text, I focus on the case when $\mathbf{1}_{\theta_H<0} = 1$ (endowment is large enough). With that and using property (30), I can rewrite (31) as

$$\max_{\theta_H}\left[-\exp\{-\gamma[W_0^H + e\mu + \theta_H(\mu - p + \Delta) - \frac{\gamma}{2}\sigma(e+\theta_H)^2]\}\right].$$

The FOC with respect to θ_H yields the demand function (4):

$$\begin{aligned}-\gamma(\mu-p+\Delta)+\gamma^2\sigma(e+\theta_H) =&0,\\ \theta_H =&\frac{1}{\gamma\sigma}(\mu-p+\Delta)-e.\end{aligned}$$

B.2 Equilibrium price and borrowing fee

B.2.1 Asset on special

I use market clearing conditions (5) and (6) as well as the optimal portfolio choice of the investors (2)–(4) to solve for the equilibrium asset price and borrowing fee. First, substitute the demand functions (3), and (4) into the market clearing condition in the lending market (6):

$$\begin{aligned}l\lambda_M\theta_M+\lambda_H\theta_H&=0,\\ l\lambda_M\left(\frac{1}{\gamma\sigma(a+b)}(l\Delta+\mu-p)+\frac{b}{a+b}\omega\right)+\lambda_H\left(\frac{1}{\gamma\sigma}(\mu-p+\Delta)-e\right)&=0,\\ (\mu-p)\left(\frac{l\lambda_M}{a+b}+\lambda_H\right)+l\Delta\left(\frac{l\lambda_M}{a+b}+\lambda_H\right)+(1-l)\lambda_H\Delta+\gamma\sigma l\lambda_M\frac{b}{a+b}\omega-\gamma\sigma\lambda_He&=0.\end{aligned}$$

which yields an expression for $p - l\Delta$:

$$p - l\Delta = \mu + \frac{1}{l\lambda_M/(a+b) + \lambda_H}\left[(1-l)\lambda_H\Delta + \gamma\sigma l\lambda_M b/(a+b)\omega - \gamma\sigma\lambda_H e\right]. \tag{32}$$

Then, combine the market clearing conditions in the lending market (6) and in the asset market (5) to get

$$\lambda_D\theta_D + (1-l)\lambda_M\theta_M = \bar{\theta}.$$

If I substitute the demand functions (2) and (3) into the expression above, then

$$\begin{aligned} \lambda_D\frac{1}{\gamma\sigma}(\mu - p) + (1-l)\lambda_M\left(\frac{1}{\gamma\sigma(a+b)}(l\Delta + \mu - p) + \frac{b}{a+b}\omega\right) &= \bar{\theta}, \\ (\mu - p + l\Delta)(\lambda_D + (1-l)\lambda_M/(a+b)) - \lambda_D l\Delta + (1-l)\gamma\sigma\lambda_M b/(a+b)\omega &= \gamma\sigma\bar{\theta}, \end{aligned}$$

which yields another expression for $p - l\Delta$:

$$p - l\Delta = \mu - \frac{1}{(1-l)\lambda_M/(a+b) + \lambda_D}\left[\lambda_D l\Delta + \gamma\sigma\bar{\theta} - \gamma\sigma(1-l)\lambda_M b/(a+b)\omega\right]. \tag{33}$$

Subtract (33) from (32) and rearrange:

$$\begin{aligned} &\frac{1}{l\lambda_M/(a+b) + \lambda_H}\left[(1-l)\lambda_H\Delta + \gamma\sigma l\lambda_M b/(a+b)\omega - \gamma\sigma\lambda_H e\right] + \\ &\qquad\qquad \frac{1}{(1-l)\lambda_M/(a+b) + \lambda_D}\left[\lambda_D l\Delta + \gamma\sigma\bar{\theta} - \gamma\sigma(1-l)\lambda_M b/(a+b)\omega\right] = 0, \\ &\Delta[\lambda_M/(a+b)(l^2\lambda_D + (1-l)^2\lambda_H) + \lambda_D\lambda_H] + \gamma\sigma(\bar{\theta}[l\lambda_M/(a+b) + \lambda_H] - e[(1-l)\lambda_M/(a+b) + \lambda_D]\lambda_H + \\ &\qquad\qquad \omega\lambda_M b/(a+b)[l\lambda_D - (1-l)\lambda_H]) = 0. \end{aligned}$$

Further rearranging yields the expression for the equilibrium borrowing fee Δ (8).

Next, rearrange (33) to get

$$\begin{aligned} p - l\Delta =& \mu - \frac{1}{(1-l)\lambda_M/(a+b) + \lambda_D}\left[\lambda_D l\Delta + \gamma\sigma\bar{\theta} - \gamma\sigma(1-l)\lambda_M b/(a+b)\omega\right], \\ p =& \mu - \frac{1}{(1-l)\lambda_M/(a+b) + \lambda_D}\gamma\sigma\left[\bar{\theta} - (1-l)\lambda_M b/(a+b)\omega\right] \\ &+ l\Delta\frac{(1-l)\lambda_M/(a+b)}{(1-l)\lambda_M/(a+b) + \lambda_D}. \end{aligned} \tag{34}$$

Substituting in the equilibrium borrowing fee Δ (8) and rearranging yields

$$
\begin{aligned}
p = \mu &+ \frac{l(1-l)\lambda_H}{l^2\lambda_D + (1-l)^2\lambda_H + (a+b)\lambda_D\lambda_H/\lambda_M}\gamma\sigma e \\
&- \frac{1}{(1-l)\frac{\lambda_M}{a+b} + \lambda_D}\left(1 + \frac{l(1-l)(l\frac{\lambda_M}{a+b} + \lambda_H)}{l^2\lambda_D + (1-l)^2\lambda_H + (a+b)\lambda_D\lambda_H/\lambda_M}\right)\gamma\sigma\bar{\theta} \\
&+ \frac{(1-l)\frac{b\lambda_M}{a+b}\lambda_H}{\frac{\lambda_M}{a+b}(l^2\lambda_D + (1-l)^2\lambda_H) + \lambda_D\lambda_H}\gamma\sigma\omega.
\end{aligned}
$$

This yields the expression for the equilibrium asset price (7).

B.2.2 General collateral asset

If the securities lending market clearing condition (6) holds with a strict inequality,

$$
l\lambda_M\theta_M + \lambda_H\theta_H > 0,
$$

or, in other words, if the lending supply from the fund managers is higher than the shorting demand from hedgers, then the equilibrium borrowing fee is zero. In this case, $-\lambda_H\theta_H$ in the model corresponds to the shorting demand observed in the data and $l\lambda_M\theta_M$ corresponds to the available lending supply which is higher than the demand. Because the fee is zero, the fund manager has no incentive to lend the asset and his portfolio demand is

$$
\theta_M = \frac{1}{\gamma\sigma(a+b)}(\mu - p) + \frac{b}{a+b}\omega.
$$

The portfolio demand of a hedger is $\theta_H = \frac{1}{\gamma\sigma}(\mu - p) - e$, and the direct investor's demand function is the same.

The equilibrium asset price is defined by the market clearing condition (5). Plugging in the demand functions with a zero borrowing fee, I get

$$
\begin{aligned}
\lambda_D\theta_D + \lambda_M\theta_M + \lambda_H\theta_H =& \bar{\theta}, \\
\lambda_D\frac{1}{\gamma\sigma}(\mu - p) + \lambda_M\left(\frac{1}{\gamma\sigma(a+b)}(\mu - p) + \frac{b}{a+b}\omega\right) + \lambda_H\left(\frac{1}{\gamma\sigma}(\mu - p) - e\right) =& \bar{\theta}, \\
(\mu - p)\left[\lambda_D + \lambda_M\frac{1}{(a+b)} + \lambda_H\right] + \gamma\sigma(\omega_\lambda - \lambda_H e - \bar{\theta}) =& 0,
\end{aligned}
$$

where $\omega_\lambda = \frac{b\lambda^A}{a+b}\omega$, as earlier. Rearranging, I get the equilibrium asset price in (10).

B.3 Economy with full lending

The presence of direct investors in my model ensures the existence of equilibrium even in the full lending economy, that is, when $l = 1$. Under full lending, the equilibrium asset price and borrowing fee for an asset on special are simplified to

$$\begin{aligned}
p =& \mu - \frac{1}{\lambda_D}\gamma\sigma\bar{\theta}, \\
\Delta =& \gamma\sigma\left(\frac{\lambda_H}{\frac{\lambda_M}{a+b} + \lambda_H} e - \frac{1}{\lambda_D}\bar{\theta} - \frac{1}{\frac{\lambda_M}{a+b} + \lambda_H}\omega_\lambda\right).
\end{aligned}$$

Under full lending, changes in endowment and benchmarking are fully balanced in the lending market and no longer passed to the equilibrium prices. Endowment e is a demand shifter, and the equilibrium fee increases with it. In contrast, ω_λ is a supply shifter and the equilibrium fee unambiguously decreases with it.

For a general collateral asset, the borrowing fee is zero and the price is still defined by (10) in the main text.

In an economy with full lending, the specialness condition becomes

$$\lambda_H\lambda_D e - \left(\frac{\lambda_M}{a+b} + \lambda_H\right)\bar{\theta} - \lambda_D\omega_\lambda > 0.$$

Therefore, an asset with a higher BMI is always less likely to be on special.

B.4 Numerical illustration

I use the following parameter values for the numerical illustration of the model:

$$\begin{aligned}
\mu =& 2, \\
\gamma =& 2, \\
\sigma =& 0.15, \\
a =& 0.1, \\
b =& 0.9, \\
\lambda_M =& 0.6, \\
\lambda_D =& 0.25, \\
\lambda_H =& 0.15,
\end{aligned}$$

$$
\begin{aligned}
e =& 7, \\
\bar{\theta} =& 1, \\
\omega =& 1 \quad \text{(for a benchmark asset)}, \\
\omega =& 0 \quad \text{(for an off-benchmark asset)}.
\end{aligned}
$$

These parameter values correspond to the equilibrium with positive holdings of direct investors (positive expected return), negative holdings of hedgers (large enough endowment), and positive equilibrium price.

In Figure 1 in the main text, panel (a) uses $l = 0.50$ and panel (b) uses $l = 0.15$. These values yield a positive borrowing fee (asset is on special). Panel (c) in in Figure 1 uses $l = 0.95$, which corresponds to the general collateral case with a zero borrowing fee. In the figure, equilibrium price is recomputed at each level of fee Δ and the given parameters to account for the fact that they are jointly determined.

B.5 Price sensitivity to benchmarking

An asset on special and a general collateral asset have different price sensitivities to benchmarking. Compare the price sensitivity of a general collateral asset,

$$
\frac{\partial p}{\partial \omega_\lambda} = \frac{1}{\frac{\lambda_M}{(a+b)} + \lambda_D + \lambda_H} \gamma \sigma,
$$

to that of a special asset,

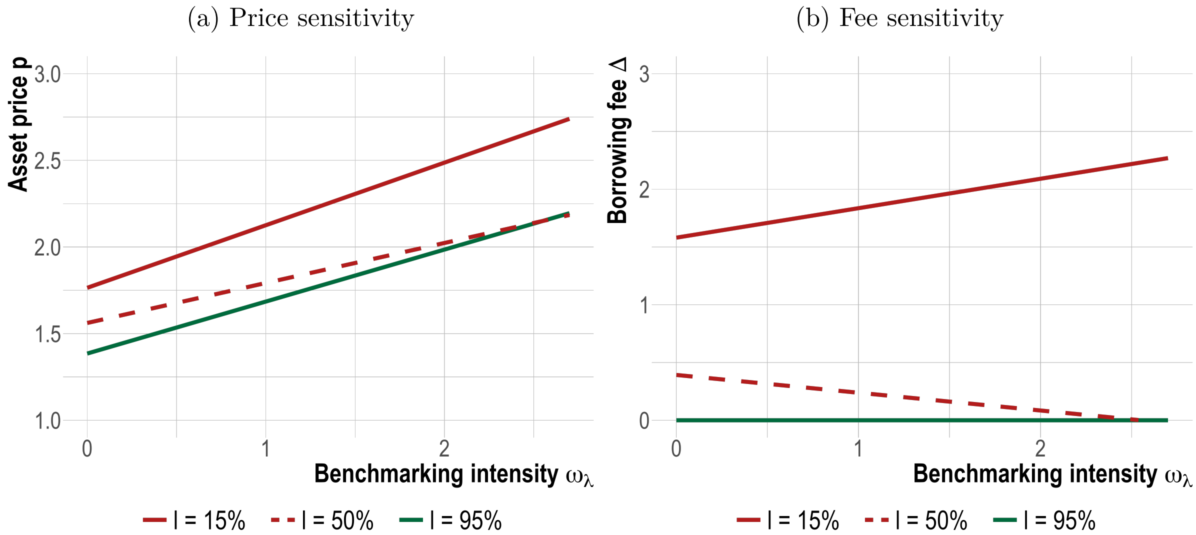
$$
\frac{\partial p}{\partial \omega_\lambda} = \gamma \sigma \bar{B} B_\omega = \frac{(1-l)\lambda_H}{\frac{\lambda_M}{a+b}(l^2 \lambda_D + (1-l)^2 \lambda_H) + \lambda_D \lambda_H} \gamma \sigma.
$$

The latter is lower if and only if

$$
\begin{aligned}
\frac{(1-l)\lambda_H}{\frac{\lambda_M}{a+b}(l^2 \lambda_D + (1-l)^2 \lambda_H) + \lambda_D \lambda_H} - \frac{1}{\frac{\lambda_M}{(a+b)} + \lambda_D + \lambda_H} <& 0, \\
\text{or equivalently,} \quad \frac{\lambda_H}{\lambda_H + \lambda_D} <& l,
\end{aligned}
$$

which is the same as condition (9), which defines equilibrium fee sensitivity to BMI for the asset on special. In this comparison, the asset on special is ex-ante different from the general collateral asset on other dimensions, for example, because hedgers are more endowed with it, that is, it has a higher e. I also assume that the change in benchmarking intensity is not large enough to make a

Figure B1: Sensitivity of equilibrium prices and fees to benchmarking



This figure plots the changes in equilibrium quantities due to changes in BMI in the model: equilibrium price in panel (a) and equilibrium borrowing fee in panel (b). In each panel, the two red lines correspond to special assets – one with the lending limit $l = 15\%$ ($C_\omega > 0$) and the other with $l = 50\%$ ($C_\omega < 0$), whereas the green line corresponds to a general collateral asset with $l = 95\%$. Appendix B.4 details all parameter values.

general collateral asset special, or the other way around.

In other words, asset pricing effects of investment mandates (or more specifically, benchmarking) are co-determined with the outcomes in the lending market of a special asset. In an economy with dominating demand effect of benchmarking in the lending market (if condition (9) does not hold), price sensitivity to BMI is higher for an asset on special or lower for a general collateral asset. This is illustrated in panel (a) of Figure B1: for the same change in BMI, an increase in the equilibrium asset price is smaller (larger) if condition (9) holds (does not hold) than the increase in the price of a general collateral asset. The equilibrium borrowing fees corresponding to these cases are plotted in panel (b).

B.6 Total derivatives of lending supply and demand with respect to BMI

B.6.1 Asset on special

For an asset on special, I find that both demand and supply always increase with benchmarking intensity ω_λ. Their sensitivity to it is the same because the lending market clearing condition is binding. Specifically, the general equilibrium responses of the shorting demand and the lending supply are given by

$$\frac{dQ^d}{d\omega_\lambda} = \lambda_H \frac{1}{\gamma\sigma}\left(\frac{\partial p}{\partial \omega_\lambda} - \frac{\partial \Delta}{\partial \omega_\lambda}\right)$$
$$= \bar{B} l \lambda_D \lambda_H,$$
$$\frac{dQ^s}{d\omega_\lambda} = \frac{\partial Q^s}{\partial \omega_\lambda} + \frac{l\lambda_M}{\gamma\sigma(a+b)}\left(l\frac{\partial \Delta}{\partial \omega_\lambda} - \frac{\partial p}{\partial \omega_\lambda}\right)$$
$$= \bar{B} l \lambda_D \lambda_H, \tag{35}$$

where the response of the supply includes the direct effect of benchmarking on supply, $\frac{\partial Q^s}{\partial \omega_\lambda}$, and the indirect effects through asset price and borrowing fee. Benchmarking-induced increase in shorting demand pushes the borrowing fee up and incentivizes fund managers to hold more of the asset despite the index effect.

B.6.2 General collateral asset

For a general collateral asset, the equilibrium lending supply and shorting demand also increase in BMI. However, since condition (6) is slack, their sensitivities are not the same.

The general equilibrium response of the shorting demand is

$$\frac{dQ^d}{d\omega_\lambda} = \frac{\partial Q^d}{\partial \omega_\lambda} + \lambda_H \frac{1}{\gamma\sigma}\frac{\partial p}{\partial \omega_\lambda}$$
$$= \frac{\lambda_H}{\frac{\lambda_M}{(a+b)} + \lambda_D + \lambda_H} > 0.$$

The index effect implies that the shorting demand is positively related to BMI in equilibrium, whereas the strength of the relationship is defined by the share of hedgers in the population of price-elastic investors.

The general equilibrium response of the lending supply is

$$\frac{dQ^s}{d\omega_\lambda} = \frac{\partial Q^s}{\partial \omega_\lambda} - \frac{l\lambda_M}{\gamma\sigma(a+b)}\frac{\partial p}{\partial \omega_\lambda}$$
$$= l\left(1 - \frac{\frac{\lambda_M}{(a+b)}}{\frac{\lambda_M}{(a+b)} + \lambda_D + \lambda_H}\right)$$
$$= l\frac{\lambda_D + \lambda_H}{\frac{\lambda_M}{(a+b)} + \lambda_D + \lambda_H} > 0, \tag{36}$$

Benchmarking-induced increase in fund managers' holdings still translates to larger supply, although the increase is not necessarily the same as that of the shorting demand: It depends on how $l(\lambda_D + \lambda_H)$ compares to λ_H. The response of the lending supply is larger if condition (9) holds.

C Economy with multiple assets

In this section, I verify robustness of my results for the risky asset with a positive borrowing fee in the presence of either a risky asset with a zero fee or another risky asset with a positive fee. I demonstrate that all key results remain valid in such more elaborate economies.

C.1 Economy with additional costless-to-short asset

I consider a simple extension of the baseline model by introducing a risky asset for which the lending market constraint is not binding.

The setup of the model is the same as in the main text, with one exception. There are now two risky assets paying cash flows $D_i,\ i = \{1, 2\}$, in period 1. The cash flows of the risky assets are given by

$$D_i = \overline{D}_i + \beta_i Z + \epsilon_i, \quad \beta_i > 0,\ i = \{1, 2\},$$

where $Z \sim N(0, \sigma_z^2)$ is a common shock and $\epsilon_i \sim N(0, \sigma_\epsilon^2)$ is an idiosyncratic one. The vectors $D \equiv (D_1, D_2)'$ and $p \equiv (p_1, p_2)'$ denote vectors of period-1 cash flows and period-0 risky asset prices, respectively. The risky assets are in fixed supply of $\overline{\theta} \equiv (\overline{\theta}_1, \overline{\theta}_2)'$ shares. The variance-covariance matrix of cash flows D can be conveniently written as

$$\Sigma = \begin{pmatrix} \beta_1^2\sigma_z^2 + \sigma_\epsilon^2 & \beta_1\beta_2\sigma_z^2 + \sigma_\epsilon^2 \\ \beta_1\beta_2\sigma_z^2 + \sigma_\epsilon^2 & \beta_2^2\sigma_z^2 + \sigma_\epsilon^2 \end{pmatrix} = \begin{pmatrix} \sigma_1^2 & \sigma_{12} \\ \sigma_{12} & \sigma_2^2 \end{pmatrix}$$

I also set $\bar{D} \equiv \mu = (\mu_1, \mu_2)'$ and $\beta \equiv (\beta_1, \beta_2)'$. Borrowing fees are also represented by the vector $\Delta \equiv (\Delta_1, \Delta_2)'$, with $\Delta_2 = 0$. Finally, the benchmark index is now a portfolio of $\omega = (\omega_1, \omega_2)'$, in which individual components $\omega_i,\ i = \{1, 2\}$, may be zero.

Below I will use an analytical expression for the inverse of Σ,

$$\Sigma^{-1} = \underbrace{\frac{1}{\sigma_1^2\sigma_2^2 - \sigma_{12}^2}}_{A} \begin{pmatrix} \sigma_2^2 & -\sigma_{12} \\ -\sigma_{12} & \sigma_1^2 \end{pmatrix} = \begin{pmatrix} A\sigma_2^2 & -A\sigma_{12} \\ -A\sigma_{12} & A\sigma_1^2 \end{pmatrix}.$$

C.1.1 Portfolio choice

Solutions to investors' problems are equivalent to the baseline model. In particular, the direct investors choose the demand function:

$$
\begin{aligned}
\theta_D =& \frac{1}{\gamma}\Sigma^{-1}(\mu - p), \qquad (37)\\
\text{i.e.} \qquad \theta_D =& \frac{1}{\gamma}\begin{pmatrix} A\sigma_2^2 & -A\sigma_{12} \\ -A\sigma_{12} & A\sigma_1^2 \end{pmatrix}\begin{pmatrix} \mu_1 - p_1 \\ \mu_2 - p_2 \end{pmatrix},\\
\begin{pmatrix} \theta_{D1} \\ \theta_{D2} \end{pmatrix} =& \frac{1}{\gamma}\begin{pmatrix} A\sigma_2^2(\mu_1 - p_1) - A\sigma_{12}(\mu_2 - p_2) \\ -A\sigma_{12}(\mu_1 - p_1) + A\sigma_1^2(\mu_2 - p_2) \end{pmatrix}
\end{aligned}
$$

Fund managers' demand is given by

$$
\begin{aligned}
\theta_M =& \frac{1}{\gamma(a+b)}\Sigma^{-1}(l\Delta + \mu - p) + \frac{b}{a+b}\omega, \qquad (38)\\
\text{i.e.} \qquad \theta_M =& \frac{1}{\gamma(a+b)}\begin{pmatrix} A\sigma_2^2 & -A\sigma_{12} \\ -A\sigma_{12} & A\sigma_1^2 \end{pmatrix}\begin{pmatrix} l\Delta_1 + \mu_1 - p_1 \\ \mu_2 - p_2 \end{pmatrix} + \frac{b}{a+b}\begin{pmatrix} \omega_1 \\ \omega_2 \end{pmatrix},\\
\begin{pmatrix} \theta_{M1} \\ \theta_{M2} \end{pmatrix} =& \frac{1}{\gamma(a+b)}\begin{pmatrix} A\sigma_2^2(l\Delta_1 + \mu_1 - p_1) - A\sigma_{12}(\mu_2 - p_2) \\ -A\sigma_{12}(l\Delta_1 + \mu_1 - p_1) + A\sigma_1^2(\mu_2 - p_2) \end{pmatrix} + \frac{b}{a+b}\begin{pmatrix} \omega_1 \\ \omega_2 \end{pmatrix}
\end{aligned}
$$

Note that $l \in (0, 1]$ is still a scalar of the same size across all risky assets.

Lastly, hedgers' demand function is

$$
\begin{aligned}
\theta_H =& \frac{1}{\gamma}\Sigma^{-1}(\mu - p + \Delta) - e, \qquad (39)\\
\begin{pmatrix} \theta_{H1} \\ \theta_{H2} \end{pmatrix} =& \frac{1}{\gamma}\begin{pmatrix} A\sigma_2^2(\Delta_1 + \mu_1 - p_1) - A\sigma_{12}(\mu_2 - p_2) \\ -A\sigma_{12}(\Delta_1 + \mu_1 - p_1) + A\sigma_1^2(\mu_2 - p_2) \end{pmatrix} - \begin{pmatrix} e_1 \\ e_2 \end{pmatrix}
\end{aligned}
$$

where $e \equiv (e_1, e_2)'$ is a vector of endowment shocks. Similar to the main text, I assume that they are large enough so that all holdings of hedgers are negative in equilibrium (net short in all risky assets).

C.1.2 Equilibrium prices and borrowing fees

I use the market clearing conditions (5) and (6) as well as the optimal portfolio choice of the investors (37)–(39) to solve for the equilibrium asset price and the borrowing fee of asset 1. To solve for the price of asset 2, I use only the asset market clearing condition (5) and set the fee to zero.

The expression for the equilibrium borrowing fee for asset 1 is

$$\Delta_1 = \frac{\gamma}{\sigma_2^2 A} \bar{B} \left(C_e e_1 - C_\theta \bar{\theta}_1 + C_\omega \omega_{\lambda 1} \right), \tag{40}$$

where C_e, C_θ, C_ω, and $\bar{B}$ are scalars defined in the main text,

$$\omega_{\lambda 1} = \frac{b}{a+b} \lambda_M \omega_1,$$

and $A = 1/(\sigma_1^2 \sigma_2^2 - \sigma_{12}^2) > 0$ if the correlation between the assets is not perfect. Notice that the equilibrium borrowing fee in the presence of asset 2, given by (40), is almost the same as the equilibrium borrowing fee in one-asset economy, given by (8) in the main text. The only difference is in the effective risk aversion. Therefore, the presence of asset 2 does not affect the key predictions of the baseline model, including the ambiguous relationship between benchmarking with either asset borrowing fee or its specialness.

The expression for the equilibrium price of asset 2 is

$$p_2 = \mu_2 + \bar{C} \frac{\gamma}{A} \left[\omega_{\lambda 2} - \bar{\theta}_2 - \lambda_H e_2 - \frac{\sigma_{12}}{\sigma_2^2} \left(\lambda_H e_1 + \bar{\theta}_1 - \omega_{\lambda 1} \right) \right], \tag{41}$$

where $\bar{C}$ is a positive scalar,

$$\bar{C} = \frac{1}{\left(\lambda_D + \frac{\lambda_M}{a+b} + \lambda_H \right) (\sigma_1^2 - \sigma_{12}^2 / \sigma_2^2)}.$$

The key intuition from the expression for equilibrium price of asset 2 (41) is the same as for the general collateral asset in the main text (see discussion near (10)). There are two differences. First, the presence of the second asset alters effective risk aversion through A and $\bar{C}$. Second, features of asset 1 affect the price of asset 2 through the covariance σ_{12}.

Finally, the equilibrium price for asset 1.

$$p_1 = \mu_1 + \frac{\gamma}{\sigma_2^2 A} \left[D_e e_1 - D_\theta \bar{\theta}_1 + D_\omega \omega_{\lambda 1} + \sigma_{12} \bar{C} \left(\omega_{\lambda 2} - \bar{\theta}_2 - \lambda_H e_2 \right) \right], \tag{42}$$

where D_e, D_θ, and D_ω are scalars:

$$D_e = B_e - \frac{\sigma_{12}^2}{\sigma_2^2}\bar{C},$$
$$D_\theta = B_\theta + \frac{\sigma_{12}^2}{\sigma_2^2}\bar{C},$$
$$D_\omega = B_\omega + \frac{\sigma_{12}^2}{\sigma_2^2}\bar{C},$$

with scalars B_e, B_θ, and B_ω defined in the main text.

In sum, the predictions of this model are very similar to the baseline economy without the second asset. In particular, the equilibrium price of asset 1 always decreases in supply and increases in its own BMI, as well as the BMI of asset 2 if they are possitively correlated.

C.2 Economy with additional costly-to-short asset

In this section, I consider a version of the economy in which both assets are on special at the same time. The setup is as in C.1 except for the binding lending market clearing for asset 2.

I use market clearing conditions (5) and (6) as well as the optimal portfolio choice of the investors (37)–(39) to solve for the equilibrium asset price and borrowing fee (in vector forms).

The expression for the equilibrium borrowing fee Δ is

$$\Delta = \gamma\Sigma\bar{B}\left(C_e e - C_\theta\bar{\theta} + C_\omega\omega_\lambda\right), \tag{43}$$

where C_e, C_θ, C_ω, and $\bar{B}$ are as in the main text. It is the exact counterpart of the expression in the main text in vector form, except for one conceptual difference – specialness of an asset (whether $\Delta > 0$) is affected by the specialness of another correlated asset. Intuitively, if assets are close substitutes, hedgers may be able to use asset 2 to hedge endowment shock in asset 1 or the other way around.

The expression for the equilibrium asset price is

$$p = \mu + \gamma\Sigma\bar{B}(B_e e - B_\theta\bar{\theta} + B_\omega\omega_\lambda), \tag{44}$$

where B_e, B_θ, B_ω, and $\bar{B}$ are exactly the same as in the main text.

In sum, the predictions of this model are virtually the same as in the baseline economy without the second asset.

D Economy with other (not benchmarked) lenders

In this section, I describe the equilibrium in an economy in which direct investors are allowed to lend up to a limit $\varphi \in (0, 1)$. All other assumptions are the same as in the baseline model in Section 3.

Direct investor's demand function is

$$\theta_D = \frac{1}{\gamma\sigma}(\mu - p + \varphi\Delta),$$

whereas the demand functions of the other investors are as in the main text. Intuitively, the direct investor deviates from the mean-variance portfolio to earn income from lending.

Direct investor's supply now contributes to the market condition in the lending market,

$$l\lambda_M\theta_M + \lambda_H\theta_H + \varphi\lambda_D\theta_D \geq 0.$$

Market clearing condition in the asset market is the same as in the baseline model (see (5)), so the solution for a general collateral asset is the same as in the main text.

D.1 Equilibrium asset price and borrowing fee

Using the updated market clearing conditions and demand functions, I arrive at the equilibrium borrowing fee for a special asset,

$$\Delta = \gamma\sigma\bar{B}\left(C_e e - C_\theta\bar{\theta} + C_\omega\omega_\lambda\right), \tag{45}$$

where C_e, C_θ, C_ω, and $\bar{C}$ are scalars:

$$\begin{aligned}
C_e =& \lambda_H\left((1-l)\frac{\lambda_M}{a+b} + (1-\varphi)\lambda_D\right),\\
C_\theta =& l\frac{\lambda_M}{a+b} + \lambda_H + \varphi\lambda_D,\\
C_\omega =& (1-l)\lambda_H - (l-\varphi)\lambda_D,\\
\bar{B} =& \frac{1}{\frac{\lambda_M}{a+b}((l-\varphi)^2\lambda_D + (1-l)^2\lambda_H) + (1-\varphi)^2\lambda_D\lambda_H}.
\end{aligned}$$

As in the baseline model, $C_e > 0$ and $C_\theta > 0$ because $l \in (0, 1)$ and $\varphi \in (0, 1)$, whereas $C_\omega < 0$ if and only if

$$l > \frac{\lambda_H + \varphi\lambda_D}{\lambda_H + \lambda_D},$$

as opposed to condition (9) in the main text. This means that the supply effect of benchmarking is less likely dominant when direct investors are allowed to lend. This is because fund managers now constitute only a part of the overall supply.

Similarly, I can get the equilibrium price for a special asset,

$$p = \mu + \gamma\sigma(B_e e - B_\theta \bar{\theta} + B_\omega \omega_\lambda), \tag{46}$$

where B_e, B_θ, and B_ω are scalars:

$$\begin{aligned}
B_e &= \bar{B}\lambda_H \left(\frac{\lambda_M}{a+b} + \lambda_H + \lambda_D\right)\left[(1-l)l\frac{\lambda_M}{a+b} + (1-\varphi)\varphi\lambda_D\right], \\
B_\theta &= \bar{B}\left(\left[l\frac{\lambda_M}{a+b} + \lambda_H + \varphi\lambda_D,\right]^2 + \frac{1}{\bar{B}}\right), \\
B_\omega &= 1 + \bar{B}C_\theta C_\omega.
\end{aligned}$$

$B_e > 0$ and $B_\theta > 0$ as in the baseline case. In contrast, B_ω may be positive or negative. When $C_\omega > 0$, that is, the demand effect of benchmarking dominates, $B_\omega > 0$, or the price increases in BMI. When $C_\omega < 0$, that is, the supply effect of benchmarking dominates, B_ω may become negative. The index effect may be negative in an economy where both direct and benchmarked investors are allowed to lend. At the same time, in the case when benchmarked investors' lending limit is stricter than or equal to the direct investors' lending limit, that is, $l \leq \varphi$, it is easy to show that $B_\omega > 0$ and C_ω may be negative or positive.

Finally, the asset is special if and only if the equilibrium fee is positive, or $C_e e - C_\theta \bar{\theta} + C_\omega \omega_\lambda > 0$, which can be written as a condition on lending limit l:

$$l < \lambda_H \frac{\left(\frac{\lambda_M}{a+b} + \lambda_D\right)e - \bar{\theta} + \omega_\lambda}{\frac{\lambda_M}{a+b}(\lambda_H e + \bar{\theta}) + (\lambda_D + \lambda_H)\omega_\lambda} - \varphi\lambda_D \frac{\lambda_H e + \bar{\theta} - \omega_\lambda}{\frac{\lambda_M}{a+b}(\lambda_H e + \bar{\theta}) + (\lambda_D + \lambda_H)\omega_\lambda}.$$

The first fraction in the condition above is the same as in the main text (see Section 3.5). Furthermore, because the BMI cannot be larger than the asset supply, i.e., $\omega_\lambda \leq \bar{\theta}$, it is easier for an asset to become a general collateral asset in this economy. This is intuitive because the additional supply from direct investors relaxes the market clearing condition in the lending market.

E Economy with costly lending

E.1 Model setup

The model setup is the same as in the main text except for how the lending limit is set. Rather than being exogenous, it is now optimally chosen by fund managers, who face a per-unit cost $c(l)$ to lend a fraction l of their risky holding, where $c(l)$ is nonnegative, non-decreasing, convex, $c(0) = 0$, and $c'(0) = 0$. I use the same notation as lending limit in the baseline model l for simplicity.

In other words, fund managers' optimization problem now depends on the cost, and they choose the level of lending:

$$\max_{\theta_M, l} \quad E_0[-\exp\{-\gamma((a+b)\theta_M(l\Delta + \bar{D} - p - c(l)) - b\omega(\bar{D} - p))\}]. \tag{47}$$

Other investors' optimization problems remain the same.

The market clearing conditions both in the long market and in the lending market are the same as in the main text.

E.2 Portfolio choice

The portfolio demands of the direct investors and hedgers are the same. In contrast, a fund manager's demand is given by

$$\theta_M = \frac{1}{\gamma\sigma(a+b)}(\mu - p) + \frac{b}{a+b}\omega + \frac{1}{\gamma\sigma(a+b)}(l\Delta - c(l)). \tag{48}$$

Intuitively, the costs enter the return-augmenting part of the fund manager's portfolio.

The chosen lending limit has to simply satisfy

$$\Delta = c'(l), \tag{49}$$

where the marginal increase in lending limit equates the marginal cost, Δ.

If I assume a certain form for the cost function, for example, quadratic costs $c(l) = \varphi + \kappa\frac{l^2}{2}$, I can get an explicit solution for l,

$$l = \frac{\Delta}{\kappa}. \tag{50}$$

E.3 Equilibrium price and borrowing fee

I use market clearing conditions (5) and (6) as well as the optimal portfolio choice of the investors (2), (4), and (48) to solve for the equilibrium asset price and borrowing fee. First, substitute the demand functions (48) and (4) into the market clearing condition in the lending market (6),

$$
\begin{aligned}
l\lambda_M\theta_M + \lambda_H\theta_H &= 0,\\
l\lambda_M\left(\frac{1}{\gamma\sigma(a+b)}(l\Delta+\mu-p-c(l)) + \frac{b}{a+b}\omega\right) + \lambda_H\left(\frac{1}{\gamma\sigma}(\mu-p+\Delta)-e\right) &= 0,
\end{aligned}
$$

which yields the following expression for $p-l\Delta$:

$$
p-l\Delta = \mu + \frac{1}{l\lambda_M/(a+b)+\lambda_H}\left[(1-l)\lambda_H\Delta + \gamma\sigma l\lambda_M b/(a+b)\omega - \gamma\sigma\lambda_H e - \frac{l\lambda_M}{a+b}c(l)\right]. \tag{51}
$$

Then, combine the market clearing conditions in the lending market (6) and in the asset market (5) to get

$$
\lambda_D\theta_D + (1-l)\lambda_M\theta_M = \bar{\theta}.
$$

Substituting the demand functions (2) and (48) into the expression above yields another expression for $p-l\Delta$,

$$
p-l\Delta = \mu - \frac{1}{(1-l)\lambda_M/(a+b)+\lambda_D}\left[\lambda_D l\Delta + (1-l)\frac{\lambda_M}{a+b}c(l) + \gamma\sigma\bar{\theta} - \gamma\sigma(1-l)\lambda_M b/(a+b)\omega\right]. \tag{52}
$$

Subtract (52) from (51) and rearrange to get the expression for the equilibrium borrowing fee Δ,

$$
\Delta = \gamma\sigma\bar{B}\left(C_e e - C_\theta\bar{\theta} + C_\omega\omega_\lambda\right) - \bar{B}C_\omega\frac{\lambda_M}{a+b}c(l), \tag{53}
$$

where C_e, C_θ, C_ω, and $\bar{B}$ are scalars:

$$
\begin{aligned}
C_e &= \lambda_H\left((1-l)\frac{\lambda_M}{a+b}+\lambda_D\right),\\
C_\theta &= l\frac{\lambda_M}{a+b}+\lambda_H,\\
C_\omega &= (1-l)\lambda_H - l\lambda_D,\\
\bar{B} &= \frac{1}{\frac{\lambda_M}{a+b}(l^2\lambda_D+(1-l)^2\lambda_H)+\lambda_D\lambda_H},
\end{aligned}
$$

and the last term in (53) means that the fee incorporates the costs that the fund managers have to incur. If the demand effect of benchmarking dominates, or $C_\omega > 0$, the fee is negatively related to the costs.

To solve for Δ and l, need to plug in the solution for $\Delta = c'(l)$ and solve the nonlinear equation in l. In the case of quadratic costs, $l = \frac{\Delta}{\kappa}$ and this nonliear equation becomes

$$\left(\frac{\lambda_M}{a+b}(l^2\lambda_D + (1-l)^2\lambda_H) + \lambda_D\lambda_H\right)\kappa l = \gamma\sigma\left(C_e e - C_\theta\bar{\theta} + C_\omega\omega_\lambda\right) - C_\omega\frac{\lambda_M}{a+b}\left(\varphi + \kappa\frac{l^2}{2}\right).$$

It has three roots and I focus on the solution with a positive and real equilibrium borrowing fee. This solution can then be plugged into expression (52) to compute the corresponding equilibrium price.

Maintaining the assumption of quadratic costs, I verify numerically that there exist solutions with the positive price, positive fee, positive expected return, and $l \in (0,1)$. Because the presence of endogenous l makes the expression for p less interpretable, I also verify that the price sensitivity to ω_λ is unambiguously positive in this model. I also find that, under admissible parameter values, C_ω may take both positive and negative values. In other words, the model with costly lending and endogenous lending limit still delivers both the demand and supply effects of benchmarking.

F Economy with costly search by borrowers

F.1 Model setup

The model setup is the same as in the main text except for how the lending limit is set. Rather than being exogenous, it is now optimally defined by the search intensity of hedgers. Hedgers are assumed to incur a utility cost $c(l)$ to search for lenders, and l is the search intensity, or the probability of meeting a long investor who lends (i.e., a fund manager). If a hedger meets a lender, they submit a demand schedule $\theta_{H1} = \theta_H$, if not, they submit $\theta_{H0} = 0$.

Hedger's problem is therefore

$$\begin{aligned}\max_{l,\theta_H} \quad & lE_0[-\exp\{-\gamma(W_0^H + e\bar{D} + \theta_H(\bar{D} - p + \Delta\mathbf{1}_{\theta_H<0}))\}] \\ & + (1-l)E_0[-\exp\{-\gamma(W_0^H + e\bar{D})\}] - c(l), \end{aligned} \tag{54}$$

or, equivalently,

$$\max_{l,\theta_H} \quad -l\exp\{-\gamma[W_0^H + e\mu + \theta_H(\mu - p + \Delta) - \frac{\gamma}{2}\sigma(e+\theta_H)^2]\}$$
$$-(1-l)\exp\{-\gamma(W_0^H + e\mu - \frac{\gamma}{2}\sigma e^2)\} - c(l). \tag{55}$$

Similarly, fund manager's problem now depends on whether they meet a hedger or not.

$$\max_{\theta_1^M,\theta_0^M} \quad lE_0[-\exp\{-\gamma((a+b)\theta_1^M(\Delta + \bar{D} - p) - b\omega(\bar{D} - p))\}]$$
$$+(1-l)E_0[-\exp\{-\gamma((a+b)\theta_0^M(\bar{D} - p) - b\omega(\bar{D} - p))\}]. \tag{56}$$

The market clearing condition in the asset market becomes

$$\lambda_D\theta_D + l(\lambda^M\theta_1^M + \lambda_H\theta_H) + (1-l)\lambda^M\theta_0^M = \bar{\theta}. \tag{57}$$

The lending market clearing condition is

$$l(\lambda^M\theta_1^M + \lambda_H\theta_H) \geq 0. \tag{58}$$

F.2 Portfolio choice

The portfolio demand of the direct investors is the same. In contrast, a fund manager's demand is given by

$$\theta_1^M = \frac{1}{\gamma\sigma(a+b)}(\mu - p) + \frac{b}{a+b}\omega + \frac{1}{\gamma\sigma(a+b)}\Delta \tag{59}$$

if they meet a hedger and

$$\theta_0^M = \frac{1}{\gamma\sigma(a+b)}(\mu - p) + \frac{b}{a+b}\omega, \tag{60}$$

if they do not.

Finally, a hedger's portfolio demand, if they meet a lender, is

$$\theta_H = \frac{1}{\gamma\sigma}(\mu - p + \Delta) - e. \tag{61}$$

The search intensity is a unique solution to

$$-\exp\{-\gamma[W_0^H + e\mu + \theta_H(\mu - p + \Delta) - \frac{\gamma}{2}\sigma(e+\theta_H)^2]\} + \exp\{-\gamma(W_0^H + e\mu - \frac{\gamma}{2}\sigma e^2)\} = c'(l). \tag{62}$$

It exists because the term on the left is a difference in expected utility under hedging and not hedging and $c(l)$ is nonnegative, strictly increasing and convex (ensuring uniqueness of the solution for search intensity l).

F.3 Equilibrium price and borrowing fee

For a positive fee to arise, lending market clearing has to bind. Therefore,

$$\lambda_H \theta_H = -l^M \theta_1^M.$$

Plugging this into the asset market clearing condition (57) and substituting demand functions,

$$\lambda_D \theta_D + (1-l)\lambda^M \theta_0^M = \bar{\theta},$$

$$\lambda_D \frac{1}{\gamma\sigma}(\mu - p) + (1-l)\lambda^M \left[\frac{1}{\gamma\sigma(a+b)}(\mu - p) + \frac{b}{a+b}\omega\right] = \bar{\theta}.$$

This gives an expression for the equilibrium asset price

$$p = \mu + \gamma\sigma A \left[(1-l)\lambda^M \frac{b}{a+b}\omega - \bar{\theta}\right],$$

where $A = \frac{1}{\lambda_D + (1-l)\lambda^M \frac{1}{(a+b)}}$. Notice that the price does not depend on the hedger's endowment shock directly. It depends on it only through the relationship between the search intensity l and the equilibrium fee Δ.

Solve for the fee using the lending market clearing, demand functions, and the equilibrium price.

$$
\begin{aligned}
\lambda_H \theta_H &= -\lambda^M \theta_1^M, \\
\lambda_H \left[\frac{1}{\gamma\sigma}(\mu - p + \Delta) - e\right] &= -\lambda^M \left[\frac{1}{\gamma\sigma(a+b)}(\mu - p) + \frac{b}{a+b}\omega + \frac{1}{\gamma\sigma(a+b)}\Delta\right], \\
\left(\lambda_H + \frac{\lambda^M}{a+b}\right)\Delta &= \gamma\sigma\lambda_H e \\
&\quad + \gamma\sigma\left(A(1-l)\left[\lambda_H + \lambda^M \frac{1}{(a+b)}\right] - 1\right)\omega_\lambda - \gamma\sigma A\bar{\theta}\left[\lambda_H + \lambda^M \frac{1}{a+b}\right],
\end{aligned}
$$

where I used $\mu - p = \gamma\sigma A\left[\bar{\theta} - (1-l)\lambda^M \frac{b}{a+b}\omega\right]$ and $\omega_\lambda = \lambda^M \frac{b}{a+b}\omega$. The coefficient on e and $\bar{\theta}$ is unambiguously positive and negative, respectively. Simplifying the coefficient on ω_λ using A, I get

$$
A(1-l)\left[\lambda_H + \lambda^M \frac{1}{(a+b)}\right] - 1 = \frac{(1-l)\lambda_H - \lambda_D}{\lambda_D + (1-l)\lambda^M \frac{1}{(a+b)}},
$$

which is positive iff

$$
\frac{\lambda_H - \lambda_D}{\lambda_H} > l. \tag{63}
$$

Thus, the demand effect of benchmarking dominates if the search intensity is small enough. Similar to the main text, the prediction is ambiguous. If there are no direct investors, or $\lambda_D = 0$, the demand effect always dominates, also in line with the main text.

The final expression for the equilibrium fee is

$$
\Delta = \frac{\gamma\sigma}{\lambda_H + \frac{\lambda^M}{a+b}}\left(\lambda_H e + A\left[(1-l)\lambda_H - \lambda_D\right]\omega_\lambda - A\left[\lambda_H + \lambda^M \frac{1}{a+b}\right]\bar{\theta}\right),
$$

which intuitively is quite similar to that in the main text.

F.4 Equilibrium search intensity

Because search intensity is chosen by hedgers, I need to solve for it to understand the condition (63). To do so, I plug the equilibrium quantities into (62)

$$
\begin{aligned}
c'(l) &= -\exp\{-\gamma[W_0^H + e\mu + \theta_H(\mu - p + \Delta) - \frac{\gamma}{2}\sigma(e + \theta_H)^2]\} + \exp\{-\gamma(W_0^H + e\mu - \frac{\gamma}{2}\sigma e^2)\} \\
&= \mathcal{E}\left[-\exp\{-\gamma[\theta_H(\mu - p + \Delta) - \frac{\gamma}{2}\sigma\left(\theta_H^2 + 2e\theta_H\right)]\} + 1\right],
\end{aligned}
$$

where $\mathcal{E} = \exp\{-\gamma(W_0^H + e\mu - \frac{\gamma}{2}\sigma e^2)\}$. Simplifying the part in the exponent using equilibrium quantities, I get

$$-\gamma[\theta_H(\mu - p + \Delta) - \frac{\gamma}{2}\sigma\theta_H^2 - \gamma\sigma e\theta_H] = -\frac{1}{2\sigma}\left[(\mu - p + \Delta - \gamma\sigma e)^2\right].$$

Therefore, the equation for the equilibrium search intensity becomes

$$c'(l) = \mathcal{E}\left[1 - e^{-\frac{1}{2\sigma}\left(\frac{\gamma\sigma}{\lambda_H + \frac{\lambda^M}{a+b}}\left[\frac{\lambda^M}{a+b}e + \omega_\lambda\right]\right)^2}\right],$$

which is an expression in model parameters. Intuitively, the marginal cost of searching is equal to the increase in hedger's expected utility from being able to trade in the asset (i.e., from locating a lender).

In the case of quadratic costs, $c(l) = \varphi + \kappa\frac{l^2}{2}$ for some positive constants $\kappa > 0$ and $\varphi \geq 0$, the equilibrium search intensity is defined by

$$\kappa l = \mathcal{E}\left[1 - e^{-\frac{1}{2\sigma}\left(\frac{\gamma\sigma}{\lambda_H + \frac{\lambda^M}{a+b}}\left[\frac{\lambda^M}{a+b}e + \omega_\lambda\right]\right)^2}\right],$$

where $\mathcal{E} = \exp\{-\gamma(W_0^H + e\mu - \frac{\gamma}{2}\sigma e^2)\}$.

Maintaining the assumption of quadratic costs, I verify numerically that there exist solutions with the positive price, positive fee, positive expected return, and $l \in (0, 1)$. Because the presence of endogenous l makes the expression for p less interpretable, I also verify that the price sensitivity to ω_λ is unambiguously positive in this model. Finally, I find that, under admissible parameter values, condition (63) is sometimes satisfied and sometimes it is not. In other words, the model with costly search and endogenous lending limit still delivers both the demand and supply effects of benchmarking.

G Evidence from the BoJ ETF purchase program

In this section, I test the predictions of my model in the Japanese equity market using the ETF purchases of the BoJ as shocks to BMI. In addition to index reconstitutions, the amount of capital benchmarked against securities is also affected by investment flows. The Japanese monetary easing program has been unique in its purchases of equity funds and its impact on benchmarking intensities of domestic stocks. The literature has shown that the purchases reduced risk premium (Barbon and Gianinazzi (2019)) while their real effects are debated (Charoenwong, Morck, and Wiwattanakantang (2021)). Maeda, Shino, and Takahashi (2022) study the securities lending market and document that the BoJ's purchases increased lending supply. They also use the annual reports of investment companies to document position-level lending limits ranging from 40% to 80%.[54] None of the papers has explored how the program affected borrowing fees.[55]

G.1 The structure of the BoJ ETF purchase program

Since 2010, the BoJ has engaged in programs known as comprehensive monetary easing and quantitative and qualitative easing, aimed at combating deflation. As part of both programs, the BoJ has increased its domestic equity holdings through purchases of ETFs linked to Japanese market indexes. Aggressive purchases led to the BoJ becoming the majority owner of those ETFs.

Within the ETF purchase program, the BoJ has bought funds tracking three major Japanese equity market indexes, namely the TOPIX, Nikkei 225, and JPX-Nikkei 400. I report the list of ETFs tracking these indexes in Table C2 of this Internet Appendix. Importantly, the BoJ's purchases have been virtually the only source of flows in the target ETFs, and Figure C1 demonstrates that the cumulative flows are closely in line with the cumulative BoJ purchases. Figure C1 also indicates the announcement dates of the major policy changes, such as the announcement of the first purchases in 2010, the introduction of the qualitative and quantitative easing program in 2013, multiple expansions of its size and changes in its composition. I provide more details on each of the announcements in Table C3 in the Internet Appendix.

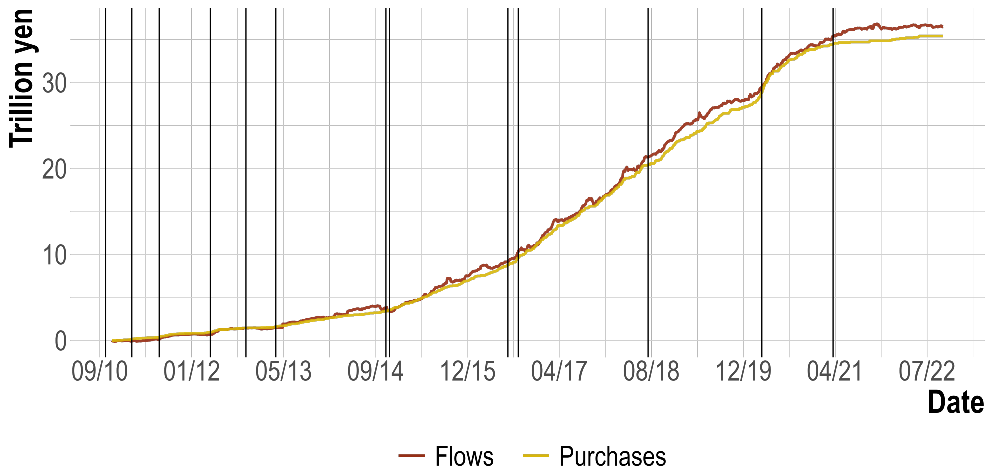
In the language of my model, the BoJ's purchases of ETFs increased the share of selected benchmarked funds in the economy and hence affected the benchmarking intensities of stocks in the major market indexes.[56] Due to the unprecedented size of the program, these changes in

[54] Japanese regulators do not impose any portfolio-level limits.

[55] An exception is contemporaneous and independent work by Shino, Katagiri, and Takahashi (2023), who use a different identification strategy to study borrowing fees and also highlight the importance of linking the spot and lending market effects of the BoJ's purchases.

[56] An important assumption behind my analysis is that ETFs are closely tracking their benchmarks. First, tracking errors are indeed low across the relevant ETFs. Morningstar reports one-year annualized tracking

Figure C1: The BoJ purchases and flows in the target ETFs



This figure plots cumulative ETF purchases of the BoJ and cumulative ETF flows (in trillion yen). Solid vertical lines indicate the BoJ announcement dates related to ETF purchases, splitting the sample into 13 policy periods used in the tests below.

benchmarking intensities are economically large, with the BoJ's ownership reaching 30% of the market value of certain stocks and buying as much as 12% in a given policy period. Furthermore, the design of the program allows me to isolate changes in benchmarking intensities that are arguably exogenous, as discussed below.

G.2 The effects of the BoJ's purchases on spot and lending markets

In this section, I use the BoJ's purchases of ETFs as a shock to BMI to test predictions of my model in the Japanese stock market. Even though the academic literature has studied the risk premium effects of the BoJ's ETF purchases, the program's impact on the lending markets has received only limited attention.

G.2.1 Changes in benchmarked capital due to the BoJ's purchases

I focus on key policy periods that followed the BoJ announcements that either expanded the program size or changed the allocation between indexes. Table C3 in the Internet Appendix lists

errors of around 115 bps for ETFs tracking the TOPIX and JPX-Nikkei 400 indexes and around 284 bps for ETFs tracking the Nikkei 225 index, with very little variation within a benchmark (all values are as of November 2022). Second, any noise in the investment of ETF flows works against finding any relationship between the BoJ's purchases and lending supply.

all announcements related to the BoJ's ETF program and classifies policy periods into reallocative and expansive ones. My analysis covers the entire history of the BoJ's holdings of ETFs.

The test is designed at the level of each policy period so that the estimates combine the announcement effects with the flow effects of the actual purchases. This is to preserve consistency with my (static) model, in which the announcement and implementation of a change in BMI occur at the same time.

For each policy period, I compute the total stock-level purchases implied by the BoJ-driven ETF flows. Specifically,

$$\begin{aligned} BoJ\,purchase_{ip} = \sum_{t \in p} BoJ\,purchase_t \times \\ (\omega_{it}^{TOPIX} \times S_t^{TOPIX} + \omega_{it}^{Nikkei225} \times S_t^{Nikkei225} + \omega_{it}^{JPXNikkei400} \times S_t^{JPXNikkei400}), \end{aligned} \tag{64}$$

where S_t^j is the share of BoJ purchases allocated to index j on day t, ω_{it}^j is the weight of stock i in index j on day t, $BoJ\,purchase_t$ is the total size of the BoJ's purchase in JPY on day t reported on the BoJ's website. The shares S_t^j are computed using ETF assets and allocation rules as defined by the BoJ's announcement for period p. I assume that the allocation rule holds not only on aggregate but also at each purchase.

Purchases defined in (64) measure the actual ownership of the BoJ, yet they cannot be used as shocks to BMI because of their expected component. Because the BoJ's policy was not bounded to a single policy period, market participants expected it to continue purchasing ETFs (e.g., at the previously announced pace). For this reason, if I were to use purchases in definition (64) as shocks, I would be assuming that expected purchases were zero. See, for example, the studies of cross-sectional effects of the Federal Reserve's quantitative easing programs (D'Amico and King (2013)).

Therefore, I construct the shocks to BMIs as changes in BoJ's purchases relative to the market value of each stock, specifically,

$$\Delta BMI_{ip}^{BoJ} = \frac{1}{MV_{ip-1}} \left(BoJ\,purchase_{ip} - BoJ\,purchase_{ip-1} \frac{Days_p}{Days_{p-1}} \right), \tag{65}$$

where MV_{ip-1} is stock i's market value in JPY based on Compustat Global price and number of shares as of the last day of period $p-1$, i.e., immediately prior to period p, $BoJ\,purchase_{ip}$ is defined above, and $\frac{Days_p}{Days_{p-1}}$ is an adjustment for duration, with $Days_p$ being the number of days in period p. In brackets, the second term is how large the purchases would have been in period p if no policy change was announced at the beginning of period p. ΔBMI^{BoJ} takes into account both reallocative and expansive changes to the program and, consistent with my model, assumes that market participants correctly impute the size of stock-level purchases in each policy period.

There is a body of literature on the pricing effects of the program that argues for the cross-sectional exogeneity of the BoJ's purchases (see, e.g., Barbon and Gianinazzi (2019)). There are two reasons why the change in BMI, as measured by ΔBMI^{BoJ}, is plausibly exogenous. The first reason is that the Nikkei 225 index is a price-weighted index, which makes $\omega^{Nikkei225}$ unrelated to the size of the stock.[57] Second, the allocation across indexes (i.e., shares S^j) was not related to the fundamentals of a given stock.

G.2.2 Regression specifications

To study how the changes in BMI affected lending market variables, I compute changes during each policy period in the following way:

$$\Delta Y_{ip} = Y_{ip}^{end} - Y_{ip-1}^{end},$$

where Y_{ip}^{end} is the borrowing fee, active lending inventory, or short quantity on loan of stock i on the last trading day of period p.[58] Finally, to measure the change in stock price, I take stock cumulative return over the entire policy period.

To test the predictions of my model, I estimate the following specification in a period-stock panel:

$$\begin{aligned} \Delta Y_{ip} = &\beta_1 \Delta BMI_{ip}^{BoJ} \times D(special)_{ip} + \beta_2 \Delta BMI_{ip}^{BoJ} \times D(not\,special)_{ip} \\ &+ \zeta' \bar{X}_{ip-1} + \nu_{sp} + \mu_i + \epsilon_{ip}. \end{aligned} \tag{66}$$

The dependent variable, ΔY_{ip}, represents the change in the stock's lending inventory (active lendable quantity of shares), short quantity on loan (Markit's measure of short interest), borrowing fee, or stock return, constructed as explained above. $D(special)_{ip} = 1$ if stock i can be considered special at the beginning of the policy period p, that is, if its average borrowing fee exceeds 1% in the month preceding the policy period p, and zero otherwise. Similarly, $D(not\,special)_{ip} = 1$ if stock i has an average borrowing fee of up to 1% in the month preceding the policy period p, and

[57] Anecdotally, market participants saw the BoJ's purchases as distorting valuations due to this feature of the Nikkei 225 index. See, for example, https://corporate.quick.co.jp/en/japanmarketsview/equity/the-market-accepted-bojs-topix-etfs-purchase-plan-quick-monthly-survey-equity-in-april-2021/.

[58] Importantly, I exclude stock-period observations when a stock has an ex-dividend date two weeks before or after the period start date, as tax-related lending around those dates significantly affects my measures of shorting demand and borrowing fees. The results are not sensitive to this filter.

zero otherwise. $\bar{X}_{ip-1}$ is a vector of controls, including log market value, log shares outstanding, log trading volume, Amihud's illiquidity, and the stock beta with respect to TOPIX return – all measured at the end of the preceding period. I include these controls to alleviate the concern that variation in ΔBMI^{BoJ} picks up stale information on stock size or liquidity due to how Japanese indexes are constructed. The estimates are virtually the same without these controls. ν_{sp} are period by $D(special)$ fixed effects, which allow for differences in trends for special and general collateral stocks, and μ_i are stock fixed effects.

G.2.3 Regression results

Table C1 reports the estimation results. Column (1) documents that the lending inventory in Japan strongly reacts to the shocks to BMI. Furthermore, Column (2) of Table C1 documents that short quantity on loan also increases in response to the change in BMI, in line with my model.[59]

Column (3) of Table C1 reports how the borrowing fee changes in response to the shock to BMI. I find a statistically strong and economically large increase in borrowing fees for special stocks, with a 1 percentage point larger shock leading to a 41 bps higher borrowing fee, or a one-standard-deviation larger shock increasing the lending fee by 13 bps. This increase in borrowing fee in response to the shock to BMI means that the demand effect of benchmarking dominates in the Japanese stock market.

Consistent with the existing literature on the impact of Japanese monetary easing on stock prices and risk premia, I find that increases in BMIs lead to considerably higher prices. As column (4) shows, a one-standard-deviation larger shock results in a 8.4% higher return for general collateral stocks and a 10.5% higher return for specials over a policy period.[60] The difference in coefficients is not statistically significant, yet its sign is consistent with the prediction of my model for the dominant demand effect of benchmarking.

The lending market in Japan has a larger number of stocks with economically significant fees (summarized in Table C5 of this Internet Appendix). Given the prevalence of the demand effect of benchmarking, any misclassification of special stocks is likely to attenuate the coefficient on the fee for special stocks and increase the coefficient for general collateral stocks. Nevertheless,

[59] Weak response for general collateral stocks is due to both how I construct ΔBMI^{BoJ} and my definition of specialness. In unreported tests, I compare estimates of sensitivity to the change in BMI in subsamples of specialness as outlined by the JSDA. There is no increase in short quantity on loan only for stocks that are extremely cheap to lend, that is, with fees below 50 bps (annualized).

[60] These estimates are upper-bound measures of price impact because of how I construct ΔBMI^{BoJ}. The average duration of a policy period in my sample is 207 days, so if the markets typically expected the program to last for 10 years, the estimates in column (4) should be divided by around $10 * 252/207 \approx 12$ to get an interpretation of price impact.

Table C1: Response of spot and lending market variables to changes in BMI due to the BoJ's ETF purchases

	Δ Lending inventory, % shares	Δ Quantity on loan, % shares	Δ Borrowing fee, %	Stock return, %
	(1)	(2)	(3)	(4)
Panel A: No interactions				
ΔBMI^{BoJ}, % MV	0.414***	0.301***	0.162***	28.248***
	(2.99)	(3.04)	(2.63)	(13.16)
Observations	17,298	17,298	17,298	17,298
Adjusted R-squared	0.093	0.037	0.115	0.373
Panel B: With specialness interactions				
ΔBMI^{BoJ}, % MV × D(not special)	0.050	0.017	0.037	26.942***
	(0.35)	(0.19)	(1.00)	(10.04)
ΔBMI^{BoJ}, % MV × D(special)	1.140***	0.867***	0.411**	33.847***
	(4.27)	(4.00)	(2.51)	(9.59)
Observations	17,298	17,298	17,298	17,298
Adjusted R-squared	0.097	0.041	0.116	0.373
$\beta_1 - \beta_2$	1.090***	0.850***	0.374**	6.904
	(3.61)	(3.67)	(2.23)	(1.58)

This table reports the estimates of specification (66) in the panel of TOPIX constituents across 13 policy periods. Panel A removes interactions with specialness. Panel B uses the full specification. The last row reports the t-test for estimation results in panel B. ΔBMI^{BoJ} is a shock to BMI in a given policy period, as defined in (65). Changes in lending market variables are computed as differences between the end of the current policy period and the preceding one; see further details in Internet Appendix G.5. A stock is considered special, or $D(special) = 1$, if its average fee prior to the policy period is above 1%. All regressions include D(special) by date and stock fixed effects. t-statistics based on standard errors clustered by stock are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

in untabulated analyses, I confirm that the findings are qualitatively the same under alternative definitions of specialness.

The prevalence of the demand effect of benchmarking suggests that there are binding lending limits in the Japanese market, similar to my results for the United States presented in Section 5. At the same time, I see that the pass-through coefficient for the changes in BMI to inventory for special stocks is very high, at around 1.1. Furthermore, I estimate the pass-through of total purchases (as opposed to changes in BMI) to special stocks and find that for general collateral stocks it is over 40%. Overall, these results suggest that lending supply in Japan may be more responsive to fees than in the United States. To address that, similar to Appendix A.13, I use an instrument for shorting demand to isolate the shift in inventory and supply due to the change in BMI from their elastic response to higher fees. I find that the pass-through from BMI to inventory is 0.79, consistent with limited lending. I do not have the micro-data on securities lending by ETFs and other institutions in Japan that would allow me to characterize the effective lending limits.

However, Maeda, Shino, and Takahashi (2022) have analyzed the financial statements of the ETF managers in Japan and found evidence of such limits. They document that the ETFs increased their position-level lending shares from 40% to over 80% between 2015 and 2019, potentially in response to the purchases by the BoJ. Overall, the evidence for the Japanese market suggests a weak pass-through from institutional holdings to lending supply, similar to my baseline results for the United States.

G.3 Additional details on Japanese setting

G.3.1 Japanese stock data

Japanese stock data come from Compustat Global, table *g_secd*. These data include stock identifiers (gvkey, SEDOL, and ISIN), date, number of shares outstanding (*cshoc*), trading volume (*cshtrd*), stock close price (*prccd*), dividend per share (*div*), and stock split ratio (*split*). I include only securities with ISO currency code (*curcdd*) of 'JPY' and that ever belonged to TOPIX or Nikkei 225 after 2006 according to Compustat Global (table *g_idxcst_his*). These data are merged with S&P securities lending data using SEDOL and date.

Table C2: Japanese ETFs tracking TOPIX, Nikkei 225, or JPX-Nikkei 400

Name	**Ticker**	**ISIN**	**Inception Date**	**SecId**	**Primary Prospectus Benchmark**
Nikko Exchange Traded Index Fund TOPIX	1308	JP3039100007	20/12/2001	F000000MDI	TOPIX PR JPY
iShares Core Nikkei 225 ETF	1329	JP3027710007	04/09/2001	F000000MRG	Nikkei 225 Average PR JPY
Daiwa ETF-TOPIX	1305	JP3027620008	11/07/2001	F000000NAO	TOPIX PR JPY
Daiwa ETF-Nikkei 225	1320	JP3027640006	09/07/2001	F000000NAZ	Nikkei 225 Average PR JPY
Nikko Exchange Traded Index Fund 225	1330	JP3027660004	09/07/2001	F000000NIZ	Nikkei 225 Average TR JPY
NEXT FUNDS TOPIX ETF	1306	JP3027630007	11/07/2001	F000000NO8	TOPIX PR JPY
NEXT FUNDS Nikkei 225 ETF	1321	JP3027650005	09/07/2001	F000000NQ6	Nikkei 225 Average PR JPY
MAXIS NIKKEI225 ETF	1346	JP3047040005	24/02/2009	F000002O43	Nikkei 225 Average TR JPY
MAXIS TOPIX ETF	1348	JP3047060003	14/05/2009	F000002T80	TOPIX PR JPY
Listed Index Fund Nikkei 225 (Mini)	1578	JP3047570001	22/03/2013	F00000POB4	Nikkei 225 Average PR JPY
NEXT FUNDS JPX-Nikkei Index 400 ETF	1591	JP3047670009	24/01/2014	F00000SGED	JPX-Nikkei Index 400 TR JPY
Listed Index Fund JPX-Nikkei Index 400	1592	JP3047680008	27/01/2014	F00000SGUR	JPX-Nikkei Index 400 TR JPY
MAXIS JPX-Nikkei Index 400 ETF	1593	JP3047690007	05/02/2014	F00000SIOI	JPX-Nikkei Index 400 TR JPY
Daiwa ETF JPX-Nikkei 400	1599	JP3047740000	26/03/2014	F00000SZ7B	JPX-Nikkei Index 400 TR JPY
iShares JPX-Nikkei 400 ETF	1364	JP3047840008	01/12/2014	F00000V1W6	JPX-Nikkei Index 400 TR JPY
One ETF Nikkei225	1369	JP3047890003	14/01/2015	F00000V7EK	Nikkei 225 Average PR JPY
SMDAM NIKKEI225 ETF	1397	JP3047920008	24/03/2015	F00000VHEG	Nikkei 225 Average PR JPY
One ETF TOPIX	1473	JP3048090009	04/09/2015	F00000W9HA	TOPIX PR JPY
One ETF JPX-Nikkei 400	1474	JP3048100006	04/09/2015	F00000W9HB	JPX-Nikkei Index 400 TR JPY
iShares Core TOPIX ETF	1475	JP3048120004	19/10/2015	F00000WFFL	TOPIX PR JPY
NZAM ETF TOPIX	2524	JP3048830008	05/02/2019	F000011UX8	TOPIX PR JPY
NZAM ETF Nikkei 225	2525	JP3048840007	05/02/2019	F000011UX9	Nikkei 225 Average PR JPY
NZAM ETF JPX-Nikkei400	2526	JP3048850006	05/02/2019	F000011UXA	JPX-Nikkei Index 400 PR JPY
SMDAM TOPIX ETF	2557	JP3048970002	13/12/2019	F000014IYK	TOPIX PR JPY
iFreeETF-TOPIX(Quarterly Div Type)	2625	JP3049170008	09/11/2020	F000015YMI	TOPIX PR JPY
iFreeETF-Nikkei225(Quarterly Div Type)	2624	JP3049160009	09/11/2020	F000015YMJ	Nikkei 225 Average PR JPY

G.3.2 Japanese ETF data

I extract Japanese ETF net assets, primary prospectus benchmarks, net asset value (NAV) returns, and tracking errors from Morningstar. I include only ETFs with 'Equity' as Global Broad Category Group and TOPIX, Nikkei 225, or JPX-Nikkei 400 as Primary Prospectus Benchmark (I include net return, price return, and total return indexes). The resultant sample of funds is reported in Table C2.

G.4 BoJ announcements

Table C3: Announcements of the BoJ pertaining to the purchases of ETFs

Date	**Key change**	**Announcement type**
28 October 2010	Announcement of first ETF purchases of 0.45 trillion yen	Expansive
14 March 2011	Increase of the total amount to 0.9 trillion yen	Expansive
04 August 2011	Increase of the total amount to 1.4 trillion yen	Expansive
27 April 2012	Increase of the total amount to 1.6 trillion yen	Expansive
30 October 2012	Increase of the total amount to 2.1 trillion yen	Expansive
04 April 2013	Increase of the total amount to 1 trillion yen per year	Expansive
31 October 2014	Increase of the total amount to 2 trillion yen per year	Expansive
19 November 2014	Inclusion of the JPX-Nikkei 400 ETFs	Reallocative
15 March 2016	Addition of human capital supporting purchases at 0.3 trillion yen per year	
29 July 2016	Increase of the total amount to 6 trillion yen per year	Expansive
21 September 2016	Change in purchases allocation with 2.7 trillion per year dedicated to TOPIX-tracking ETFs and the other 3 trillion per year split across three indexes as before	Reallocative
31 July 2018	Change in purchases allocation with 4.2 trillion yen per year dedicated to TOPIX-tracking ETFs and the other 1.5 trillion yen per year split across three indexes as before	Reallocative
19 December 2019	Establishing lending ETF shares from BoJ holdings	
16 March 2020	Increase of the total amount to 12 trillion yen per year	Expansive
31 March 2020	Establishment of the amount of cash collateral for lending of ETFs	
01 May 2020	Change in allocation from total market value to the amount outstanding in circulation	
19 March 2021	Revision to the lending program	
23 March 2021	Change in purchases allocation with 11.7 trillion yen per year dedicated to TOPIX-tracking ETFs only	Reallocative

This table is based on the official BoJ announcement documents, publicly available at https://www.boj.or.jp/en/mopo/measures/mkt_ope/ope_t/index.htm. Horizonal lines separate policy periods used in the regression analysis.

G.5 Variable definitions and descriptive statistics

Table C4: Key variable definitions and descriptive statistics (Japan)

Variable	Definition	Units	Source (field)	Mean	Median	St. dev.	p1	p99
ΔBMI^{BoJ}	Change in BoJ purchases as fraction of stock market value relative to the expected pace, adjusting for the difference in period duration. See definition in (65).	% MV		0.01	0.01	0.30	-1.08	1.01
BoJ purchase	Fraction of stock market value purchased by the Bank of Japan in a given policy period. JPY purchases are defined in (64).	% MV	BoJ website, Refinitiv, Morningstar, Compustat Global	0.30	0.07	0.53	0.00	2.19
Δ Lending inventory	Difference between the average daily active inventory (ActiveLendableQuantity) as a share of shares outstanding (cshoc) in the last month of the period and the last month of the preceding period.	% shares	Markit (ActiveLendableQuantity) and Compustat Global (cshoc)	0.33	0.10	1.79	-4.86	6.66
Δ Quantity on loan	Difference between the average daily short quantity on loan (ShortLoanQuantity) as a share of shares outstanding (cshoc) in the last month of the period and the last month of the preceding period.	% shares	Markit (ShortLoanQuantity) and Compustat Global (cshoc)	0.23	0.05	1.59	-4.23	5.71
Δ Borrowing fee	Difference between the average daily borrowing fee (IndicativeFee) in the last month of the period and the last month of the preceding period.	%	Markit (IndicativeFee)	-0.10	0.00	1.31	-4.58	4.38
Stock return	Cumulative return over the policy period. Daily total return is computed as (prccd + div)*split / lag(prccd).	%	Compustat Global	5.79	2.14	36.80	-62.39	135.37
Lending inventory	Active inventory on announcement date.	% shares	Markit (ActiveLendableQuantity)	5.10	4.09	4.57	0.00	18.19
Quantity on loan	Shorting demand on announcement date.	% shares	Markit (ShortLoanQuantity)	1.12	0.50	1.73	0.00	8.58
Borrowing fee	IndicativeFee averaged over the month preceding the announcement date.	%	Markit (IndicativeFee)	1.56	0.62	1.86	0.32	8.25
D(special)	1 if IndicativeFee > 1%, 0 otherwise	Boolean		0.36	0.00	0.48	0.00	1.00
Markit score	Markit's Daily Cost of Borrow Score, where 1 is cheapest and 10 is most expensive, averaged over the month preceding the announcement date.	1-10		1.69	1.00	1.06	1.00	5.05
Log shares outstanding	Logarithm of shares outstanding	Log shares	Compustat Global (cshoc)	17.84	17.76	1.54	12.60	21.56
Amihud's illiquidity	Module of return divided by dollar trading volume, or abs(ret)/(cshtrd*prccd), scaled by 10^9.		Compustat Global	0.60	0.15	1.25	0.00	5.92
Log trading volume	Logarithm of trading volume	Log shares	Compustat Global (cshtrd)	12.01	11.98	2.12	6.75	16.96
Market value	Logarithm of market capitalization value, or $ln(prccd * cshoc/10^6)$	Million yen	Compustat Global	202.8	40.4	664.2	2.9	2,968.4
β^{TOPIX}	Stock beta with respect to TOPIX index, computed on a one-year rolling window of daily total stock returns, with at least three months of data.		Compustat Global, Morningstar	0.93	0.92	0.35	0.20	1.81

Table C5: Key sample summary statistics (Japan)

	I. General collateral stocks						II. Special stocks					
Variable	No. obs.	Mean	Median	St. dev.	p1	p99	No. obs.	Mean	Median	St. dev.	p1	p99
ΔBMI^{BoJ}, % MV	11,006	-0.00	0.01	0.29	-1.13	0.92	6,292	0.03	0.01	0.31	-0.98	1.13
Bank of Japan purchase, % MV	11,006	0.31	0.07	0.56	0.00	2.38	6,292	0.29	0.06	0.47	0.00	1.97
Δ Lending inventory, % shares	11,006	0.23	0.14	1.62	-4.91	5.23	6,292	0.50	0.05	2.03	-4.75	8.09
Δ Shorting demand, % shares	11,006	0.29	0.07	1.39	-3.02	5.24	6,292	0.13	0.01	1.89	-5.98	6.26
Δ Borrowing fee, %	11,006	0.13	0.00	0.75	-0.75	3.50	6,292	-0.50	-0.29	1.86	-6.25	5.00
Stock return, %	11,006	5.16	2.64	31.58	-58.42	108.83	6,292	6.91	1.32	44.46	-67.97	170.04
Lending inventory, % shares	11,006	7.06	6.39	4.39	0.22	19.24	6,292	1.67	0.74	2.25	0.00	9.96
Shorting demand, % shares	11,006	0.94	0.45	1.40	0.00	6.73	6,292	1.44	0.63	2.17	0.00	11.19
Borrowing fee, %	11,006	0.54	0.51	0.13	0.30	0.96	6,292	3.35	2.88	2.12	1.00	10.21
D(special)	17,298	0.36	0.00	0.48	0.00	1.00						
Active utilization, %	11,006	7.96	3.49	12.51	0.00	64.19	6,292	66.18	100.00	41.23	0.00	100.00
Market value, JPY billion	11,006	300.31	77.96	813.70	5.14	3,653.92	6,292	32.16	15.37	94.52	2.14	279.65

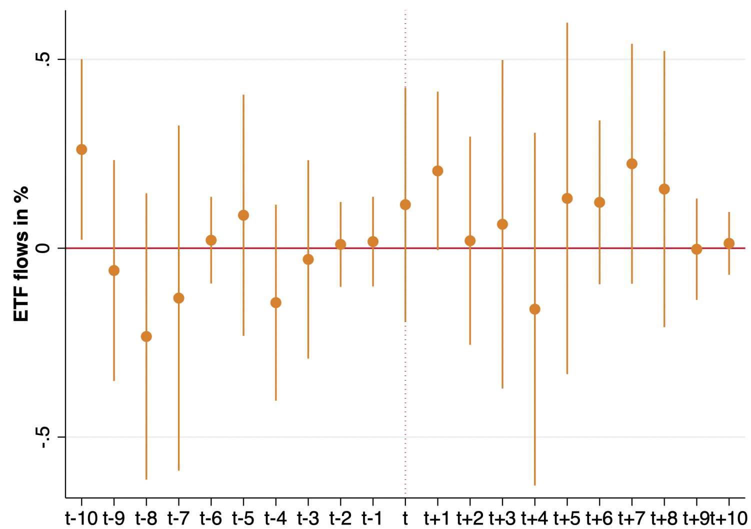
This table reports the summary statistics for the key samples analyzed in this Internet Appendix. Statistics for general collateral stocks are presented in panel I and those for special stocks are presented in panel II. The full sample includes stocks that were TOPIX constituents in 2010–2022. Changes in all variables are computed from the end of one policy period to the other, over the 13 periods outlined in Internet Appendix G. A stock is considered special if its average fee in the month preceding the policy period is above 1% and a general collateral stock otherwise. All variables are defined in Table C4.

G.6 Reaction of ETF flows to BoJ announcements and purchases

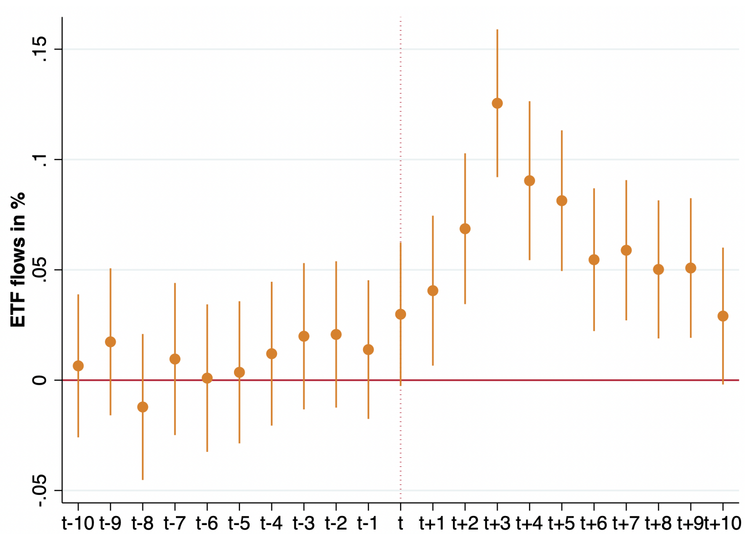
Figure C2 illustrates that the combined eligible ETF flows do not react to the BoJ announcements and strongly react to the purchases.

Figure C2: BoJ purchases and aggregate eligible ETF flows

(a) BoJ announcements



(b) BoJ purchases



This figure plots estimates of univariate regressions of eligible ETF flows onto D(BoJ announcement) in panel (a) and D(BoJ purchase) in panel (b). $D(BoJ\,announcement) = 1$ if there was a BoJ announcement on day t, and zero otherwise. Similarly, $D(BoJ\,purchase) = 1$ if there was a BoJ purchase on day t, and zero otherwise. The 99%-confidence bands are based on HAC-robust standard errors. Flows are winsorized at 99%.