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

Taisiya Sikorskaya†

October 8, 2023

Link to the most recent version

Abstract

Institutional ownership is thought to facilitate short-selling. Indeed, short sellers typically borrow from the holdings of institutions. Yet, institutional demand, and hence lending supply, is endogenous. This paper isolates changes in this demand due to investment mandates (benchmark indexes) to shed new light on the role of institutions in lending markets. In a model with benchmarked fund managers who supply their risky holdings for lending, the equilibrium price and lending supply are both higher for the benchmark asset. Larger supply alleviates short-selling constraints, while higher shorting demand (due to inflated price) exacerbates them. Two quasi-natural experiments, the Russell index reconstitution and the Bank of Japan purchases, confirm that stocks with more institutional capital benchmarked against them have larger lending supply and demand. Ultimately, they are *costlier* to short. In both 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, shorting fee, index effect, Russell, ETF, BoJ, Nikkei

*I thank Anna Pavlova for her invaluable guidance. I am also grateful to Adem Atmaz, Andrea Barbon, Süleyman Başak, Svetlana Bryzgalova, Andrea Buffa, Nuno Clara, João Cocco, Vincent Fardeau, Dimas Fazio, Julian Franks, Francisco Gomes, Roberto Gomez Cram, Marco Grotteria, Stephan Jank, Igor Kuznetsov, Cam Harvey, Satoru Matsuhashi, Dmitriy Muravyev, Lakshmi Naaraayanan, Tsvetelina Nenova, Adam Reed, Pedro Saffi, Koji Takahashi, Dimitri Vayanos, and Stephane Verani as well as seminar participants at the Dauphine Finance PhD Workshop, HEC PhD Workshop on Incentives in Finance, Junior Academic Research Seminar in Finance, London Business School, NFA meeting, Transatlantic Doctoral Conference, and USC Marshall PhD Conference for helpful comments. This research has been generously supported by the AQR Asset Management Institute at London Business School. I also thank S&P Global (IHS Markit) team for support with the securities lending data, FTSE Russell for providing proprietary data, and investment practitioners for insights into securities lending in the United States and Japan.

†London Business School, tsikorskaya@london.edu

1 Introduction

Short-selling is key to price discovery in financial markets. To sell assets short, market participants must first borrow them. Academic research on short sales, spanning nearly six decades (Seneca (1967)), suggests that asset pricing anomalies are more prevalent in securities with binding short-selling constraints, or those that are expensive to borrow.[1] Yet, the formation of these constraints remains opaque (U.S. Securities and Exchange Commission (2021)).

It is hardly surprising that the conventional view expects institutional ownership to alleviate 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 horizon, are well-suited to lend their holdings and generate significant revenues by doing so.[3] At the same time, they can only lend what they own, and hence the same asset characteristics that drive institutional demand also determine 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, or the borrowing fee.

In this paper, I put 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 the fact that institutions are bound to their investment mandates. Benchmarking, which involves evaluating fund manager performance against a market index (benchmark), serves as a key mechanism for enforcing investment mandates and has been shown to influence asset prices.[4] Despite this, the potential of mandate-driven institutional investors to 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, in both theory and data, that it is strong enough to challenge the conventional view on the role of institutions in the short-selling markets.

[1] See, for example, Chen, Hong, and Stein (2002), Geczy, Musto, and Reed (2002), Drechsler and Drechsler (2014), 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 a benchmark index such as the S&P 500 or the Russell 1000. Academic research indicates that institutions tilt their portfolios toward stocks included in their benchmark indexes, thereby raising these stocks' prices and inducing excess correlations in returns (Basak and Pavlova (2013)). This phenomenon is closely related to market segmentation (He and Xiong (2013)) and is also featured in preferred-habitat models of the term structure of interest rates (Vayanos and Vila (2021)).

I develop a model with benchmarked fund managers who supply a part of their risky holdings for lending. These managers optimally tilt their portfolios to the asset in their benchmark index, increasing both its price and lending supply. Simple intuition suggests that a larger supply should reduce borrowing fees and alleviate short-selling constraints (supply effect of benchmarking). However, the model shows that benchmarking may increase fees because it inflates the asset price and hence attracts higher shorting demand (overvaluation, or demand effect). I test the predictions of the model using two quasi-natural experiments based on the Russell index reconstitution and the exchange-traded fund (ETF) purchases of the Bank of Japan (BoJ). Both feature exogenous 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, coupled 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 capital to lending supply.

I build intuition using a tractable model of asset prices and borrowing fees in the presence of benchmarking. It introduces a market for asset lending 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 also contribute to the lending supply. Fund managers can lend their risky holdings to short-sellers in exchange for a fee, up to a lending limit,[5] while direct investors are not permitted to lend. The shorting demand 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 channels of benchmarking effects coexist, it is not immediately apparent how borrowing fees relate to benchmarking. By clearing the asset spot and lending markets at the same time, I demonstrate that this relationship in equilibrium depends on a simple condition related to the fund managers' lending limit. When the managers are too constrained in lending (i.e., the lending limit is tight), the demand effect prevails, resulting in higher borrowing fees for the benchmark asset.

The model features different predictions for an asset that is not costly 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

[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. In the baseline model, the lending limit is exogenous. Allowing funds to choose the lending limit endogenously to balance lending costs yields the same key findings. See Appendix E.

clearing condition binds, resulting in a strictly positive borrowing fee. Whether this fee increases or decreases with benchmarking depends on the lending limit as discussed above.

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 share liquidity. Additionally, since stocks in major indexes often attract more analyst coverage, the amount of capital benchmarked to a stock may be related to analyst disagreement, which is usually associated with more short-selling in the literature. Therefore, to test the model's predictions, I turn to two quasi-natural experiments.

In the first experiment, 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 ETFs benchmarked against them, I use a comprehensive measure of the amount of capital benchmarked against a stock, expressed as a fraction of its market value. This measure is referred to as benchmarking intensity (Pavlova and Sikorskaya (2023)). I argue that the mechanical nature of the Russell reconstitution creates a plausibly exogenous change in benchmarking intensity, allowing me to test the predictions of the theory.[6] First, I 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)), experiencing an average increase in benchmarking intensity of 8.6 percentage points.

Using comprehensive S&P Global (Markit) buyside data, I offer 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 benchmarking intensity. It is true for both general collateral stocks and stocks on special, which I define empirically as those with annualized borrowing fees up to and above 1%, respectively, following the literature (for example, Aggarwal, Saffi, and Sturgess (2015)). 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 fee increasing by 21bps for each percentage point increase in benchmarking intensity, or by over 25% for stocks added to the Russell 2000. These findings are not driven by how I define special stocks, as I demonstrate together with other robustness tests in Section 5.2.5.

In the second experiment, I examine the ETF purchases conducted by the BoJ to test my model's predictions in a different context. Since 2010, the BoJ has implemented a comprehensive monetary easing program aimed at combating deflation. This program involves increasing holdings of domestic equities through the purchase of ETFs linked to Japanese market indexes. In the

[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 5.1.

language of my model, these purchases increase the share of funds benchmarked to particular indexes within the economy, thereby changing the benchmarking intensities of Japanese stocks. Due to the unprecedented scale of the program, these changes in benchmarking intensities are economically large. For instance, the BoJ's indirect ownership in certain stocks has reached 30% of their market value, with purchases reaching as much as 12% during specific policy periods. Furthermore, the composition of these purchases generates exogenous variation in benchmarking intensity across Japanese stocks, allowing me to identify the impact on the lending market.[7] To measure changes in benchmarking intensity, I focus on the unexpected component of purchases, which is most in line with my model, rather than the total purchases.

I find that increases in benchmarking intensities due to the BoJ's purchases lead to both larger lending supply and greater shorting demand in the cross-section of Japanese stocks. Moreover, the borrowing fees of stocks on special tend to rise in response to the purchases, revealing the dominant demand effect of benchmarking in the Japanese lending market. These results are both statistically and economically strong, with a 1 percentage point increase in benchmarking intensity resulting in a 41bps increase in fees. I provide further support for the mechanism by studying flows to ETFs eligible for the BoJ's purchases. I observe that the ETF flows are not sensitive to the BoJ announcements, yet react very strongly to the BoJ's purchases with a delay of several days. The supply effects accrue with a similar timeline, corroborating that the ETFs offer newly purchased securities for lending.

So why does the demand effect of benchmarking dominate in the data? In my model, this is primarily influenced by the lending limits imposed on fund managers' holdings. Naturally, when these lending limits are too restrictive, managers undersupply their holdings for lending. Meanwhile, the shorting demand continues to rise due to the influence of benchmarking on asset prices. In both the United States and Japan, the prevalence of the demand effect suggests that these lending limits must be binding.

To explore whether lending limits are indeed restrictive in the data, I collect lending information for U.S. investment management companies from their NPORT-P and NCEN 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 4).[9]

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

[7] A similar identification strategy is employed in Barbon and Gianinazzi (2019), who investigate the pricing effects of the BoJ's purchase program.

[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.

[9] In Japan, Maeda, Shino, and Takahashi (2022) use the annual reports of investment companies to document position-level lending limits ranging from 40% to 80%. Japanese regulators do not impose any portfolio-level limits.

tutions by funds benchmarked to the Russell indexes. I document that these funds frequently lend out 90%–100% of the position values in special stocks transitioning between the Russell indexes, and the borrowing fees for these stocks exhibit a positive correlation with how much is on loan. However, there are many special stocks that the benchmarked funds do not lend at all, although the model predicts that they should. Therefore, I acknowledge that the lending limit in my model could also represent a simplified form of various real-world frictions, such as lender market power or search costs, that contribute to the weak supply response to benchmarking. I discuss these frictions in more detail in Section 5.3.2.

Finally, I demonstrate that lending limits have broader implications beyond their impact on borrowing fees. Specifically, the lending limit affects how likely an asset is special (that is, how likely the lending market constraint binds), as well as the extent to which the price of a special asset reacts to benchmarking. As the lending limit is relaxed, the sensitivity of the asset price to benchmarking generally decreases. In a scenario where there is no lending limit and fund managers can lend the full value of their risky holdings, the model predicts that benchmarking has no effect on the price of a special asset. These findings emphasize the potential and novel role for lending limits in various applications of investment mandates, such as the design of targeted purchases by central banks and sustainable investing.

Overall, my results underscore the weakness of the pass-through from institutional capital to lending supply. It is crucial to identify the specific frictions behind this pass-through to understand the formation of short-selling constraints, the asset-pricing implications of institutional mandates, and the welfare effects for end investors.

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)).[10] 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)). Ample lending supply has also been linked to higher price efficiency (Saffi and Sigurdsson (2011)), with several contemporaneous papers debating the effects of passive ownership on price efficiency through lending (Palia and Sokolinski (2021), Bhojraj and Zhao (2021), and von Beschwitz, Honkanen, and Schmidt (2022)). I exploit benchmarking to

[10] 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.

offer a new perspective on how institutional ownership impacts short-selling constraints. Although benchmarking increases supply, I find that borrowing fees rise when benchmarked fund ownership increases. I provide position-level evidence of the weak pass-through to supply of both active and passive ownership 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.

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,[11] but they bind only for certain (special) stocks.[12] 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 (Forthcoming)). Securities that are subject to more disagreement are typically 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 account for how institutional incentives affect 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.

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). 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 investment mandates in delegated asset management (for example, Binsbergen, Brandt, and Koijen (2008), He and Xiong (2013)) and investor styles (Barberis and Shleifer (2003)).[13] However, none of these papers has examined how benchmarking or mandates affect the asset lending market. My model suggests that in some cases, the feedback through the lending market may negate the effects of benchmarking on price.[14]

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

[12] 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).

[13] Closely related literature investigates preferred habitats in fixed income markets (for example, Greenwood and Vayanos (2014) and Vayanos and Vila (2021)).

[14] There is also developing literature that incorporates downward-sloping demand curves for stocks in the

This paper is related to literature quantifying the effects of benchmark 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.[15] In this strand of literature, my paper is closest to Chang, Hong, and Liskovich (2015), which documents 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), which proposes benchmarking intensity as a measure of how much capital is benchmarked against an asset. I show that benchmarking intensity is strongly related to lending supply and document a novel heterogeneity in the index effect for stocks that are on special in the lending market.

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) studies the securities lending market and documents that the BoJ's purchases increased lending supply. None of the papers has explored how the program affected borrowing fees.[16] I link together the effects of the program in the spot and lending markets, show that special stocks experience an increase in borrowing fees, and document higher returns of special stocks in response to the purchases.[17]

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 for a fee. Three distinct groups of participants operate within this market: (i) lenders, which include institutional investors—some utilizing custodians for lending and others employing in-house lending agents, (ii) borrowers, comprising hedge funds, proprietary trading desks, and market makers, and (iii) prime brokers. Typically, hedge funds and market makers procure securities from their prime brokers, who subsequently borrow from mutual funds, pension funds, and other beneficial owners.

Stock lending markets in the United States and Japan have similar structures. A comprehensive description of the U.S. market can be found in D'Avolio (2002), Kolasinski, Reed, and

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.

[15] 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).

[16] In contemporaneous and independent work, Shino, Katagiri, and Takahashi (2023) argue that the cumulative BoJ's purchases, when considered over the horizons of 1-2 years, lowered borrowing fees in the Japanese market and attenuated the impact of the purchases on asset prices.

[17] I also discuss implications for bond quantitative easing and repo markets in Section 7.

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)). Comparable overviews for Japan are provided by the Japanese Securities Dealers Association (JSDA), which establishes regulations for securities lending in Japan, and Huszár and Prado (2019).[18]

Borrowing fees are typically not quoted directly but are derived from quoted rebate rates. Security borrowers provide cash collateral to the security 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 seen 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, a majority of the securities lending income accrues back to the fund assets, approximately 80% for investment companies in the United States (Johnson and Weitzner (Forthcoming)) and 50% for ETFs in Japan.[19]

3 Model

To illustrate the main mechanism, I develop a simple and tractable model of asset prices and borrowing fees in the presence of benchmarking. It builds upon Brennan (1993) and Banerjee and Graveline (2013) and introduces a market for asset lending to an economy with fund managers benchmarked to a market index. The distinguishing feature of the model is that benchmarking-induced demand affects both asset price and lending supply. Because an asset that belongs to a benchmark index has an inflated price, the shorting demand for it is also higher. The goal of the model is to characterize the relationship between benchmarking, asset prices, and borrowing fees.

3.1 Model setup

There are two periods, $t = \{0, 1\}$. 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 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

[18] Contrary to the United States, a portion of the Japanese securities lending market is centralized and intermediated by the Japanese Securities Finance company. According to data from the Japan Exchange Group https://www.jpx.co.jp/markets/statistics-equities/margin/06.html, only around 7% of lending occurred in that market during my sample period.

[19] See, for instance, the prospectus of BlackRock TOPIX ETF at https://www.blackrock.com/jp/individual-en/en/literature/prospectus/ishares-topix-etf-prospectus-jp-en.pdf.

of the risky asset.[20]

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 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 $U(w)$. I denote the mass of managers by λ_M. 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.[21]

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).[22] 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 punish any deviation from the benchmark. Because the fund's performance monotonically increases in securities lending, managers lend out all portfolio shares up to the limit l.

Hedgers, the third type of investors, are endowed with $e\bar{D}$ units of consumption at $t = 1$

[20] Extending to the case of multiple benchmark indexes does not change key results.

[21] There are various microfoundations for this parameter, which I discuss in Section 5.3. Empirically, this parameter is closest to the utilization of lendable inventory for special stocks, which is around 75% in my data. See Table 1.

[22] Ma, Tang, and Gómez (2019) and Evans, Gómez, Ma, and Tang (Forthcoming) 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.

so that they engage in short selling at $t = 0$ for hedging purposes. This assumption is similar to that of Banerjee and Graveline (2013). Each hedger chooses a portfolio θ_H to maximize expected 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. 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 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.[23]

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.[24]

[23] As I show in Appendix D, implications of benchmarking are qualitatively the same if I allow limited lending by direct investors.

[24] I could instead assume that fund managers receive a windfall gain when their fund family or lending agent lend 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 Appendix B.4). 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

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

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 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.[25] If instead the shorting demand is higher than 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 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

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

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

where B_e, B_θ, B_ω, and $\bar{B}$ are nonnegative scalars because $l \in (0, 1]$,[26]

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

Term ω_λ above represents benchmarking intensity 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.[27]

Equation (7) highlights two sources of price pressure in my model. The first source is induced by benchmarking through $B_\omega \omega_\lambda$. It implies that if an asset's benchmarking intensity ω_λ increases, for example, due to an addition to a market index, its price goes up (known as the index effect). The second source of price pressure stems from the endowment of hedgers, $B_e e$. This is a general 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.[28] 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

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

where C_e, C_θ, and C_ω are scalars,

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

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

[27]ω_λ is an equivalent of the benchmarking intensity introduced in Pavlova and Sikorskaya (2023), although it is based on one benchmark index rather than multiple indexes.

[28]In line with that, Johnson and Weitzner (Forthcoming) 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).

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 benchmarking intensity ω_λ depends on the sign of C_ω. If the population masses of hedgers and direct investors satisfy the following condition,

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

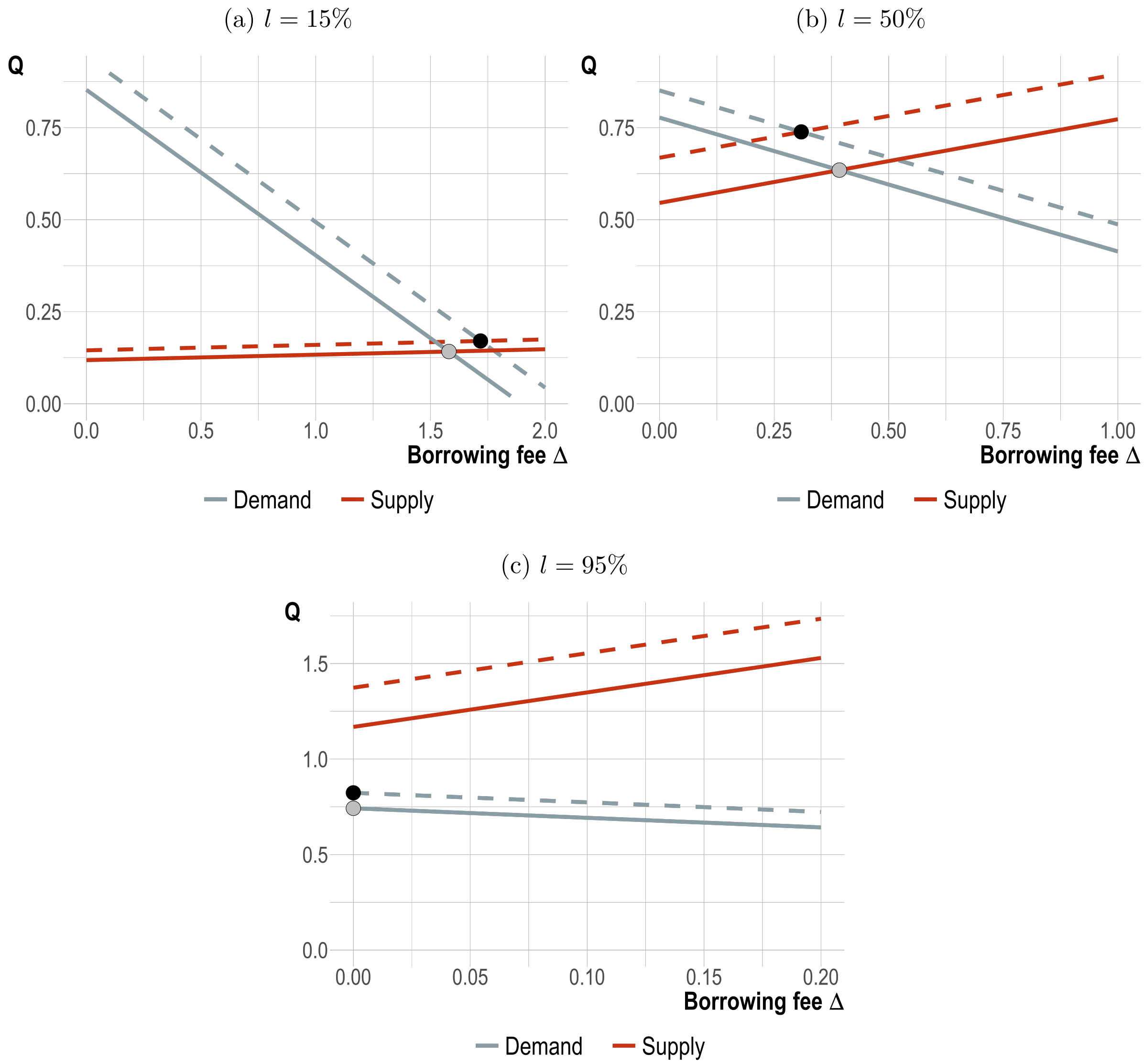
then $C_\omega < 0$ and the equilibrium borrowing fee decreases in benchmarking intensity ω_λ. This condition compares the share of hedgers relative to direct investors with the lending limit l. When the limit is lenient enough, the supply effect of benchmarking dominates in the lending market. This 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 Appendix A.1). Furthermore, in 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.

I provide a numerical illustration in Figure 1. Panel (a) depicts the shift in the lending market equilibrium due to an increase in the benchmarking intensity when $C_\omega > 0$ (setting $l = 15\%$). In this case, the equilibrium borrowing fee is higher when benchmarking intensity is larger, 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 benchmarking intensity is higher because the supply shift is larger.

It is useful to discuss equilibria under full lending, or $l = 1$, and no lending, or $l = 0$. Under full lending, fund managers lend out any new purchase of a benchmark asset, so benchmarking does not affect asset prices. Furthermore, only the supply effect of benchmarking is present, so the borrowing fee unambiguously decreases in benchmarking intensity ω_λ. I provide further details in Appendix B.3. Under no lending, fund managers are not allowed to lend assets and the lending market cannot clear. Hedgers have zero holdings in the risky asset. If I extend the model to allow lending by direct investors instead, only the demand effect of benchmarking on borrowing fees is present and benchmarking inflates asset prices, as I show in Appendix D.

Finally, the key model predictions are not driven by the assumption of an exogenous lending limit. In Appendices E and F, I solve extensions of the model with costly lending by fund managers and costly search by hedgers, respectively, whereby the limit l is endogenously chosen by agents. Although less tractable, such models deliver the same key results, including unambiguously positive index effect and condition (9) for the relationship between the equilibrium borrowing fee and benchmarking intensity.

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 (grey) dot marks the equilibrium for the (not) benchmarked 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). Appendix B.4.4 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[29]

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

Notice that, as for the asset on special, the price increases in benchmarking intensity 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 benchmarking intensity.

3.3.3 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

$$\frac{(1-l)\lambda_H}{\frac{\lambda_M}{a+b}(l^2\lambda_D + (1-l)^2\lambda_H) + \lambda_D\lambda_H} - \frac{1}{\frac{\lambda_M}{(a+b)} + \lambda_D + \lambda_H} < 0,$$

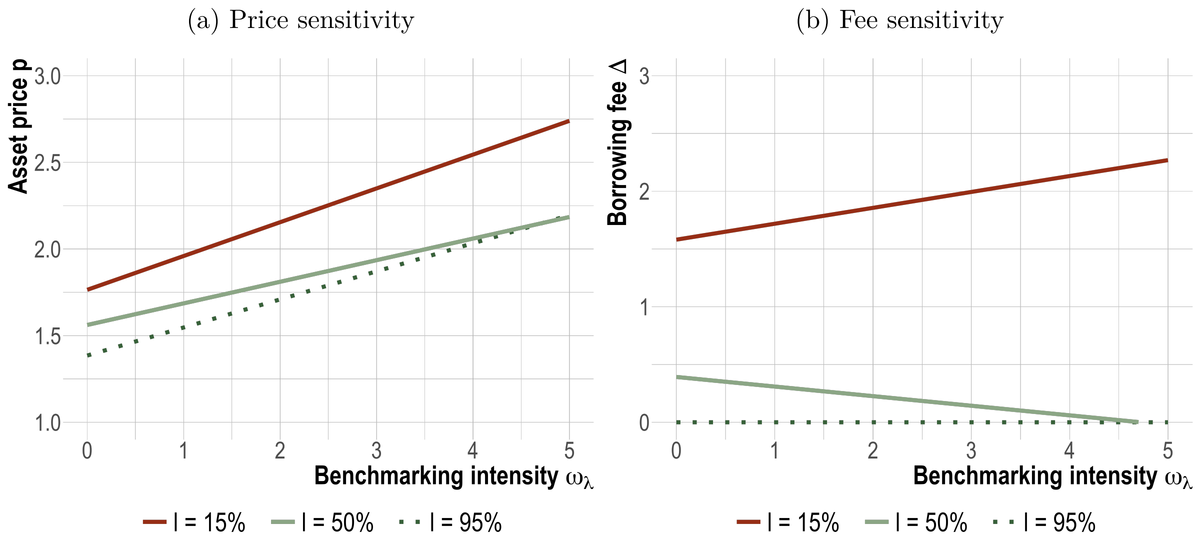
$$\text{or equivalently,} \quad \frac{\lambda_H}{\lambda_H + \lambda_D} < l,$$

which is the same as condition (9), which defines equilibrium fee sensitivity to benchmarking intensity 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 general collateral asset special, or the other way around.

In other words, asset pricing effects of investment mandates (or more specifically, index effects) 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)

[29] This case is derived in Appendix B.4.

Figure 2: Sensitivity of equilibrium prices and fees to benchmarking



This figure plots the changes in equilibrium quantities due to changes in benchmarking intensity in the model: equilibrium price in panel (a) and equilibrium borrowing fee in panel (b). In each panel, the two solid lines correspond to special assets with the lending limit $l = 15\%$ ($C_\omega > 0$) and $l = 50\%$ ($C_\omega < 0$), whereas the dotted line corresponds to a general collateral asset with $l = 95\%$. Appendix B.4.4 details all parameter values.

does not hold), price sensitivity to benchmarking intensity is higher for an asset on special or lower for a general collateral asset. This is illustrated in panel (a) of Figure 2: for the same change in benchmarking intensity, 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).

3.4 Demand and supply in the lending market

To understand how benchmarking affects equilibrium in the lending market, it is instructive to analyze the first-order derivatives of the demand and supply in the lending market with respect to ω_λ. Demand is defined by the shorting needs of hedgers:

$$Q^d = -\lambda_H \theta_H = \lambda_H \left[\frac{1}{\gamma\sigma} (p - \mu - \Delta) + e \right],$$

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

$$\begin{aligned} Q^s =& l\lambda_M \theta_M \\ =& l\lambda_M \left(\frac{1}{\gamma\sigma(a+b)} (l\Delta + \mu - p) + \frac{b}{a+b}\omega \right). \end{aligned} \tag{11}$$

So my model features a downward-sloping shorting demand and an upward-sloping lending supply for special assets.[30] In the data, lending supply is indistinguishable from shorting demand, as they both manifest in the number of shares on loan. At the same time, term $\lambda_M \theta_M$ above corresponds to lendable shares in the data, or the total lendable inventory.

3.4.1 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

$$\begin{aligned}\frac{dQ^d}{d\omega_\lambda} =& \lambda_H \frac{1}{\gamma\sigma}\left(\frac{\partial p}{\partial \omega_\lambda} - \frac{\partial \Delta}{\partial \omega_\lambda}\right)\\ =& \bar{B} l \lambda_D \lambda_H,\\ \frac{dQ^s}{d\omega_\lambda} =& \frac{\partial Q^s}{\partial \omega_\lambda} + \frac{l\lambda_M}{\gamma\sigma(a+b)}\left(l\frac{\partial \Delta}{\partial \omega_\lambda} - \frac{\partial p}{\partial \omega_\lambda}\right)\\ =& \bar{B} l \lambda_D \lambda_H,\end{aligned} \tag{12}$$

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.

3.4.2 General collateral asset

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

$$\begin{aligned}\frac{dQ^d}{d\omega_\lambda} =& \frac{\lambda_H}{\frac{\lambda_M}{(a+b)} + \lambda_D + \lambda_H} > 0,\\ \frac{dQ^s}{d\omega_\lambda} =& l\frac{\lambda_D + \lambda_H}{\frac{\lambda_M}{(a+b)} + \lambda_D + \lambda_H} > 0,\end{aligned} \tag{13}$$

[30] Empirically, Kolasinski, Reed, and Ringgenberg (2013) find that 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 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 the response of the lending supply is larger if condition (9) holds. Derivation details are in Appendix B.4.2.

3.5 When do short-selling constraints bind?

The model explains how benchmarking contributes to the specialness of the asset, or in other words, to whether shorting constraints bind. From (8), there will be a strictly positive fee to borrow the asset if and only if

$$C_e e - C_\theta \bar{\theta} + C_\omega \omega_\lambda > 0. \tag{14}$$

That is, an asset for which (14) 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). An asset with a higher benchmarking intensity 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 (14) 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.

The intuition is slightly different for the case with full lending ($l = 1$). As I show in Appendix B.3, the demand effect of benchmarking is not present if $l = 1$ and an asset with a higher benchmarking intensity ω_λ is always less likely to be on 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 and borrowing fees in the presence of both benchmarking and securities lending. The model implies the following relationships. If an asset's benchmarking intensity 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 two quasi-natural experiments to test the predictions of my model. I also validate assumptions of the model using novel regulatory data.

4 Data

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 database includes daily stock-level data on borrowing activity, including 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.[31] The daily data are available from July 2006, and my sample runs through September 2022. I provide institutional details on the US and Japanese markets for borrowing stock in Appendix 2.

The U.S. equity sample is an annual panel of stocks that were the Russell 3000 constituents in 2006-2018. To build the stock-level benchmarking intensity 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 Appendix. Historical benchmark weights are from FTSE Russell, Morningstar, and CRSP. Details on specific indexes are reported in Section A.2.2 in the 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 Appendix. Details on funds data are in Appendix A.2.3.

For the U.S. sample, I also collect information on funds securities lending from NPORT-P and N-CEN filings. NPORT-P 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 Appendix A.2.6.

The Japanese equity sample is from Compustat Global and includes all Tokyo Stock Price Index (TOPIX) constituents from December 2010 to September 2022. Details on sample construction are in Appendix A.2.7.

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

Data on the ETF purchase program of the BoJ is from the bank's website. It includes both announced changes in the size and composition of the purchases and the daily data on aggregate purchases.[32] To construct stock-level purchases of the BoJ, I use historical constituent weights for the TOPIX, Nikkei 225, and JPX-Nikkei 400 indexes available from Refinitiv. The Japanese ETF data are from Morningstar. Details and the list of ETFs are in Appendix A.2.8. The TOPIX returns are from Morningstar.

4.2 Key summary statistics

Table 1 describes the key data samples used in this paper. Panel A reveals that a typical general collateral stock next to the Russell cutoff has 28% of its shares in lending inventory and close to 5% currently loaned to short-sellers. On average, it costs 39bps per annum to borrow such a stock. Panel II of the table shows that 5% of stocks next to the Russell cutoff are special. They are costly to borrow, with the average borrowing fee at 5.6%. Special stocks have over 17% of their shares on loan, on average, which implies a utilization of over 75% of lending inventory.

Panel B of Table 1 shows that a general collateral stock in the Japanese sample has 7% of its shares in lendable inventory and 1% of shares are on loan, on average. In Japan, a short-seller would need to pay 54bps per annum to borrow such a stock. Panel II of the table reveals that 36% of stocks are special, and their average borrowing fee is 3.3% per annum. The short interest on special stocks in Japan is considerably lower than that in the United States, but the average utilization of lending inventory is comparable at over 66%.

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 the U.S. and Japanese samples in Appendix A.3. All variables are winsorized at 0.5% and 99.5% (or at 0% and 99% if taking only positive values).

[32]See https://www.boj.or.jp/en/mopo/measures/mkt_ope/ope_t/index.htm for announcements and https://www3.boj.or.jp/market/en/menu_etf.htm for purchases. Accessed on November 1, 2022.

Table 1: Key sample summary statistics

Variable	I. General collateral stocks						II. Special stocks					
	No. obs.	Mean	Median	St. dev.	p1	p99	No. obs.	Mean	Median	St. dev.	p1	p99
Panel A: U.S. data (sample of 500 stocks around the Russell cutoff in 2007–2018)												
ΔBMI, % MV	13,046	0.09	-0.04	2.56	-9.03	9.46	638	0.96	0.24	3.50	-6.37	12.19
Δ Lending inventory, % shares	13,046	-0.03	0.07	1.88	-6.09	5.25	638	0.32	0.21	2.74	-7.54	8.22
Δ Shorting demand, % shares	13,046	0.21	0.06	1.86	-5.20	6.41	638	-0.35	-0.29	3.10	-7.57	7.44
Δ Borrowing fee, %	13,046	0.01	0.00	0.21	-0.15	0.25	638	0.19	-0.21	4.09	-10.48	16.15
Stock return, %	13,046	-0.85	-0.60	9.18	-26.10	23.45	638	-0.50	-0.27	13.80	-36.93	34.25
BMI in May, % MV	13,046	22.11	23.19	6.19	4.97	33.31	638	18.46	18.88	7.28	2.67	31.53
Lending inventory in May, % shares	13,046	28.46	28.81	8.57	6.34	48.71	638	17.84	17.02	8.96	1.85	42.49
Shorting demand in May, % shares	13,046	5.06	3.23	5.38	0.06	24.09	638	17.06	15.74	8.88	1.75	41.36
Borrowing fee in May, %	13,046	0.39	0.38	0.09	0.25	0.80	638	5.61	3.12	6.26	1.02	31.82
Active utilization in May, %	13,046	15.55	10.58	15.07	0.20	64.18	638	75.75	80.02	17.29	31.41	98.64
Market value, USD million	13,046	3,485.80	2,470.96	2,899.64	526.99	13,512.05	638	2,187.51	1,670.28	1,589.00	499.47	7,984.77
Panel B: Japanese data (TOPIX stocks across policy periods in 2010–2022)												
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
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 the paper. Statistics for general collateral stocks are presented in panel I and those for special stocks are presented in panel II. Panel A presents stocks 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. Panel B presents 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 Section 6.1. 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. ΔBMI and ΔBMI^{BoJ} are changes in benchmarking intensities (amount of capital benchmarked against a stock relative to its market value), as defined in Sections 5.1 and 6.2, respectively. 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 Appendix A.3.

5 Russell Reconstitution

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

5.1 Russell reconstitution, benchmarking, and lending supply

The Russell indexes undergo an annual reconstitution every June. All eligible stocks are ranked based on their market capitalization value, and the top stocks are assigned to the Russell 1000. This ranking is based on a fixed date in May, so any shock to a stock near the Russell 1000 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)).[33]

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

$$BMI_{it} = \frac{\sum_{j=1}^{J} \lambda_{jt}\omega_{ijt}}{MV_{it}}, \tag{15}$$

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, driven by 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 an increase in benchmarking intensity of 8.6 percentage points. Appendix A.5 illustrates the discontinuity and provides a detailed decomposition of changes in BMI around the cutoff.

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 expected to be related to the limit on lending, as I discuss in Appendix A.14. 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 Appendix A.8

[33] I discuss this in more detail and also explain how my approach avoids common issues with the Russell cutoff in Section A.4 of the Appendix.

that using the index membership dummy delivers the same qualitative 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 the lending supply of stocks added to their benchmarks and reduce the lending supply of stocks removed from their benchmarks. Figure 3 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 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)). Appendix A.6 shows that these patterns are significant at a stock level and provides further details.

Therefore, an increase in the amount of capital benchmarked against a stock is likely to be positively related to lending supply, as my model predicts. I formally test model predictions for borrowing quantitites and fees with respect to BMI in the next section.

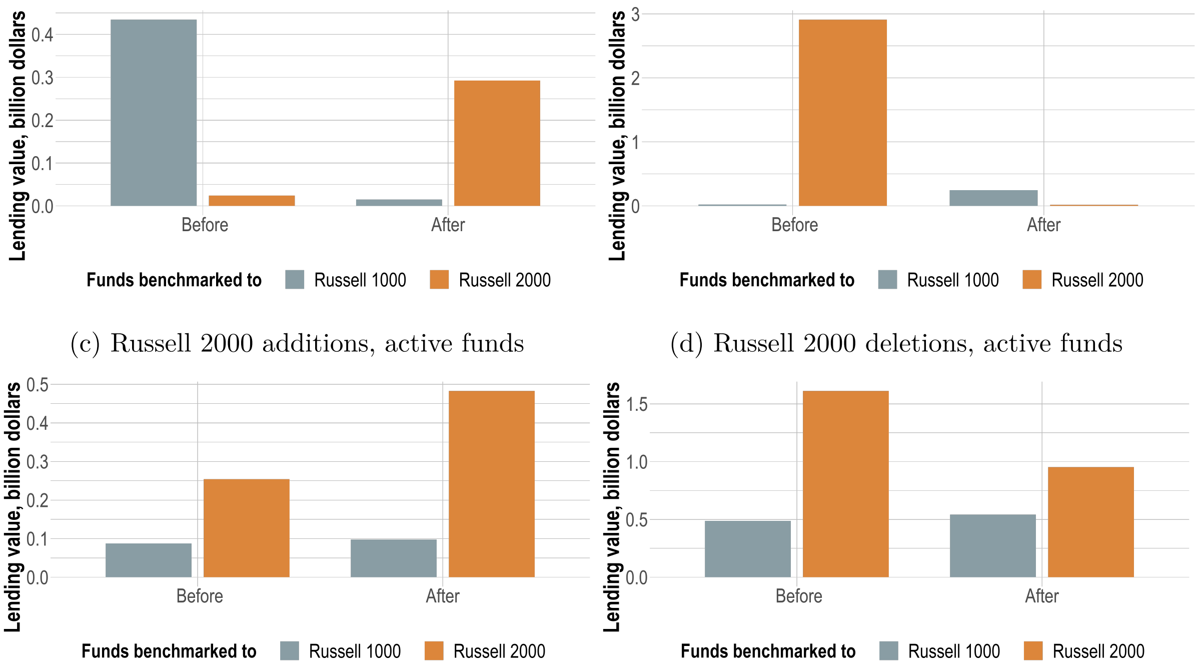
Figure 3: Aggregate fund lending of the Russell 2000 index additions and deletions

(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 lending of the Russell 2000 additions and deletions before (March–May) and after (July–September) the Russell reconstitutions of 2020–2022, according to funds' NPORT-P 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 Appendix A.6.

5.2 Benchmarking effects on spot and lending markets

The model in Section 3 predicts that an increase in benchmarking intensity leads to increases in asset price, lending inventory, and shorting demand, whereas the prediction for the borrowing fee is ambiguous. In this section, I test the 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:

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

$$\Delta Y_{it} = \beta_1 \Delta BMI_{it} \times D(special)_{it} + \beta_2 \Delta BMI_{it} \times D(not\, special)_{it} + \zeta' \bar{X}_{it} + \nu_{st} + \epsilon_{it}. \tag{17}$$

The dependent variable, ΔY_{it}, is the change in the stock's lending inventory (active lendable quantity of shares), shorting demand (short quantity on loan), 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.[34] 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 (15)), which effectively compares the pre- and post-reconstitution levels of BMI.

Specification (17) 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 it has an average borrowing fee of over 1% in May of year t, and zero otherwise (following Aggarwal, Saffi, and Sturgess (2015)). In Appendix Table A8, I show that the results are qualitatively the same if the specialness is defined in relative terms (using percentiles of the fee distribution), which is another popular definition in the literature (D'Avolio (2002)).

An underlying assumption is that special and general collateral stocks are different across some dimension orthogonal to BMI, which is driving shorting demand. In the model, it is represented by the size of hedgers' endowment e. Most of the literature takes disagreement, for example, as measured by the dispersion of analyst forecasts (Diether, Malloy, and Scherbina (2002)), as the main driver of short-selling. Given the mechanical nature of the Russell reconstitution, disagreement should not be related to changes in BMI.[35] I validate this assumption in Appendix A.15 and show that my estimates are virtually unaffected if changes in disagreement are included as controls.

In the 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. $\text{BandingControls}_{it}$ 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 5.2.5). 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 Appendix A.5. Finally, μ_{st} and ν_{st} are year by $D(special)$ fixed effects, which allow for differences in trends for special and general collateral stocks.

[34] I could also use the change from May of year t to May of year $t+1$ instead. Consistent with my model, the effect of benchmarking is permanent, or in other words, it is present as long as the stock remains in the benchmark. See Appendix A.9 for longer-horizon regression results.

[35] 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.

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

	Δ Lending inventory, % shares	Δ Shorting demand, % shares	Δ Borrowing fee, %	Stock return, %
	(1)	(2)	(3)	(4)
Panel A: No interactions				
ΔBMI, % MV	0.175***	0.136***	0.013**	0.122***
	(18.68)	(14.45)	(2.30)	(2.98)
Observations	13,684	13,684	13,684	13,684
Adjusted R-squared	0.143	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)	(13.99)	(-1.25)	(2.59)
ΔBMI, % MV × D(special)	0.121***	0.211***	0.207***	0.306*
	(3.38)	(5.49)	(3.97)	(1.72)
Observations	13,684	13,684	13,684	13,684
Adjusted R-squared	0.144	0.090	0.106	0.202
$\beta_1 - \beta_2$	-0.059	0.082**	0.211***	0.200
	(-1.63)	(2.15)	(4.09)	(1.11)

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. 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 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.

5.2.2 Results for the lending inventory and shorting demand

Estimation results are presented in Table 2. Column (1) shows that a change in a stock's BMI is indeed significantly related to the change in the lendable inventory of its shares. On average, a 1 percentage point increase in BMI is associated with an 18bps increase in the lending inventory. This is consistent with the Russell case studies discussed in Section 5.1 and in Appendix A.6 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 shorting demand. Consistent with the prediction of my model, shorting demand 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 13bps for general collateral stocks and 21bps for special stocks per 1 percentage point increase in BMI.

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 benchmarking intensity, which implies that the demand effect of benchmarking dominates in Russell reconstitutions. The increase is economically significant, with the fee rising by 21bps for every 1 percentage point increase in BMI. This implies that additions to the Russell 2000 that are also on special see their borrowing fees increase by 1.5 percentage points (their average BMI change is 7.4 percentage points), which is a growth of over 25% relative to the level in May.[36]

Importantly, column (3) 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 shares are on loan to short-sellers, as shown by the descriptive statistics in Table 1.

These results shed a new light on the role of institutional ownership in the formation of short-selling constraints. The literature has typically associated institutional ownership with 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% in their sample) is associated with a decrease in fees of 5.6bps, on average, for general collateral and special stocks in 2006-2010. Estimates in column (3) of Table 2 imply an increase in fees of 39bps (621bps) in response to a 30% change in BMI for the pooled (special) sample. A one-standard-deviation increase in BMI leads to a 3.2bps (72.5bps) increase in fees in the pooled (special) sample. For more comparability, in Appendix A.14, I provide estimates for the implied change in institutional ownership around the Russell cutoff. So despite increasing the lending supply, institutional capital leads to higher borrowing fees.

Results thus far suggest that the pass-through from benchmarking intensity to lending supply is too weak. For example, estimates in column (1) of Table 2 imply that one dollar of new benchmarked capital translates into only 18 cents of new lending inventory. In Appendix A.14, I argue that measurement noise can explain only part of this weak response and that the undersupply 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 inventory is also limited, at below 70% in my sample.[37]

[36] In Appendix A.8, I get the same magnitude when estimating equation (17) using an index membership dummy rather than the change in BMI.

[37] Results in Appendix A.14 provide further support for the mechanism in my model because I see that institutional ownership increases with benchmarking intensity. It implies that the increases in lending inventory and supply are driven by the switch from non-institutions, which are less likely to lend.

5.2.4 Results for the stock price

Consistent with my model's prediction for the stock price, Table 2 shows that price pressure is the highest for stocks experiencing the largest increase in BMI, all else being equal. As column (4) of Table 2 shows, a 1 percentage point increase in BMI leads to a 12bps 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 significantly stronger for special stocks, with the magnitude of the coefficient on ΔBMI increasing threefold for these stocks. 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 (16) is the sensitivity of 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.[38] The difference in these estimates is consistent with prior literature linking the size of the index effect to idiosyncratic volatility and arbitrage risk in general (for example, Wurgler and Zhuravskaya (2002) and Petajisto (2009)).

The model in Section 3 also predicts that benchmarking may make an asset special if the demand effect dominates. In Appendix A.12, I study switches from a general collateral to 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, also due to the small number of switches in my sample period.

5.2.5 Robustness and further discussion

In this section, I address 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 I report the robustness tests with respect to this choice in Appendix A.10. Furthermore, due to the small number of special stocks, I do not include the interactions of control variables with specialness in the baseline specification. Appendix Table A9 demonstrates that the results are qualitatively the same if such interactions

[38] The estimate for general collateral stocks is an upper bound for the true elasticity because of how the change in BMI is constructed (as shown in Appendix A.14). It is an upper bound also because I assume that all rebalancing occurs in June. 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. The aggregate estimate in panel A and the estimate for special stocks are likely to be upper bounds for the same two reasons. However, my model suggests that a shock to BMI is not sufficient to recover the slope of the demand curve for special stocks. As I show in Appendix B.4.3, the estimates presented in this section are likely to be biased upward, albeit to a very limited extent.

are present or if fewer controls are included. 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 Appendix Table A8.

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 ($logMV$) that Russell uses for index assignment at the end of May, the index membership dummy 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) and Wei and Young (2021) discuss potential issues with construction of the sample and controls, which I largely avoid by using the proprietary Russell ranking variable, Russell 3000E index, and preliminary lists. I discuss this in detail in Section A.4 of the Appendix. In Appendix A.5, I also show that a change in stocks' 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 stock-level float factor as of May and include the bid-ask spread to account for any staleness in the float factor.

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 shorting quantity for special stocks, a shift in demand must have occurred. However, the positive coefficient in column (1) 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 tests. The advertised inventory represents the total potential number of shares available for lending (not the number of shares available at current fee levels).[39] Second, in Appendix A.11, I exploit an instrument for demand for special stocks to show that the coefficient on the change in BMI 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, consistent with the empirical evidence for prevailingly flat supply curve discussed in Section 3.4. 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 (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 also 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

[39] 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).

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).

Finally, an alternative interpretation of my results is that market participants perceive borrowing from benchmarked funds as less risky. This could be due to, for example, the less frequent recall of previously loaned shares by lenders with a longer investment horizon.[40] However, I find no evidence of changes in the borrowing fee risk premia as implied by option prices around the Russell cutoff. Table A15 in the Appendix reports these results. It also documents that the borrowing fees implied by option prices increase with the same magnitude as Markit's fees, further validating my measure of borrowing costs.

5.3 What drives limited lending?

Results in the previous section suggest that institutions may exacerbate short-selling constraints as borrowing fees increase with benchmarking intensity. In the model, it is the lending limit on fund managers' holdings that is driving a wedge between demand and supply response to benchmarking. The observed dominant demand effect of benchmarking and the weak pass-through from BMI to lending inventory suggest that managers underprovide their holdings for lending.

In this section, I discuss explicit limits on lending 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 factors that potentially contribute to the limited pass-through from fund ownership to lending supply.

5.3.1 Evidence on 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 NPORT-P and NCEN 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 never binds. Appendix A.1 combines NPORT-P and NCEN 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 Appendix demonstrates that the percentage of fund net assets on loan (for all funds that lend) is significantly below the regulatory limit.

Funds may also have limits on lending at the position level, driven by their investment policies. Figure 4 plots effective lent shares for several prominent investment companies in the

[40] See the discussion of short-selling risk in Engelberg, Reed, and Ringgenberg (2018) and Muravyev, Pearson, and Pollet (2022b).

United States. Because lending is affected by demand, the share of a holding that is on loan can be anywhere between 0% and 100%. However, the bunching of lent shares reveals that investment managers impose position-level limits on securities lending.[41] For example, Vanguard funds seem to have an effective limit of 95%, whereas State Street funds limit their lending to 90% of position values. 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. Figure A6 in the Appendix shows that the same limits emerge if I focus on stocks on special.

If the limited lending of 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 Appendix A.6, I use the NPORT-P data on Russell 2000 additions and deletions in the 2020–2022 reconstitutions to demonstrate that both are indeed true in the data. First, as Figure A5 in Appendix illustrates, 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 figure also reveals that many funds do not lend these special stocks at all. This is puzzling in light of my model because funds seem to forgo income from lending these high-fee stocks. Second, the regression analysis in the same appendix explores whether the increase in borrowing fees 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 relationship is present only for special stocks.

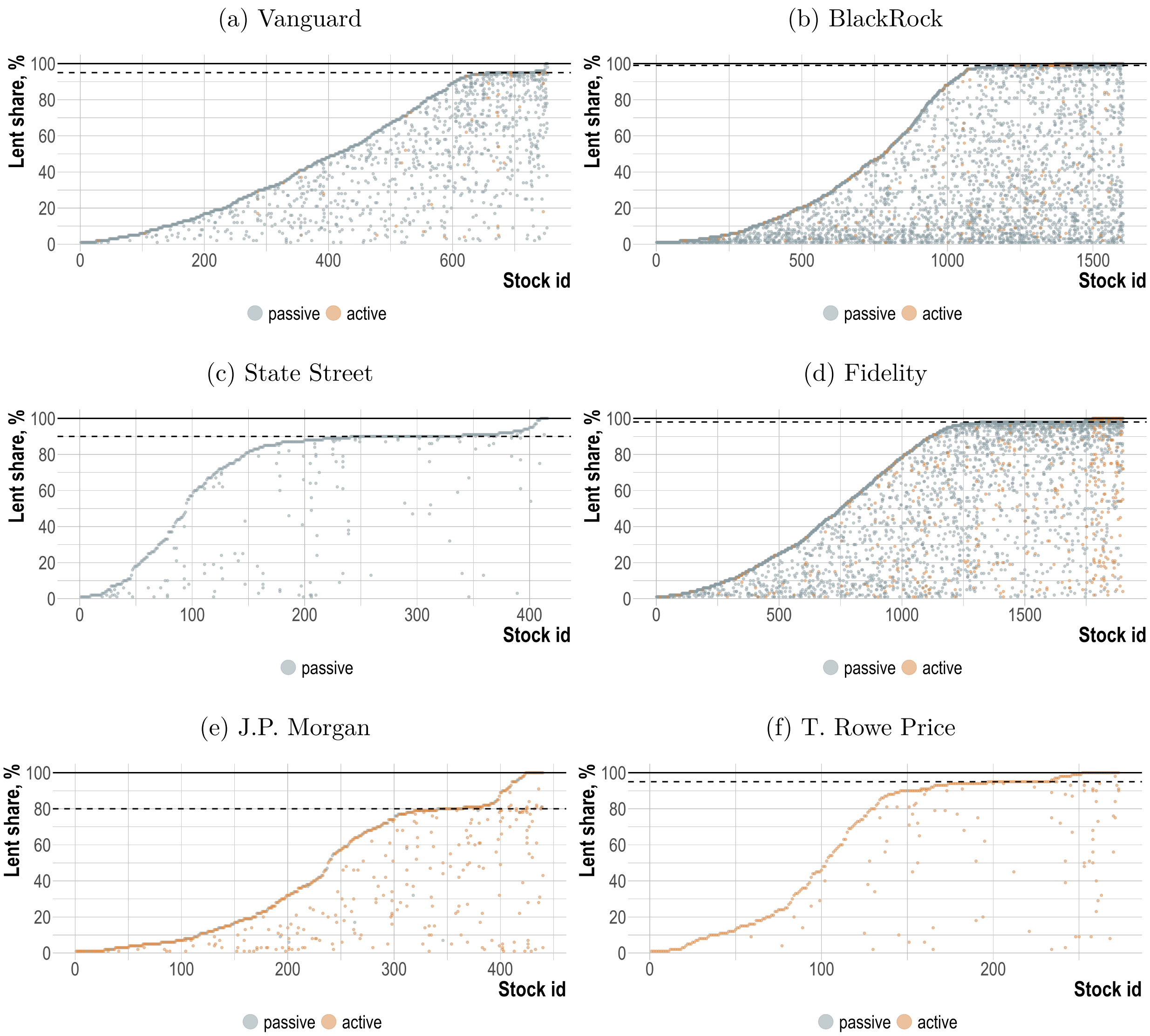
5.3.2 Further discussion of lending limits

In addition to the explicit lending limits discussed in the previous section, it is important to emphasize other factors, such as lending market participation costs, concentration of lenders, and search frictions, that could contribute to the limited pass-through from BMI to lending supply. These factors can also explain sparse lending of special stocks around the Russell reconstitutions documented in the previous section.

First, my results above abstract from the costs of lending. Not all funds are permitted to engage in securities lending, according to their investment policies. Anecdotally, industry practitioners cite reputational concerns, fiduciary duty to investors, and small investment scale as drivers of a fund manager's decision not to lend. 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 actually

[41] Figure 4 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 (2020), who finds that allocation of lending across funds is proportional to their AUM.

Figure 4: 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 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%.

participate in lending activities. Having decided to lend, funds have a choice to set up an in-house lending agent, turn to their custodians, or hire a third-party lending agent to run their lending program. Therefore, the observed lent shares may be a result of a cost-benefit trade-off. In 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, it has been demonstrated in the literature that lender concentration can have a detrimental effect on lending supply, leading to reduced quantities available for lending (Prado, Saffi, and Sturgess (2016) and Chen, Kaniel, and Opp (2022)). In Appendix A.13, I document 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 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. However, it is plausible that the level of lender concentration 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 in the securities lending markets, 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 (U.S. Securities and Exchange Commission (2021)). It is reasonable to expect that some of these frictions would be alleviated with an increase in capital benchmarked against a stock, as benchmarked owners are widely known to supply their holdings for lending. Nevertheless, in Appendix F, I augment 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 my main findings.

To summarize, I find that the lending supply of U.S. stocks is strongly related to the amount of capital benchmarked to them. However, overvaluation induced by benchmarking also attracts higher short-selling demand. On net, the demand effect of benchmarking dominates, as the borrowing fees increase with benchmarking intensity. Consistent with the model's intuition, I find that funds' lending limits appear to be binding, depressing the pass-through from new benchmarked capital to lending supply. There may be other drivers of partial lending, and my results call for better understanding of the weak response of supply to benchmarking. Since the estimates are based on the Russell index reconstitutions, they are local to the Russell cutoff. To test my model in an external setting, I turn to the ETF purchases of the BoJ in the next section.

6 ETF Purchases of the Bank of Japan

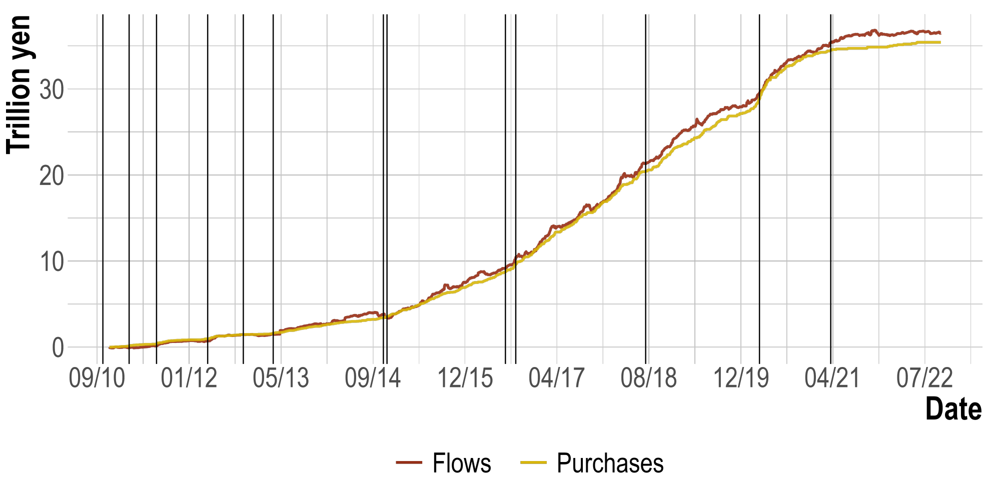
In this section, I test the predictions of my model in the Japanese equity market using the ETF purchases of the BoJ as shocks to benchmarking intensity.

6.1 BoJ ETF purchase program

Since 2010, the BoJ has been engaging in a comprehensive monetary easing program aimed at fighting deflation. As part of this program, the BoJ has been increasing its domestic equity holdings through purchases of ETFs linked to Japanese market indexes. Aggressive ETF purchases led to the BoJ becoming the majority owner of those ETFs.

Within the ETF purchase program, the BoJ 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 Appendix Table A2. Importantly, the BoJ's purchases were virtually the only source of flows in the target ETFs, and Figure 5 demonstrates that the cumulative flows are closely in line with the cumulative BoJ purchases.

Figure 5: 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. See further details in Table A19 in the Appendix.

Figure 5 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 (QQE) program in 2013, the expansion of its size, and the change in its composition. I provide more details on each of the announcements in Table A19 in the 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.[42] Due to the unprecedented size of the program, these changes in 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.

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. In the next section, I corroborate that the BoJ's purchases have contributed to the lending supply of Japanese stocks and test the predictions of my model.

6.2 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 benchmarking intensity to test predictions of my model in the Japanese stock market. I design the test 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.

6.2.1 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 A19 in the Appendix lists 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.

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

$$\begin{aligned} BoJ\,purchase_{ip} = &\sum_{t \in p} BoJ\,purchase_t \times \\ &(\omega_{it}^{TOPIX} \times S_t^{TOPIX} + \omega_{it}^{Nikkei225} \times S_t^{Nikkei225} + \omega_{it}^{JPXNikkei400} \times S_t^{JPXNikkei400}), \end{aligned} \tag{18}$$

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

[42] An important assumption behind my analysis is that ETFs are closely tracking their benchmarks. First, tracking errors are indeed very low across the relevant ETFs. Morningstar reports one-year annualized tracking errors of around 115bps for ETFs tracking the TOPIX and JPX-Nikkei 400 indexes and around 284bps 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 a strong relationship between the BoJ's purchases and lending supply.

but also at each purchase.

Purchases defined in (18) measure the actual ownership of the BoJ, yet they cannot be used as shocks to benchmarking intensity 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 (18) as shocks, I would be assuming that expected purchases were zero. Instead, I construct the shocks to BMIs as a change in BoJ's purchases relative to the market value of each stock, specifically,

$$\Delta BMI_{ip}^{BoJ} = \frac{1}{MV_{ip-1}} \left(BoJ\, purchase_{ip} - BoJ\, purchase_{ip-1} \frac{Days_p}{Days_{p-1}} \right), \tag{19}$$

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 subtracted term is the size of purchases that would be expected for period p if no policy change was announced at the beginning of period p. Such a definition takes into account both reallocative and expansive changes to the program and, consistent with my model, assumes that market participants have perfect foresight of the 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 benchmarking intensity, 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. Second, the allocation across indexes (i.e., shares S^j) was not related to the fundamentals of any given stock. In Appendix A.5.2, I look into index methodologies for computing constituent weights ω to further argue that the variation in BMIs driven by the BoJ's purchases is not related to stock fundamentals.

6.2.2 Regression specifications

To study how these shocks 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 shorting demand of stock i on the last trading day of period p.[43] Finally, to measure the change in stock price, I take its cumulative

[43]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 (discussed in detail in Appendix A.23). Table A20 in the Appendix

return over the entire policy period. When the variables are constructed this way, my estimates can be interpreted as the total effect of purchases, versus their announcement or flow effects separately.

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

$$\Delta Y_{ip} = \beta_1 \Delta BMI_{ip}^{BoJ} \times D(special)_{ip} + \beta_2 \Delta BMI_{ip}^{BoJ} \times D(not\, special)_{ip} + \zeta' \bar{X}_{ip-1} + \nu_{sp} + \mu_i + \epsilon_{ip}. \tag{20}$$

The dependent variable, ΔY_{ip}, is the change in the stock's lending inventory (active lendable quantity of shares), shorting demand (short quantity on loan), borrowing fee, or its price, 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 it has an average borrowing fee of over 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 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 (discussed in Appendix A.5.2). 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.

6.2.3 Regression results

Table 3 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 3 documents that shorting demand also increases in response to the change in BMI, in line with my model.[44]

Column (3) of Table 3 reports how the borrowing fee changes in response to the shock to benchmarking intensity. 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 41bps higher borrowing fee, or one sample standard deviation of the shock increasing the lending fee by 12bps. 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 price impact of Japanese monetary easing, I find that increases in BMIs lead to considerably higher prices. As column (4) shows, a 1 percentage point larger shock results in a 27% higher return for general collateral stocks and a 33% higher

shows that results are not sensitive to this filter.

[44] Weak response for general collateral stocks seems to be driven by my definition of specialness. In Appendix Table A23, I provide estimates of sensitivity to the change in BMI in subsamples of specialness as outlined by the JSDA. There is no increase in shorting demand only for stocks that are extremely cheap to lend, that is, with fees below 50bps (annualized).

Table 3: Response of spot and lending market variables to changes in BMI due to the BoJ's ETF purchases

	Δ Lending inventory, % shares	Δ Shorting demand, % shares	Δ Borrowing fee, %	Stock return, %
	(1)	(2)	(3)	(4)
Panel A: No interactions				
ΔBMI^{BoJ}, % MV	0.414***	0.301***	0.162***	28.738***
	(2.99)	(3.04)	(2.63)	(13.13)
Observations	17,298	17,298	17,298	17,298
Adjusted R-squared	0.093	0.037	0.115	0.375
Panel B: With specialness interactions				
ΔBMI^{BoJ}, % MV × D(not special)	0.050	0.017	0.037	26.525***
	(0.35)	(0.19)	(1.00)	(10.05)
ΔBMI^{BoJ}, % MV × D(special)	1.140***	0.867***	0.411**	33.152***
	(4.27)	(4.00)	(2.51)	(9.48)
Observations	17,298	17,298	17,298	17,298
Adjusted R-squared	0.097	0.041	0.116	0.375
$\beta_1 - \beta_2$	1.090***	0.850***	0.374**	6.626
	(3.61)	(3.67)	(2.23)	(1.53)

This table reports the estimates of specification (20) 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 (19). 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 Appendix A.3. A stock is considered special, or $D(special) = 1$, if its 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.

return for specials over a policy period. See implied estimates for the price elasticity of demand and comparison with the literature in Appendix A.19. 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 is less mature than that of the United States, as manifested in a large number of stocks with economically significant fees (summarized in Table 1). 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, in Appendix Table A21, I show that the findings are qualitatively the same under alternative definitions.

Finally, 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. 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, Appendix Table A22, documents a similar magnitude for the pass-through of total purchases (as opposed to changes in BMI) to special stocks and shows that for general collateral stocks it is over 40%. These results suggest that lenders other than ETFs step in as the shorting demand increases and it becomes lucrative to lend.[45] 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% in response to the purchases by the BoJ. Column (3) of Appendix Table A22 corroborates such a trend because the pass-through of the BoJ's purchases increases in the second half of my sample.

7 Concluding Remarks

Short-selling plays a crucial role in price discovery within financial markets. However, 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 benchmarking 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 my 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. By exploiting plausibly exogenous variation in how much capital is benchmarked against stocks in the United States and Japan, I find that the 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 underprovide 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 market participation constraints, lender concentration, and search costs. This paper abstracts from strategic actions that may also limit lending (for example,

[45] It may happen because of lenders other than ETFs. Although the BoJ purchases imply that ETFs increase their holdings in the asset, active funds' holdings change indirectly as well, due to changes in prices and fees. As asset price goes up due to the purchases, active funds allocate less to the mean-variance fraction of their portfolio. At the same time, due to higher demand of hedgers, driven by the higher price, active funds allocate more to the return-augmenting part of their portfolio (see equation (3)), so they may hold more and lend more in the end. Because this channel operates through the equilibrium borrowing fee, it requires that the increase in supply from ETF holdings is not sufficient to match the increase in shorting demand. In Appendix D, I show that the intuition is similar when investors with fully elastic demand contribute to lending supply.

Honkanen (2020) and Greppmair, Jank, Saffi, and Sturgess (2020)). Nevertheless, formulating an optimal policy action depends on which friction is key and requires further research.

The magnitude of the index effect has been decreasing over time, particularly for additions to the S&P 500 index, as documented by Bennett, Stulz, and Wang (2020) and Greenwood and Sammon (2022). My results imply that relaxing limits on lending counteracts benchmarking price pressures. Therefore, the trends in the index effect may be explained by lending policies of benchmarked fund managers becoming more accommodating over time.

My findings have implications for the design of unconventional monetary policy. Recent literature on bond quantitative easing (QE) 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 (2018) demonstrate that the introduction of lending of bonds from the central bank's portfolio mitigates scarcity effects. My findings are for equity markets and emphasize the potential role of lending limits in influencing the effectiveness of QE, an aspect not previously considered in the literature. Therefore, by adjusting the lending program and its lending limits,[46] 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 account of distributional effects because the primary beneficiaries of securities lending revenues are fund investors.

References

Agarwal, Vikas, William H. Fung, Yee Cheng Loon, and Narayan Y. Naik, 2011, Risk and return in convertible arbitrage: Evidence from the convertible bond market, *Journal of Empirical Finance* 18, 175–194.

Aggarwal, Reena, Pedro A. C. Saffi, and Jason Sturgess, 2015, The role of institutional investors in voting: Evidence from the securities lending market, *The Journal of Finance* 70, 2309–2346.

[46]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).

Altman, Edward I., 1968, Financial ratios, discriminant analysis and the prediction of corporate bankruptcy, *The Journal of Finance* 23, 589–609.

Appel, Ian, Todd Gormley, and Donald Keim, 2019, Standing on the shoulders of giants: The effect of passive investors on activism, *Review of Financial Studies* 32, 2720–2774.

——— , 2021, Identification using Russell 1000/2000 index assignments: A discussion of methodologies, *Critical Finance Review,* forthcoming.

Arrata, William, Benoît Nguyen, Imène Rahmouni-Rousseau, and Miklos Vari, 2020, The scarcity effect of QE on repo rates: Evidence from the euro area, *Journal of Financial Economics* 137, 837–856.

Asquith, Paul, Andrea S. Au, Thomas Covert, and Parag A. Pathak, 2013, The market for borrowing corporate bonds, *Journal of Financial Economics* 107, 155–182.

Asquith, Paul, Parag A. Pathak, and Jay R. Ritter, 2005, Short interest, institutional ownership, and stock returns, *Journal of Financial Economics* 78, 243–276.

Atmaz, Adem, Suleyman Basak, and Fangcheng Ruan, Forthcoming, Dynamic equilibrium with costly short-selling and lending market, *The Review of Financial Studies*.

Baklanova, Viktoria, Cecilia Caglio, Frank M. Keane, and R. Burt Porter, 2016, A pilot survey of agent securities lending activity, *SSRN Electronic Journal*.

Banerjee, Snehal, and Jeremy J. Graveline, 2013, The cost of short-selling liquid securities, *The Journal of Finance* 68, 637–664.

——— , 2014, Trading in derivatives when the underlying is scarce, *Journal of Financial Economics* 111, 589–608.

Barberis, Nicholas, and Andrei Shleifer, 2003, Style investing, *Journal of Financial Economics* 68, 161–199.

Barbon, Andrea, and Virginia Gianinazzi, 2019, Quantitative easing and equity prices: Evidence from the ETF program of the Bank of Japan, *The Review of Asset Pricing Studies* 9, 210–255.

Basak, Suleyman, and Anna Pavlova, 2013, Asset prices and institutional investors, *American Economic Review* 103, 1728–1758.

Beneish, M.D., C.M.C. Lee, and D.C. Nichols, 2015, In short supply: Short-sellers and stock returns, *Journal of Accounting and Economics* 60, 33–57.

Bennett, Benjamin, Rene M. Stulz, and Zexi Wang, 2020, Does joining the S&P 500 index hurt firms?, *SSRN Electronic Journal*.

Bhojraj, Sanjeev, and Wuyang Zhao, 2021, Ownership structure and short covering: Evidence from earnings announcements, *SSRN Electronic Journal*.

Binsbergen, Jules H. Van, Michael W. Brandt, and Ralph S. J. Koijen, 2008, Optimal decentralized investment management, *The Journal of Finance* 63, 1849–1895.

Blocher, Jesse, Adam V. Reed, and Edward D. Van Wesep, 2013, Connecting two markets: An equilibrium framework for shorts, longs, and stock loans, *Journal of Financial Economics* 108, 302–322.

Boyer, Brian H., 2011, Style-related comovement: Fundamentals or labels?, *The Journal of Finance* 66, 307–332.

Brennan, Michael, 1993, Agency and asset pricing, Working paper.

Buffa, Andrea M., and Idan Hodor, 2023, Institutional investors, heterogeneous benchmarks and the comovement of asset prices, *Journal of Financial Economics* 147, 352–381.

Buffa, Andrea M., Dimitri Vayanos, and Paul Woolley, 2022, Asset management contracts and equilibrium prices, *Journal of Political Economy* 130, 3146–3201.

Chague, Fernando, Rodrigo De-Losso, Alan De Genaro, and Bruno Giovannetti, 2017, Well-connected short-sellers pay lower loan fees: A market-wide analysis, *Journal of Financial Economics* 123, 646–670.

Chakrabarti, Rajesh, Wei Huang, Narayanan Jayaraman, and Jinsoo Lee, 2005, Price and volume effects of changes in MSCI indices –nature and causes, *Journal of Banking & Finance* 29, 1237–1264.

Chang, Yen-Cheng, Harrison Hong, and Inessa Liskovich, 2015, Regression discontinuity and the price effects of stock market indexing, *Review of Financial Studies* 28, 212–246.

Charoenwong, Ben, Randall Morck, and Yupana Wiwattanakantang, 2021, Bank of Japan equity purchases: The (non-)effects of extreme quantitative easing, *Review of Finance* 25, 713–743.

Chen, Joseph, Harrison Hong, and Jeremy C. Stein, 2002, Breadth of ownership and stock returns, *Journal of Financial Economics* 66, 171–205.

Chen, Shuaiyu, Ron Kaniel, and Christian C. Opp, 2022, Market power in the securities lending market, *SSRN Electronic Journal*.

Cohen, Lauren, Karl B. Diether, and Christopher J. Malloy, 2007, Supply and demand shifts in the shorting market, *The Journal of Finance* 62, 2061–2096.

Corradin, Stefano, and Angela Maddaloni, 2020, The importance of being special: Repo markets during the crisis, *Journal of Financial Economics* 137, 392–429.

Cuoco, Domenico, and Ron Kaniel, 2011, Equilibrium prices in the presence of delegated portfolio management, *Journal of Financial Economics* 101, 264–296.

D'Amico, Stefania, Roger Fan, and Yuriy Kitsul, 2018, The scarcity value of treasury collateral: Repo-market effects of security-specific supply and demand factors, *Journal of Financial and Quantitative Analysis* 53, 2103–2129.

D'Avolio, Gene, 2002, The market for borrowing stock, *Journal of Financial Economics* 66, 271–306.

Diamond, Douglas W., and Robert E. Verrecchia, 1987, Constraints on short-selling and asset price adjustment to private information, *Journal of Financial Economics* 18, 277–311.

Diether, Karl B., Christopher J. Malloy, and Anna Scherbina, 2002, Differences of opinion and the cross section of stock returns, *The Journal of Finance* 57, 2113–2141.

Doshi, Hitesh, Redouane Elkamhi, and Mikhail Simutin, 2015, Managerial activeness and mutual fund performance, *Review of Asset Pricing Studies* 5, 156–184.

Drechsler, Itamar, and Qingyi (Freda) Song Drechsler, 2014, The shorting premium and asset pricing anomalies, *SSRN Electronic Journal*.

Duffie, Darrell, 1996, Special repo rates, *The Journal of Finance* 51, 493–526.

——— , Nicolae Gârleanu, and Lasse Heje Pedersen, 2002, Securities lending, shorting, and pricing, *Journal of Financial Economics* 66, 307–339.

Edelen, Roger M., Ozgur S. Ince, and Gregory B. Kadlec, 2016, Institutional investors and stock return anomalies, *Journal of Financial Economics* 119, 472–488.

Engelberg, Joseph E., Adam V. Reed, and Matthew C. Ringgenberg, 2018, Short-selling risk, *The Journal of Finance* 73, 755–786.

Evans, Richard B., Juan-Pedro Gómez, Linlin Ma, and Yuehua Tang, Forthcoming, Peer versus pure benchmarks in the compensation of mutual fund managers, *Journal of Financial and Quantitative Analysis*.

Fama, Eugene F., and Kenneth R. French, 2007, Disagreement, tastes, and asset prices, *Journal of Financial Economics* 83, 667–689.

Gabaix, Xavier, and Ralph S. J. Koijen, 2020, In search of the origins of financial fluctuations: The inelastic markets hypothesis, *SSRN Electronic Journal*.

Gârleanu, Nicolae, Leonid Kogan, and Stavros Panageas, 2012, Displacement risk and asset returns, *Journal of Financial Economics* 105, 491–510.

Geczy, Christopher C., David K. Musto, and Adam V. Reed, 2002, Stocks are special too: An analysis of the equity lending market, *Journal of Financial Economics* 66, 241–269.

Glossner, Simon, 2021, The effects of institutional investors on firm outcomes: Empirical pitfalls of quasi-experiments using Russell 1000/2000 index reconstitutions, *Critical Finance Review,* forthcoming.

Greenwood, Robin M., 2005, Short- and long-term demand curves for stocks: Theory and evidence on the dynamics of arbitrage, *Journal of Financial Economics* 75, 607–649.

——— , and Marco Sammon, 2022, The disappearing index effect, *SSRN Electronic Journal*.

Greenwood, Robin M., and Dimitri Vayanos, 2014, Bond supply and excess bond returns, *Review of Financial Studies* 27, 663–713.

Greppmair, Stefan, Stephan Jank, Pedro A. C. Saffi, and Jason Sturgess, 2020, Securities

Lending and Information Acquisition, *SSRN Electronic Journal*.

Gromb, Denis, and Dimitri Vayanos, 2010, Limits of Arbitrage, *Annual Review of Financial Economics* 2, 251–275.

Harris, Lawrence, and Eitan Gurel, 1986, Price and volume effects associated with changes in the S&P 500 list: New evidence for the existence of price pressures, *Journal of Finance* 41, 815–829.

He, Zhiguo, and Wei Xiong, 2013, Delegated asset management, investment mandates, and capital immobility, *Journal of Financial Economics* 107, 239–258.

Hong, Harrison, and Jeremy C. Stein, 2003, Differences of opinion, short-sales constraints, and market crashes, *Review of Financial Studies* 16, 487–525.

Honkanen, Pekka, 2020, Securities lending and trading by active and passive funds, *SSRN Electronic Journal*.

Huszár, Zsuzsa R., and Melissa Porras Prado, 2019, An analysis of over-the-counter and centralized stock lending markets, *Journal of Financial Markets* 43, 31–53.

Jarrow, Robert, 1980, Heterogeneous expectations, restrictions on short sales, and equilibrium asset prices, *The Journal of Finance* 35, 1105–1113.

Johnson, Travis L., and Gregory Weitzner, Forthcoming, Distortions caused by lending fee retention, *Management Science*.

Jones, Charles M., and Owen A. Lamont, 2002, Short-sale constraints and stock returns, *Journal of Financial Economics* 66, 207–239.

Kaplan, Steven N., Tobias J. Moskowitz, and Berk A. Sensoy, 2013, The effects of stock lending on security prices: An experiment, *The Journal of Finance* 68, 1891–1936.

Kashyap, Anil, Natalia Kovrijnykh, Jian Li, and Anna Pavlova, 2023, Is there too much benchmarking in asset management?, *American Economic Review* 113, 1112–1141.

Kaul, Aditya, Vikas Mehrotra, and Randall Morck, 2000, Demand curves for stocks do slope down: New evidence from an index weights adjustment, *Journal of Finance* 55, 893–912.

Koijen, Ralph S. J., and Motohiro Yogo, 2019, A demand system approach to asset pricing, *Journal of Political Economy* 127, 1475–1515.

Kolasinski, Adam C., Adam V. Reed, and Matthew C. Ringgenberg, 2013, A multiple lender approach to understanding supply and search in the equity lending market, *The Journal of Finance* 68, 559–595.

Krishnamurthy, Arvind, 2002, The bond/old-bond spread, *Journal of Financial Economics* 66, 463–506.

———, and Annette Vissing-Jorgensen, 2012, The aggregate demand for treasury debt, *Journal of Political Economy* 120, 233–267.

Lewellen, Jonathan, 2011, Institutional investors and the limits of arbitrage, *Journal of Financial Economics* 102, 62–80.

Ma, Linlin, Yuehua Tang, and Juan-Pedro Gómez, 2019, Portfolio manager compensation in the U.S. mutual fund industry, *Journal of Finance* 74, 587–638.

Maeda, Kou, Junnosuke Shino, and Koji Takahashi, 2022, Counteracting large-scale asset purchase program: The Bank of Japan's ETF purchases and securities lending, *Economic Analysis and Policy* 75, 563–576.

Miller, Edward M., 1977, Risk, uncertainty, and divergence of opinion, *The Journal of Finance* 32, 1151–1168.

Muravyev, Dmitriy, Neil D. Pearson, and Joshua M. Pollet, 2018, Why does options market information predict stock returns?, *SSRN Electronic Journal*.

———, 2022a, Anomalies and their short-sale costs, *SSRN Electronic Journal*.

———, 2022b, Is there a risk premium in the stock lending market? Evidence from equity options, *The Journal of Finance* 77, 1787–1828.

Nagel, Stefan, 2005, Short sales, institutional investors and the cross-section of stock returns, *Journal of Financial Economics* 78, 277–309.

Nashikkar, Amrut J., and Lasse Heje Pedersen, 2007, Corporate bond specialness, *SSRN Electronic Journal*.

Palia, Darius, and Stanislav Sokolinski, 2021, Passive asset management, securities lending and stock prices, *SSRN Electronic Journal*.

Pastor, Lubos, Robert F. Stambaugh, and Lucian A. Taylor, 2015, Scale and skill in active management, *Journal of Financial Economics* 116, 23–45.

Pástor, Ľuboš, Robert F. Stambaugh, and Lucian A. Taylor, 2021, Sustainable investing in equilibrium, *Journal of Financial Economics* 142, 550–571.

Pavlova, Anna, and Taisiya Sikorskaya, 2023, Benchmarking intensity, *The Review of Financial Studies* 36, 859–903.

Pelizzon, Loriana, Marti G. Subrahmanyam, Davide Tomio, and Jun Uno, 2018, Central bank-driven mispricing, *SSRN Electronic Journal*.

Petajisto, Antti, 2009, Why do demand curves for stocks slope down?, *Journal of Financial and Quantitative Analysis* 44, 1013–1044.

Prado, Melissa Porras, Pedro A. C. Saffi, and Jason Sturgess, 2016, Ownership structure, limits to arbitrage, and stock returns: Evidence from equity lending markets, *Review of Financial Studies* 29, 3211–3244.

Reed, Adam V., 2013, Short selling, *Annual Review of Financial Economics* 5, 245–258.

Saffi, Pedro A. C., and Kari Sigurdsson, 2011, Price efficiency and short selling, *Review of Financial Studies* 24, 821–852.

Seneca, Joseph J., 1967, Short interest: Bearish or bullish?, *The Journal of Finance* 22, 67–70.

Shino, Junnosuke, Mitsuru Katagiri, and Koji Takahashi, 2023, To lend or not to lend: The bank of japan's ETF purchase program and securities lending, BIS Working Papers 1113.

Shleifer, Andrei, 1986, Do demand curves for stocks slope down?, *Journal of Finance* 41, 579–590.

Shumway, Tyler, 1997, The delisting bias in CRSP data, *The Journal of Finance* 52, 327–340.

Sloan, Richard G., 1996, Do stock prices fully reflect information in accruals and cash flows about future earnings?, *The Accounting Review* 71, 289–315.

S&P Global, 2023, Securities Finance H2 2022 review, S&P Global Market Intelligence.

The Investment Company Institute, 2014, Securities Lending by Mutual Funds, ETFs, and Closed-End Funds: The Market, ICI Viewpoints on Securities Lending.

Thornock, Jacob, 2013, The effects of dividend taxation on short selling and market quality, *The Accounting Review* 88, 1833–1856.

U.S. Securities and Exchange Commission, 2021, SEC Proposes Rule to Provide Transparency in the Securities Lending Market [Press release], .

Vayanos, Dimitri, and Jean-Luc Vila, 2021, A preferred-habitat model of the term structure of interest rates, *Econometrica* 89, 77–112.

Vayanos, Dimitri, and Pierre-Olivier Weill, 2008, A search-based theory of the on-the-run phenomenon, *The Journal of Finance* 63, 1361–1398.

von Beschwitz, Bastian, Pekka Honkanen, and Daniel Schmidt, 2022, Passive ownership and short selling, *International Finance Discussion Paper* pp. 1–62.

Wei, Wei, and Alex Young, 2021, Selection bias or treatment effect? A re-examination of Russell 1000/2000 index reconstitution, *Critical Finance Review,* forthcoming.

Wooldridge, Jeffrey M., 2002, *Econometric Analysis of Cross Section and Panel Data* (MIT Press Books).

Wurgler, Jeffrey, and Ekaterina Zhuravskaya, 2002, Does arbitrage flatten demand curves for stocks?, *Journal of Business* 75, 583–608.

A Internet Appendix

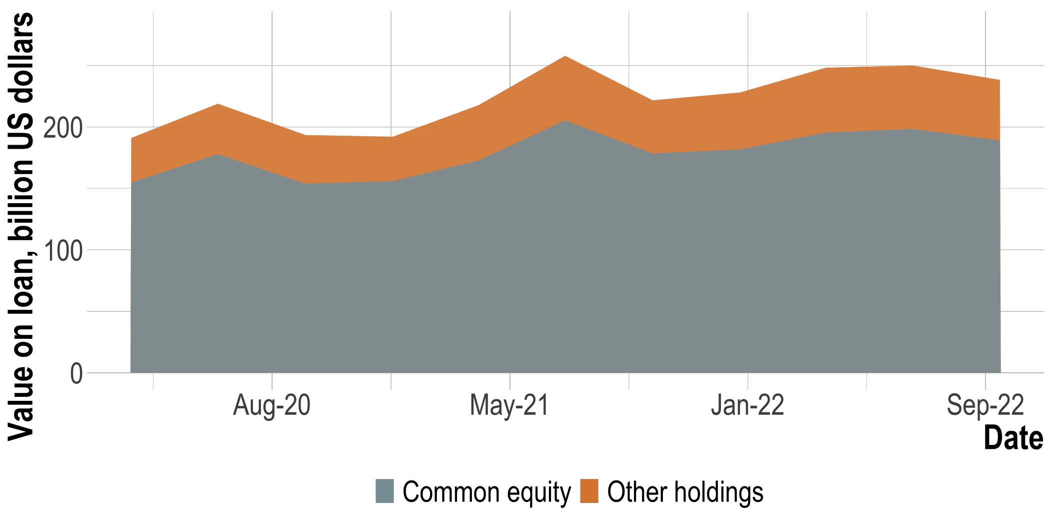
A.1 Aggregate insights into the lending activity of U.S. investment companies from regulatory filings

This section provides aggregate descriptive statistics using NPORT-P 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

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 NPORT-P filings

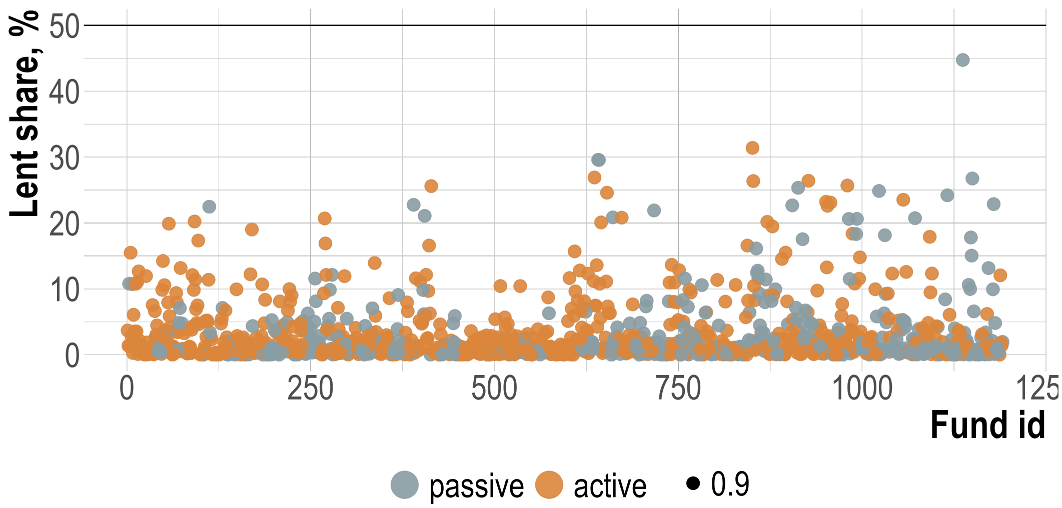


This figure plots the aggregate value on loan as reported in NPORT-P filings for all investment companies in the United States. Common equity value is the total of loan values with the asset category 'EC' and the 'Long' payoff profile.

A.1.2 Aggregate lending descriptive statistics

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

Figure A2: Fund-level value on loan as reported in NPORT-P filings



This figure plots the value on loan relative to fund net assets as reported in NPORT-P 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%.

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.[47] 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 benchmarks 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 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).[48] 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 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.

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

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

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).[49]

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

3. SEC Mutual Fund Prospectus Risk/Return Summary datasets (MFRR).[50] 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[51] 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.[52] 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). 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 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.

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

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

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

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*}.[53] 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 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 NPORT-P, NPORT-P/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. NPORT-P filings are quarterly (holdings schedule), and N-CEN filings are annual. If there are amended filings for the same report date (NPORT-P/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.

[53]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%.

1. Fields from NPORT-P and NPORT-P/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 NPORT-P 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.2.7 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.

A.2.8 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 A2.

Table A2: 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

A.3 Variable definitions and descriptive statistics

Table A3: 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 (15) 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 Shorting demand	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
Shorting demand 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
(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 (NPORT-P 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 demand	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 demand (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

(Table continues on the next page.)

Table A3: Key variable definitions and descriptive statistics (continued)

Variable	Definition	Units	Source (field)	Mean	Median	St. dev.	p1	p99
Panel C: Japanese data (policy period sample)								
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 (19).	% 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 (18).	% 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 Shorting demand	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 Bborrowing 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
Shorting demand	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
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

A.4 Russell Reconstitution

Russell indexes undergo a yearly reconstitution at the end of June. 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.[54] 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.[55] Ranks are computed based on the proprietary measure of the total market capitalization of eligible securities. FTSE Russell has shared with me this proprietary market capitalization measure. They also provided 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 and avoid selection in sample construction. See Wei and Young (2021) for the discussion of the selection issue.

In the second step of the reconstitution, each stock in the index is assigned a weight based on

[54] Exceptions are recent years, when the rank days were 05/27/2016, 05/12/2017, and 05/11/2018.

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

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.

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. Moreover, an idiosyncratic shock to the market value on the rank date can bring the stock to the other side of the cutoff. Hence, the assignment of stocks to Russell indexes is as good as random.

A.5 What drives variation in BMI?

A.5.1 Variation in BMI stemming from the Russell reconstitutions

Figure A3 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.4 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,

$$\omega_{ijt} = \frac{MV_{it}\mathbf{1}_{ijt}}{\sum_{k=1}^{N} MV_{kt}\mathbf{1}_{kjt}} = \frac{MV_{it}\mathbf{1}_{ijt}}{\text{IndexMV}_{jt}}, \tag{21}$$

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 (15) as

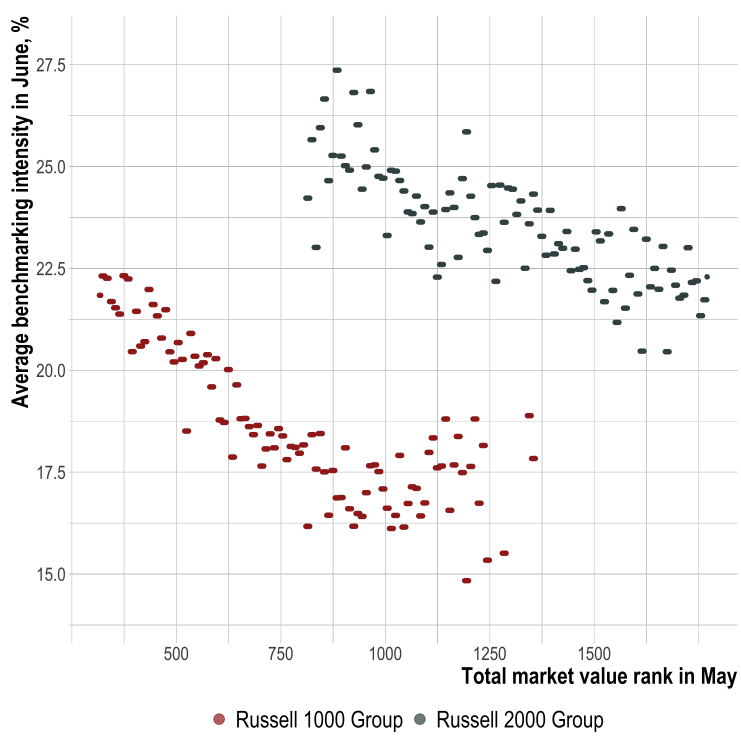
$$BMI_{it} = \sum_{j=1}^{J} \frac{\lambda_{jt}\mathbf{1}_{ijt}}{\sum_{k=1}^{N} MV_{kt}\mathbf{1}_{kjt}} = \sum_{j=1}^{J} \frac{\lambda_{jt}\mathbf{1}_{ijt}}{\text{IndexMV}_{jt}}. \tag{22}$$

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, (22) 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

Figure A3: 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).

results are robust to controlling for them.

A.5.2 Variation in BMI stemming from the ETF purchases of the BoJ

Japanese BMIs are different because their considerable shares are driven by the price-weighted Nikkei 225 index. In contrast to value-weighted index weights defined in (21), which are applicable to TOPIX and JPX-Nikkei 400, the weights in any price-weighted index, such as Nikkei 225, are computed as

$$\omega_{ijt} = \frac{P_{it}\mathbf{1}_{ijt}}{\sum_{k=1}^{N} P_{kt}\mathbf{1}_{kjt}}, \tag{23}$$

where the index membership dummy $\mathbf{1}_{ijt}$ is equal to 1 if stock i belongs to price-weighted index j at time t and P_{it} is the price of stock i at time t.[56] Using this definition and recognizing that $MV_{it} = P_{it}Shares_{it}$, I can write out and simplify changes in BMIs stemming from the ETF purchases of the BoJ in the following way.

$$\begin{aligned}
\Delta BMI_{it}^{BoJ} =& \frac{1}{MV_{it}} BoJ\, purchase_t(¥)\times \\
&(\omega_{it}^{TOPIX} * S_t^{TOPIX} + \omega_{it}^{Nikkei225} * S_t^{Nikkei225} + \omega_{it}^{JPXNikkei400} * S_t^{JPXNikkei400}) \\
=& \frac{1}{MV_{it}} BoJ\, purchase_t(¥)\times \\
&\Bigg(\frac{MV_{it}\mathbf{1}_{it}^{TOPIX}}{\text{IndexMV}_t^{TOPIX}} * S_t^{TOPIX} + \frac{P_{it}\mathbf{1}_{it}^{Nikkei225}}{\sum_{k=1}^{N} P_{kt}\mathbf{1}_{kt}^{Nikkei225}} * S_t^{Nikkei225} \\
&+ \frac{MV_{it}\mathbf{1}_{it}^{JPXNikkei400}}{\text{IndexMV}_t^{JPXNikkei400}} * S_t^{JPXNikkei400}\Bigg) \\
=& BoJ\, purchase_t(¥)\times \\
&\Bigg(\frac{\mathbf{1}_{it}^{TOPIX}}{\text{IndexMV}_t^{TOPIX}} * S_t^{TOPIX} + \frac{\mathbf{1}_{it}^{Nikkei225}}{Shares_{it}\sum_{k=1}^{N} P_{kt}\mathbf{1}_{kt}^{Nikkei225}} * S_t^{Nikkei225} \\
&+ \frac{\mathbf{1}_{it}^{JPXNikkei400}}{\text{IndexMV}_t^{JPXNikkei400}} * S_t^{JPXNikkei400}\Bigg).
\end{aligned}$$

That is, the changes in BMIs are driven by stock's membership in the target market indexes, ETF assets benchmarked to these indexes, index total market values, size of BoJ purchases, the number of shares outstanding, and a sum of prices of Nikkei 225 constituents. As long as the stock remains in the target indexes and I control for the number of shares outstanding, changes in its BMI due to the BoJ purchases of ETFs are unlikely related to its fundamentals. Similar to the Russell case above, I include liquidity controls to alleviate concerns that index float adjustments may affect the results.[57]

---

[56] Formally, Nikkei 225 also applies price adjustment factors that allow for historical continuity in case of stock splits and may cap constituent weights, see https://indexes.nikkei.co.jp/nkave/archives/file/nikkei_stock_average_guidebook_en.pdf. I abstract from such special cases here.

[57] TOPIX, e.g., uses float adjustments; see https://www.jpx.co.jp/english/markets/indices/topix/tvdivq00000030ne-att/e_cal2_30_topix.pdf.

A.6 Case studies on funds' lending around the Russell reconstitutions

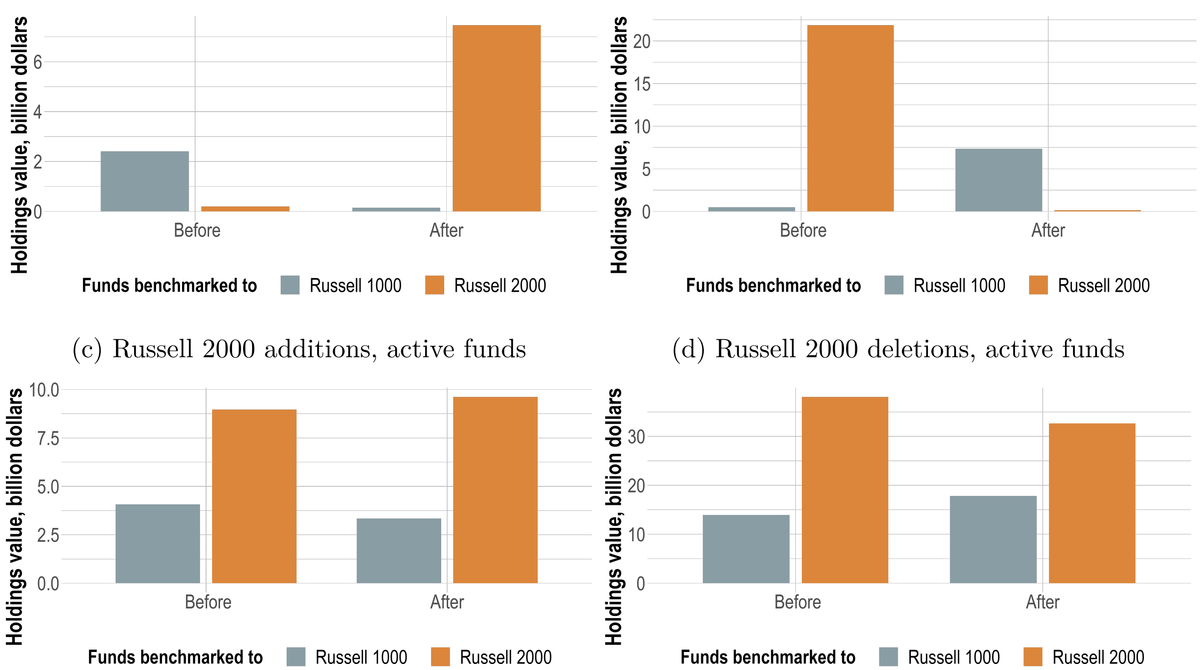
In this section, I illustrate changes in the lending supply of stocks whose index membership changed in the Russell reconstitutions of 2020–2022. My sample is limited to these years because the loan value data by fund comes from NPORT-P filings, available from the last quarter of 2019. I identify additions 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 NPORT-P.

First, I confirm that the aggregate holdings of funds follow changes in their benchmarks. For example, Figure A4 (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 3 in the main text confirms that aggregate lending is a mirror image of aggregate holding.

These aggregate changes in ownership and lending are also detectable at a stock level. Table A4 reports changes in the ownership of funds with different benchmarks and changes in their

Figure A4: Aggregate fund holdings of the Russell 2000 index additions and deletions

(a) Russell 2000 additions, passive funds (b) Russell 2000 deletions, passive 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 NPORT-P filings. Only funds with an identified benchmarks and types are included. Russell 1000 group includes Russell Midcap funds.

Table A4: 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 NPORT	Russell 1000		Russell Midcap		Russell 2000		Total NPORT	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 NPORT" column includes only domestic equity funds identified, as described in Section A.2.3.

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 behaviour 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 A5 illustrates, the majority of stocks that moved indexes in the Russell reconstitutions are not on loan (panels (a) and (b)). However, conditional on lending, they 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 specification:

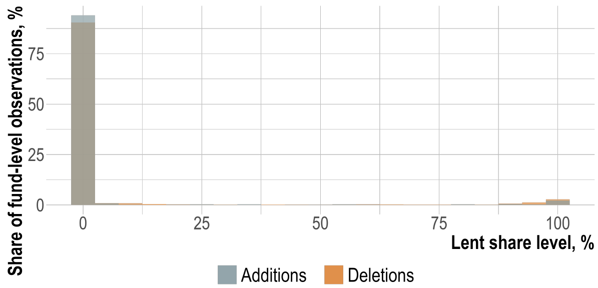
$$\begin{aligned} Change\,in\,Fee_{ijt} =& \beta_1 LentShare_{ijt} \times D(special)_{ijt} + \beta_2 LentShare_{ijt} \times D(not\,special)_{ijt} \\ &+ \nu_{sjt} + \epsilon_{ijt}. \end{aligned} \tag{24}$$

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.[58] $LentShare_{ijt}$ is the share of holdings in stock i on loan

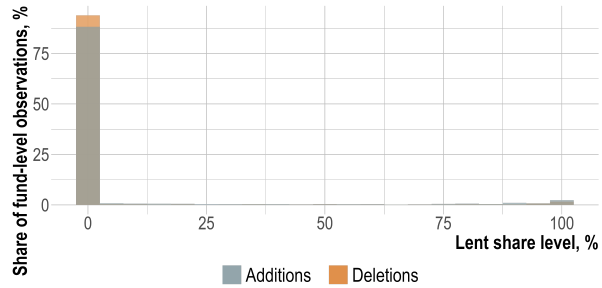
[58]Because funds have different report dates, I use observations three months around the reconstitution to

Figure A5: Lent share frequency for the Russell 2000 additions and deletions

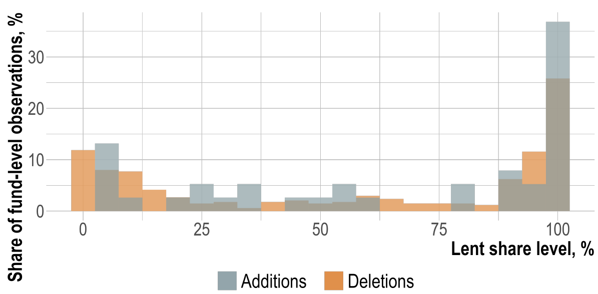
(a) Russell 1000 funds



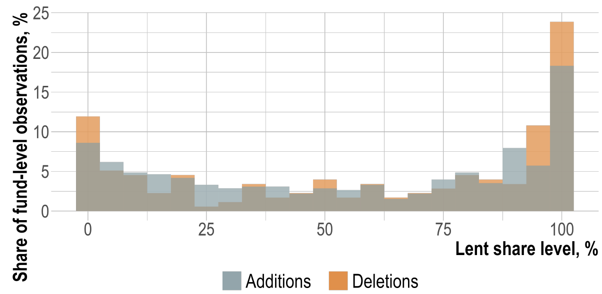
(b) Russell 2000 funds



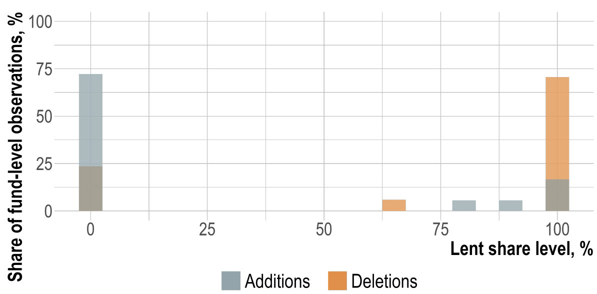
(c) Russell 1000 funds (conditional)



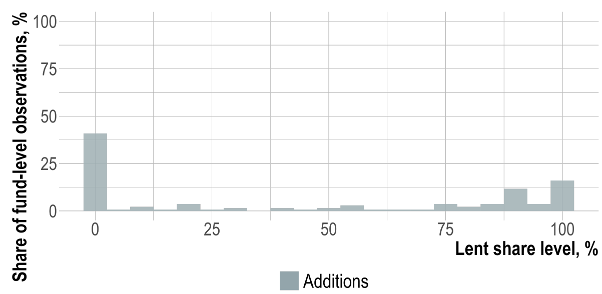
(d) Russell 2000 funds (conditional)



(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%.

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

account for all quarterly NPORT-P reports. For any given fund, I effectively include one observation before and one observation after the reconstitution.

Table A5: 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 (24) 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.

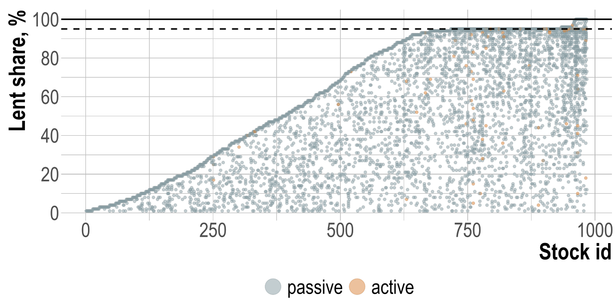
fee before the reconstitution is up to 1%, and zero otherwise. ν_{sjt} are specialness by year fixed effects. I also consider a version of specification (24) in which all variables are simple averages across funds.

Table A5 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 4bps larger change in borrowing fee 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 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 15bps in response to a 1 percentage point increase in the lent share of special stocks.

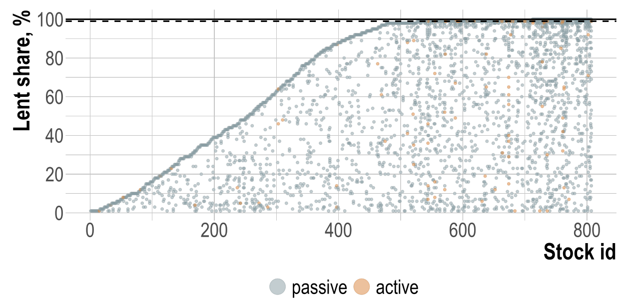
A.7 Illustration of lending shares at position level for prominent investment managers in the United States

Figure A6: Illustration of lending shares at position level for prominent investment managers in the United States, special stocks only

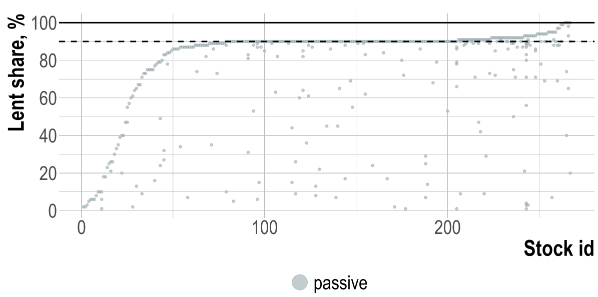
(a) Vanguard



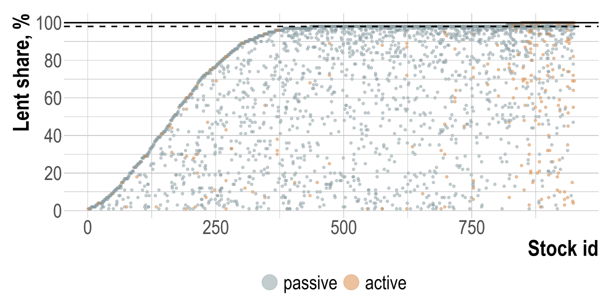
(b) BlackRock



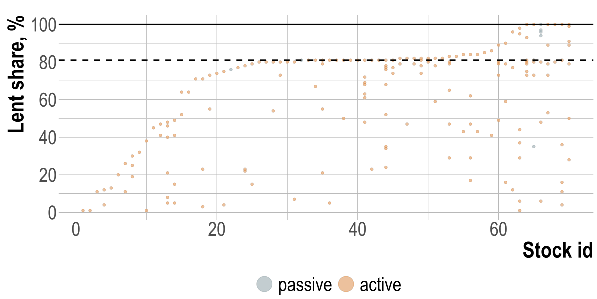
(c) State Street



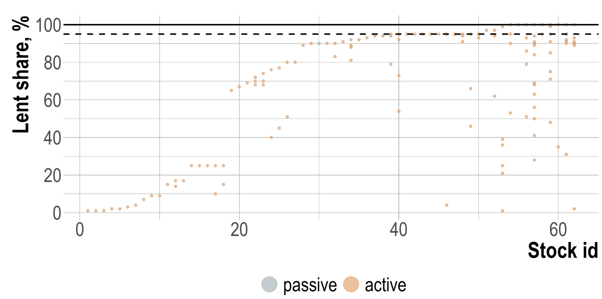
(d) Fidelity



(e) J.P. Morgan



(f) T. Rowe Price



This figure plots the share of each special holding that is on loan for funds managed by BlackRock, Vanguard, State Street, Fidelity, J.P. Morgan, and T. Rowe Price. The data is as of 2021 and rounded to percentage points. Stock is considered special if its borrowing fee is above 1% on the report date. I include only domestic equity funds with a defined active or passive type, as described in 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%.

A.8 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 Shorting demand, % shares	Δ Borrowing fee, %	Stock return, %
	(1)	(2)	(3)	(4)
Panel A: No interactions				
D(in Russell 2000)	2.109***	2.026***	0.286*	1.330*
	(12.54)	(12.36)	(1.94)	(1.79)
Observations	9,658	9,658	9,658	9,658
Adjusted R-squared	0.175	0.129	0.163	0.241
Panel B: With specialness interactions				
D(in Russell 2000) × D(not special)	2.162***	2.041***	0.179	1.153
	(12.94)	(12.39)	(1.34)	(1.57)
D(in Russell 2000) × D(special)	1.515***	1.857***	1.485***	3.318**
	(5.06)	(5.42)	(3.56)	(2.39)
Observations	9,658	9,658	9,658	9,658
Adjusted R-squared	0.176	0.129	0.178	0.241
$\beta_1 - \beta_2$	-0.647**	-0.184	1.306***	2.164*
	(-2.53)	(-0.58)	(3.60)	(1.82)

This table reports the estimates of specification (16) (panel A) and specification (17) (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.9 BMI effects on spot and lending markets in the long run

In this section, I analyze longer-horizon changes in spot and lending markets around Russell reconstitutions. The baseline results persist at one-year horizon in line with the predictions of the model.

Table A7 reports the estimates of specification (17) for a one-year change in lending variables and stock prices. Baseline results for lending variables persist over this longer horizon in terms of both statistical significance and economic magnitudes. The estimates for special stocks imply that no new lenders step in during the year after the reconstitution to earn the larger fee. For stock prices, I find larger magnitudes yet no statistical significance for special stocks.

Table A7: Long-run response of lending variables to changes in BMI

	Δ Lending inventory, % shares	Δ Shorting demand, % shares	Δ Borrowing fee, %	Stock return, %
	(1)	(2)	(3)	(4)
ΔBMI, % × D(not special)	0.213***	0.027	0.004	0.507**
	(10.44)	(1.39)	(0.68)	(2.52)
ΔBMI, % × D(special)	0.153**	0.214**	0.182**	0.946
	(2.33)	(2.27)	(2.47)	(1.28)
Observations	11,998	11,998	11,998	11,998
Adjusted R-squared	0.184	0.112	0.060	0.260
$\beta_1 - \beta_2$	-0.059	0.187**	0.178**	0.439
	(-0.88)	(1.96)	(2.43)	(0.58)

This table reports the estimates of specification (17) in the panel of stocks within 500 ranks around the Russell cutoff in 2007-2018. 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.10 Alternative specifications for U.S. regressions

A.10.1 Alternative definitions of specialness

Table A8: Response of lending variables to changes in BMI

	Δ Lending inventory, % shares	Δ Shorting demand, % shares	Δ Borrowing fee, %	Stock return, %
	(1)	(2)	(3)	(4)
Panel A: Top tercile				
ΔBMI × D(not special)	0.185***	0.128***	-0.006*	0.098**
	(18.46)	(14.07)	(-1.92)	(2.39)
ΔBMI × D(special)	0.137***	0.165***	0.079***	0.204*
	(6.64)	(6.60)	(3.53)	(1.92)
Observations	13,684	13,684	13,684	13,684
Adjusted R-squared	0.143	0.088	0.042	0.203
Panel B: Top quintile				
ΔBMI × D(not special)	0.176***	0.127***	-0.004	0.115***
	(18.30)	(13.82)	(-1.38)	(2.78)
ΔBMI × D(special)	0.165***	0.193***	0.135***	0.177
	(5.80)	(6.05)	(3.52)	(1.19)
Observations	13,684	13,684	13,684	13,684
Adjusted R-squared	0.142	0.088	0.069	0.201
Panel C: Top decile				
ΔBMI × D(not special)	0.176***	0.132***	-0.000	0.116***
	(18.43)	(13.95)	(-0.12)	(2.78)
ΔBMI × D(special)	0.162***	0.215***	0.283***	0.277
	(3.76)	(4.68)	(3.54)	(1.14)
Observations	13,684	13,684	13,684	13,684
Adjusted R-squared	0.144	0.087	0.132	0.200
Panel D: Markit score above 1				
ΔBMI × D(not special)	0.178***	0.127***	-0.004	0.106***
	(18.60)	(13.74)	(-1.37)	(2.59)
ΔBMI × D(special)	0.142***	0.210***	0.159***	0.247*
	(4.58)	(6.24)	(3.83)	(1.65)
Observations	13,684	13,684	13,684	13,684
Adjusted R-squared	0.144	0.090	0.088	0.202

This table reports the estimates of specification (17) 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), or if it has Markit's proprietary Daily Cost of Borrow Score, averaged over May, above 1 (panel D). 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 A9: Response of lending variables to changes in BMI

	Δ Lending inventory, % shares	Δ Shorting demand, % shares	Δ Borrowing fee, %	Stock return, %
	(1)	(2)	(3)	(4)
Panel A: Removing liquidity controls				
ΔBMI × D(not special)	0.180***	0.129***	-0.003	0.080*
	(19.03)	(14.05)	(-1.10)	(1.96)
ΔBMI × D(special)	0.121***	0.211***	0.207***	0.275
	(3.40)	(5.41)	(3.97)	(1.50)
Observations	13,684	13,684	13,684	13,684
Adjusted R-squared	0.144	0.088	0.105	0.194
Panel B: Adding interactions of controls with stock specialness				
ΔBMI × D(not special)	0.178***	0.133***	-0.000	0.102**
	(18.75)	(14.26)	(-0.26)	(2.53)
ΔBMI × D(special)	0.131***	0.171***	0.185***	0.369
	(3.09)	(3.69)	(2.59)	(1.61)
Observations	13,684	13,684	13,684	13,684
Adjusted R-squared	0.145	0.091	0.120	0.203

This table reports the estimates of changes in specification (17) 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 A10: Response of lending variables to changes in BMI

	Δ Lending inventory, % shares	Δ Shorting demand, % 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***
	(16.05)	(11.27)	(-1.26)	(4.37)
ΔBMI, % × D(special)	0.168***	0.240***	0.204***	0.180
	(3.57)	(5.36)	(2.71)	(0.91)
Observations	7,765	7,765	7,765	7,765
Adjusted R-squared	0.174	0.110	0.097	0.209
Panel B: Band width of 300				
ΔBMI, % × D(not special)	0.191***	0.128***	-0.008*	0.141***
	(16.87)	(11.54)	(-1.65)	(3.03)
ΔBMI, % × D(special)	0.132***	0.225***	0.223***	0.479**
	(3.40)	(5.99)	(3.66)	(2.47)
Observations	9,852	9,852	9,852	9,852
Adjusted R-squared	0.161	0.103	0.102	0.209
Panel C: Band width of 750				
ΔBMI, % × D(not special)	0.177***	0.125***	-0.001	0.069**
	(23.22)	(16.90)	(-0.56)	(2.06)
ΔBMI, % × D(special)	0.145***	0.214***	0.157***	0.217
	(4.64)	(6.23)	(3.38)	(1.35)
Observations	18,767	18,767	18,767	18,767
Adjusted R-squared	0.136	0.077	0.085	0.194

This table reports the estimates of specification (17) 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 Identification with a demand shift

If supply in the lending market moves in response to changes in borrowing fees, the sensitivity of special stocks' inventory to BMI 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.

In order to tackle potential endogeneity due to simultaneity in supply and demand, I need an exogenous demand shifter (Wooldridge (2002)). I turn to discretionary accruals as an instrument for demand. I follow Kolasinski, Reed, and Ringgenberg (2013), who use 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 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.

In particular, I run 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). The simultaneity concern is strongest for the shorting quantity variable (short quantity on loan). However, I use both change in inventory (active lendable shares) and change in demand (short quantity on loan) as the dependent variable ΔY_{it} to confirm that none of my estimates is significantly affected by the simultaneity bias. The rest of the specification is the same as in the baseline test, described near equation (16).

Results are reported in Table A11. Columns (1) and (4) report the estimates of 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 borrowing fee change, with the effective F-statistic above 27. For both quantity on loan and inventory, the second-stage estimate for the change in fee is positive, but close to zero and insignificant. This is consistent with the supply schedule being flat with respect to fee for most (even special) stocks. Importantly, the coefficients on ΔBMI are almost the same as the baseline estimates. These results, together with the findings in the main text, imply that an increase in BMI results in a shift in the lending supply curve.

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.11 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.

A.12 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 specialness status of stocks in my sample is quite persistent. A total of 88% 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, 58% of stocks remain special. These probabilities are similar in the full sample of Russell 3000 constituents, at 81% and 82% in July and May of the following year, respectively.

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%	86%	14%
D(special in May)	12%	88%	42%	58%
Panel B: Full sample				
D(not special in May)	97%	3%	81%	19%
D(special in May)	9%	91%	18%	82%

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:

$$\begin{aligned} D(special)_{it+h} = {} & \alpha D(special)_{it} + \beta \Delta BMI_{it} + \gamma \Delta BMI_{it} \times D(special)_{it} \\ & + \zeta' \bar{X}_{it} + \nu_t + \epsilon_{it+h}, \end{aligned} \tag{25}$$

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 44% higher chance of being special in May of the next year. Furthermore, Table A13 shows that a change in BMI has a 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 60bps larger probability for each 1 percentage point increase in BMI). At a one-year horizon, this estimate is 90bps 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)	0.853***	0.439***
	(58.73)	(19.19)
ΔBMI, %	-0.000	0.000
	(-0.61)	(0.16)
ΔBMI, % × D(special)	0.006	0.009
	(1.52)	(1.63)
Observations	13,691	13,691
Adjusted R-squared	0.735	0.159

This table reports the estimates of specification (25) 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.13 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 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. Finally, I document a statistically significant but small in size increase in borrowing fee volatility for special stocks.

Table A14 reports the estimates of specifications (16) and (17) for additional dependent variables, namely, active utilization, active utilization (short), 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. Tenure is the loan-size-weighted average number of days from start date to present for all transactions. Lender and borrower concentration levels are computed by Markit and represent Herfindahl-Hirschman indexes for the lender 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.

Table A15 reports the estimates of specifications (16) and (17) for dependent variables related to borrowing fee risk, namely, change borrowing fee volatility and change in borrowing fee risk premium implied by option prices (adjusted). I compute fee volatility as standard deviation of borrowing fee over one month and over three months (annualized, in %). I also include change in option-implied borrowing fee adjusted for early exercise and the Markit's borrowing fee used in the main text. 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).[59] I report all estimates for the sample of stocks with available option-implied fees (i.e., optionable stocks in 2007–2015) and the estimates for fee volatility for my baseline sample.

[59] I thank Dmitry Muravyev for sharing the data.

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

	Change in					
	active utilization, %	active utilization (short), %	loan tenure, days	lender concentration, %	borrower concentration, %	inventory concentration, %
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: No interactions						
ΔBMI, % MV	0.287***	0.337***	-0.532***	-0.279***	-0.266***	-0.012*
	(8.42)	(8.90)	(-4.14)	(-5.54)	(-5.13)	(-1.83)
Observations	13,684	13,369	13,684	7,962	7,962	13,691
Adjusted R-squared	0.078	0.090	0.023	0.019	0.006	0.083
Panel B: With specialness interactions						
ΔBMI, % MV × D(not special)	0.274***	0.326***	-0.558***	-0.303***	-0.281***	-0.007
	(8.96)	(9.27)	(-4.14)	(-5.71)	(-5.15)	(-1.25)
ΔBMI, % MV × D(special)	0.441**	0.543*	-0.234	-0.009	-0.094	-0.064**
	(2.25)	(1.85)	(-0.56)	(-0.18)	(-1.64)	(-2.13)
Observations	13,684	13,369	13,684	7,962	7,962	13,691
Adjusted R-squared	0.078	0.090	0.023	0.019	0.008	0.083
$\beta_1 - \beta_2$	0.167	0.216	0.324	0.293***	0.187***	-0.057*
	(0.87)	(0.74)	(0.78)	(4.58)	(2.88)	(-1.94)

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. 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.

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

	Change in (p.p.)						
	borrowing fee	option-implied borrowing fee	option-implied fee risk premium	fee volatility (one-month)	fee volatility (three-month)	fee volatility (one-month)	fee volatility (three-month)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: No interactions							
ΔBMI, %	0.010	0.003	-0.005	0.006*	0.004	0.007**	0.007
	(1.55)	(0.25)	(-0.53)	(1.83)	(0.80)	(2.32)	(1.33)
Observations	7,684	7,684	7,684	7,684	7,684	13,674	13,674
Adjusted R-squared	0.103	0.049	0.034	0.055	0.055	0.042	0.031
Panel B: With specialness interactions							
ΔBMI, % × D(not special)	-0.004	-0.015	-0.010	-0.003	-0.008*	-0.002	-0.005
	(-1.28)	(-1.64)	(-1.16)	(-1.62)	(-1.92)	(-1.29)	(-1.39)
ΔBMI, % × D(special)	0.188***	0.220***	0.058	0.116***	0.150***	0.113***	0.141***
	(2.80)	(2.94)	(0.94)	(3.38)	(3.17)	(3.71)	(3.24)
Observations	7,684	7,684	7,684	7,684	7,684	13,674	13,67
Adjusted R-squared	0.126	0.056	0.035	0.092	0.072	0.071	0.044
$\beta_1 - \beta_2$	0.192***	0.234***	0.068	0.118***	0.157***	0.115***	0.145***
	(2.90)	(3.14)	(1.09)	(3.49)	(3.31)	(3.79)	(3.35)

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. 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. In columns (6) and (7), standard errors are clustered by stock. *** p<0.01, ** p<0.05, * p<0.1.

A.14 Pass-through from BMI to lending supply

My results for the Russell reconstitutions in Section 5 suggest that the pass-through from benchmarking intensity to lending supply is too weak. In this section, I argue that this weakness stems from both the insufficient response of inventory and its limited utilization.

My estimates in column (1) of Table 2 in the main text 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 Appendix A.10. 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 be consistent with the strength of the relative performance component in their compensation, or the level of $b/(a+b)$ in the data. If I assume a lower weight on active funds, the estimate of the pass-through increases. Table A16 reports the sensitivity estimates of lending inventory to BMI assuming different weights on active funds' assets in BMI. The estimated sensitivity monotonically 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%.[60] Therefore, the estimates in Tables 2 and A16 suggest that the true pass-through value 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, as shown in equation (11) in 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 percentage point increase in BMI, as shown in Appendix A.13. I discuss several factors that may be driving incomplete utilization in the data in Section 5.3.2.

Therefore, the weak response of supply to BMI must be driven by both the insufficient response of inventory and its limited utilization. Correspondingly, the total response of lending supply in the model is given by equation (12), which combines the effect of the pass-through to inventory with limited utilization. See also the expression for general collateral stocks in equation (13). The model predicts that the total supply response is bounded from above by the lending limit l and otherwise depends on the composition of investors. Interestingly, because funds are partially sensitive to the asset price, so they do not increase their holdings l:1 relative to the change in BMI.

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 instrumental vari-

[60] This assumption is not realistic as the case studies in Appendix A.6 show a large contribution of active funds to lending around Russell reconstitutions and the aggregate NPORT-P data suggests almost equal contribution in recent years.

Table A16: Response of lending inventory to changes in BMI for different levels of active funds' contribution

	Δ Lending inventory, % shares				
	(1)	(2)	(3)	(4)	(5)
ΔBMI, % MV (0% active)	0.589***				
	(11.75)				
ΔBMI, % MV (20% active)		0.451***			
		(15.81)			
ΔBMI, % MV (40% active)			0.328***		
			(17.36)		
ΔBMI, % MV (60% active)				0.253***	
				(18.09)	
ΔBMI, % MV (80% active)					0.205***
					(18.51)
Observations	13,684	13,684	13,684	13,684	13,684
Adjusted R-squared	0.123	0.137	0.141	0.143	0.144

This table reports the estimates of specification (16) 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 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.

able.[61] In particular, I estimate the following two-stage least squares regression:

$$\Delta IO_{it} = \kappa \Delta BMI_{it} + \delta' \bar{X}_{it} + \mu_{st} + \varepsilon_{it}, \tag{26}$$

$$\Delta Y_{it} = \alpha \widehat{\Delta IO}_{it} + \zeta' \bar{X}_{it} + \nu_{st} + \epsilon_{it}. \tag{27}$$

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.[62] The rest of the specification is the same as in the baseline test; see equation (16).

Table A17 reports the estimation results. The first-stage results confirm that ΔBMI is a strong instrument for ΔIO, with F-statistic of 117.1 in my sample. Second-stage results emphasize that the pass-through from institutional ownership to lending inventory is at 67% (or 42% for special stocks). Interestingly, the OLS estimate is 8.8% (significantly biased downward). Finally, the table also reports the magnitudes of how changes in other lending variables and stock prices

[61] Using ΔBMI as an instrument for changes in institutional ownership is proposed in Pavlova and Sikorskaya (2023). ΔBMI remains a valid instrument in my application because it affects all dependent variables only through changes in ownership. In that sense, my baseline results are reduced-form estimates.

[62] 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.

respond to changes in institutional ownership.

A.15 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 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.[63]

Table A18 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 fewer information asymmetries resulting in analysts disagreeing less about their 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)-(7) show that the estimates are virtually unaffected.

[63] 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/.

Table A17: Response of lending variables to changes in institutional ownership (IO) instrumented by changes in benchmarking intensity (BMI)

	Δ Lending inventory, % shares			Δ Shorting demand, % shares	Δ Borrowing fee, %	Stock return, %	Δ Lending inventory, % shares	Δ Shorting demand, % shares	Δ Borrowing fee, %	Stock return, %
	OLS	IV					IV			
	(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, % × D(not special)							0.695***	0.500***	-0.013	0.415***
							(19.11)	(14.05)	(-0.95)	(2.65)
ΔIO, % × 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 (26) (panel A) and specification (27) (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.

Table A18: Disagreement and changes in BMI

	EPS dispersion in May	Δ EPS dispersion	Δ EPS dispersion	Δ Lending inventory, % shares	Δ Shorting demand, % shares	Δ Borrowing fee, %	Stock return, %
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
BMI in May, %	-0.341*						
	(-1.70)						
ΔBMI, %		0.105	2.093				
		(0.62)	(1.63)				
ΔBMI, % × D(not special)				0.175***	0.119***	-0.003	0.098**
				(16.81)	(12.29)	(-1.01)	(2.27)
ΔBMI, % × D(special)				0.112***	0.213***	0.192***	0.341*
				(2.89)	(5.22)	(3.55)	(1.81)
ΔEPS dispersion × D(not special)				-0.001	0.000	0.000*	-0.016***
				(-1.47)	(0.37)	(1.70)	(-3.06)
ΔEPS dispersion × D(special)				-0.006***	0.001	0.004	-0.028**
				(-2.71)	(0.80)	(1.51)	(-2.05)
Observations	11,420	11,420	502	11,420	11,420	11,420	11,420
Adjusted R-squared	0.044	0.001	-0.011	0.150	0.092	0.124	0.208
$\beta_1 - \beta_2$				-0.063	0.094**	0.195***	0.242
				(-1.59)	(2.33)	(3.62)	(1.27)

This table reports the estimates of specification (17) 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.

A.16 BoJ announcements

Table A19: 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

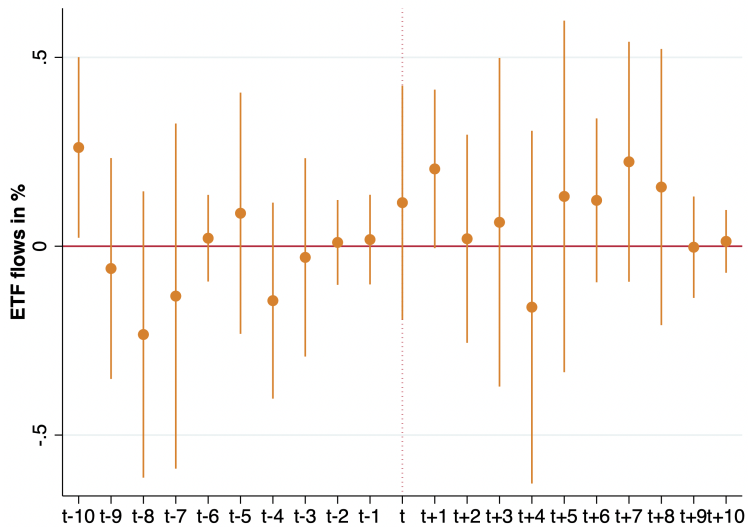
This table is based on the official BoJ announcement documents, publicly available at https://www.boj.or.jp/en/mopo/measures/mkt_ope/ope_t/index.htm. Horizonal lines separate policy periods used in the regression analysis.

A.17 Reaction of ETF flows to BoJ announcements and purchases

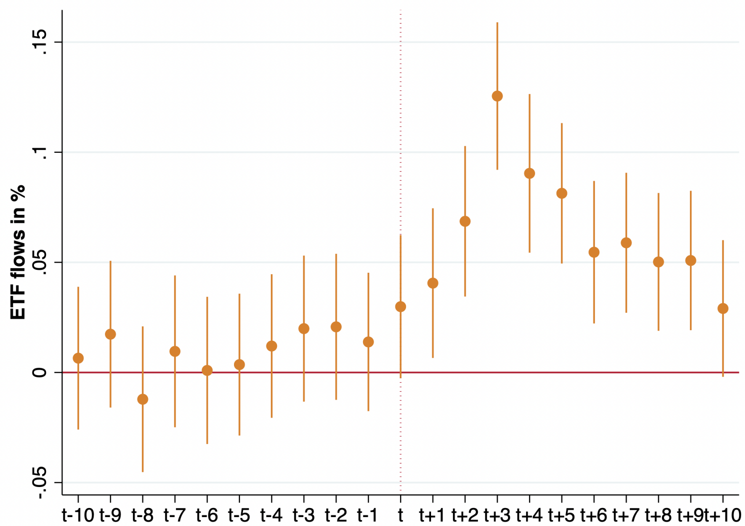
Figure A7 illustrates that the combined eligible ETF flows do not react to the BoJ announcements and strongly react to the purchases.

Figure A7: BoJ purchases and aggregate eligible ETF flows

(a) BoJ announcements



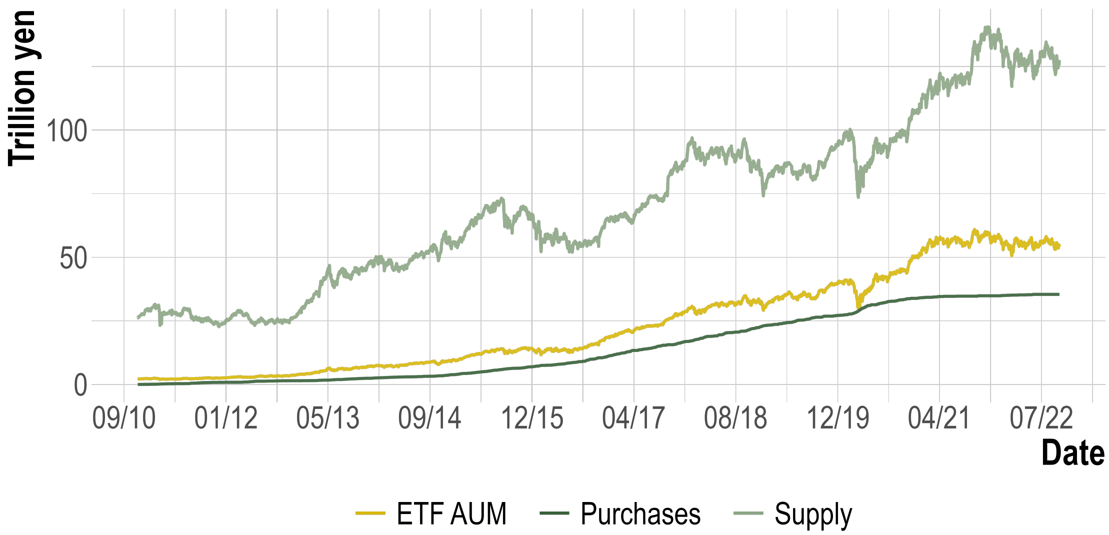
(b) BoJ purchases



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%.

A.18 The BoJ's ETF purchases and lending supply of Japanese stocks

Figure A8: ETF assets and lending supply in Japan



This figure plots the total assets under management (AUM) of the ETFs purchased by the BoJ, cumulative purchases, and the active lending inventory (supply) of Japanese stocks (in trillion yen).

A.19 Implied estimates of price elasticity of demand for Japanese stocks

In this section, I compare my price impact estimates in Table 3 to estimates in the literature. My average price impact estimate in panel A corresponds to the elasticity of -1/29 = -0.03, which implies very steep demand curves for Japanese stocks. Finally, as in the U.S. sample, the implied elasticity for special stocks is smaller (at -1/33 = -0.03) than that of general collateral stocks (-1/27 = -0.04).

My price impact estimate in Table 3 is larger than the short-term estimate of around 5 implied in Greenwood (2005), which is based on Nikkei 225 redefinition that happened in April 2000. It is also larger than the estimate of around 1 computed on BoJ's purchases in Barbon and Gianinazzi (2019) for the horizon of one year. The sample of Barbon and Gianinazzi includes two program expansions in 2014 and 2016, and they follow a different empirical design. The first difference is that I study the BoJ's purchases relative to the market value of a stock. This is to ensure that I can interpret the magnitudes of the pass-through to the lending inventory and compare them with the results for the U.S. sample. Second, I use changes in BMI^{BoJ} because they reflect the change in expectation of purchases as opposed to the level. In the two events that Barbon and Gianinazzi study, there is a smaller difference between the two approaches than in my sample because I include reallocative announcements (that changed the share of Nikkei 225 index within the purchases). Finally, due to the policy changes regarding the index shares after the sample period of Barbon and Gianinazzi, I do not drop JPX-Nikkei 400, and I compute index shares S_t^j using eligible ETF assets rather than assuming that they are equal for the TOPIX and Nikkei 225 indexes.

A.20 Alternative specifications for tests with changes in BMI due to the BoJ's ETF purchases

A.20.1 Alternative handling of ex-dividend dates

Table A20: Response of spot and lending market variables to changes in BMI due to the BoJ's ETF purchases, excluding observations around dividend record dates

	Δ Lending inventory, % shares	Δ Shorting demand, % shares	Δ Borrowing fee, %	Stock return, %
	(1)	(2)	(3)	(4)
Panel A: No filter				
BoJ purchase × D(not special)	-0.140	0.059	0.020	16.953***
	(-1.62)	(0.98)	(0.99)	(11.97)
Change in BMI × D(special)	1.140***	0.677***	0.315**	29.992***
	(5.44)	(4.17)	(2.37)	(11.45)
Observations	22,283	22,283	22,283	22,283
Adjusted R-squared	0.148	0.024	0.131	0.374
Panel B: Removing a week around an ex-dividend date				
BoJ purchase × D(not special)	0.205	-0.010	-0.007	26.208***
	(1.62)	(-0.13)	(-0.24)	(11.16)
Change in BMI × D(special)	1.113***	0.732***	0.349**	34.198***
	(4.39)	(3.49)	(2.25)	(10.00)
Observations	19,728	19,728	19,728	19,728
Adjusted R-squared	0.106	0.027	0.127	0.375
Panel C: Removing a month around an ex-dividend date				
BoJ purchase × D(not special)	0.043	-0.031	0.041	27.404***
	(0.30)	(-0.32)	(1.10)	(9.93)
Change in BMI × D(special)	1.124***	1.004***	0.445**	32.266**
	(4.05)	(4.41)	(2.58)	(8.88)
Observations	15,479	15,479	15,479	15,479
Adjusted R-squared	0.089	0.042	0.118	0.369

This table reports the estimates of specification (20) in the panel of TOPIX constituents across 13 policy periods. In panel A, no observations are excluded. Stock-period observations are excluded if the stock's dividend record date is within a week (panel B), or a month (panel C) of the announcement date. ΔBMI^{BoJ} is a shock to BMI in a given policy period, as defined in (19). Changes in lending market variables are computed as differences between the end of the current policy period and the preceding one, see details in Appendix A.3. A stock is considered special, or $D(special) = 1$, if its 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.

A.20.2 Alternative definitions of specialness

Table A21: Response of spot and lending market variables to changes in BMI due to the BoJ's ETF purchases, alternative measures of specialness

	Δ Lending inventory, % shares	Δ Shorting demand, % shares	Δ Borrowing fee, %	Stock return, %
	(1)	(2)	(3)	(4)
Panel A: Above median				
ΔBMI^{BoJ} × D(not special)	0.018	0.032	0.055	25.245***
	(0.11)	(0.31)	(1.38)	(8.77)
ΔBMI^{BoJ} × D(special)	0.937***	0.590***	0.245*	32.285***
	(4.42)	(3.31)	(1.94)	(10.76)
Observations	17,298	17,298	17,298	17,298
Adjusted R-squared	0.072	0.037	0.047	0.383
Panel B: Top tercile				
ΔBMI^{BoJ} × D(not special)	0.073	0.059	0.039	26.932***
	(0.51)	(0.65)	(0.95)	(10.30)
ΔBMI^{BoJ} × D(special)	1.161***	0.820***	0.390**	32.228***
	(4.55)	(3.68)	(2.42)	(9.28)
Observations	17,298	17,298	17,298	17,298
Adjusted R-squared	0.097	0.041	0.117	0.375
Panel C: Top quintile				
ΔBMI^{BoJ} × D(not special)	0.258*	0.149	0.066	27.797***
	(1.77)	(1.64)	(1.45)	(11.26)
ΔBMI^{BoJ} × D(special)	0.863***	0.867***	0.313	30.454***
	(2.74)	(3.06)	(1.53)	(7.09)
Observations	17,298	17,298	17,298	17,298
Adjusted R-squared	0.081	0.043	0.155	0.371
Panel D: Top decile				
ΔBMI^{BoJ} × D(not special)	0.263*	0.181**	0.075	27.962***
	(1.87)	(1.97)	(1.48)	(12.14)
ΔBMI^{BoJ} × D(special)	1.524***	1.265***	0.288	29.975***
	(4.11)	(2.67)	(0.82)	(5.16)
Observations	17,298	17,298	17,298	17,298
Adjusted R-squared	0.071	0.043	0.150	0.369
Panel E: Above 150bps				
ΔBMI^{BoJ} × D(not special)	0.082	0.061	0.069*	26.518***
	(0.58)	(0.68)	(1.69)	(10.45)
ΔBMI^{BoJ} × D(special)	1.094***	0.931***	0.443***	33.040***
	(4.06)	(4.16)	(2.60)	(8.94)
Observations	17,298	17,298	17,298	17,298
Adjusted R-squared	0.108	0.043	0.140	0.375
Panel F: Above 500bps				
ΔBMI^{BoJ} × D(not special)	0.288**	0.197**	0.079	27.783***
	(2.04)	(2.12)	(1.51)	(12.16)
ΔBMI^{BoJ} × D(special)	1.656***	1.284**	0.445	32.371***
	(4.31)	(2.53)	(1.11)	(4.92)
Observations	17,298	17,298	17,298	17,298
Adjusted R-squared	0.071	0.043	0.132	0.367

This table reports the estimates of specification (20) in the panel of TOPIX constituents across 13 policy periods. ΔBMI^{BoJ} is a shock to BMI in a given policy period, as defined in (19). Changes in lending market variables are computed as differences between the end of the current policy period and the preceding one, see details in Appendix A.3. A stock is considered special, or $D(special) = 1$, if its average fee is above median (panel A), in the top tercile (panel B), top quintile (panel C) or top decile (D) of the fee distribution, or above 150bps (panel E) or 500bps (panel F) in the last trading month of the preceding policy period, and zero otherwise. The latter cutoffs are most in line with the classification of the JSDA (see, e.g., https://www.fsb.org/wp-content/uploads/JSDA-on-1411DEG.pdf). 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.

A.21 Response of lending supply to the BoJ's purchases

Table A22: Response of lending inventory to the BoJ's ETF purchases

	Δ Lending inventory, % shares		
	Full sample	QQE	After 2016
	(1)	(2)	(3)
BoJ purchase, % MV × D(not special)	0.486***	0.431***	1.071***
	(7.00)	(5.95)	(8.04)
BoJ purchase, % MV × D(special)	1.287***	1.326***	1.433***
	(7.37)	(7.09)	(6.52)
Observations	17,502	9,845	5,842
Adjusted R-squared	0.104	0.083	0.085

This table reports the estimates of specification (20) in the panel of TOPIX constituents using total BoJ purchases as the main independent variable. Column (1) reports estimates in the full sample, column (2) during the Quantitative and Qualitative Easing phase (since 2013), and column (3) after 2016. BoJ purchase (%) measures the total stock-level purchases of the BoJ in a given policy period, as defined in (18), scaled by the market value of the stock at the end of the preceding period. Changes in lending supply are computed as differences between the end of the current policy period and the preceding one; see details in Appendix A.3. A stock is considered special, or $D(special) = 1$, if its fee prior to the policy period is above 1%. All regressions include controls and 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.

A.22 Specialness subsamples

Table A23: Response of spot and lending market variables to changes in BMI due to the BoJ's ETF purchases by specialness level

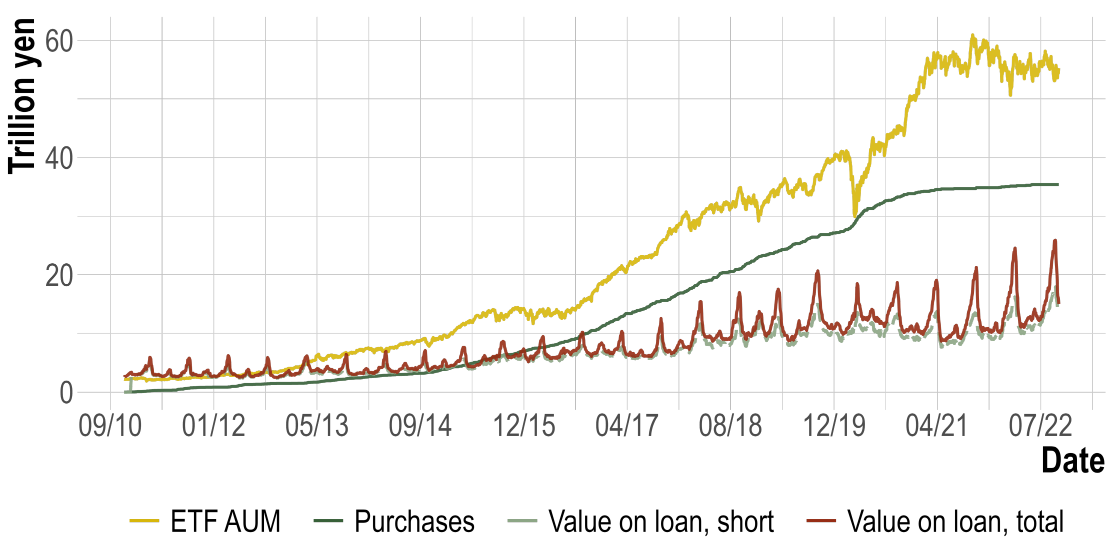
	Δ Lending inventory, % shares	Δ Shorting demand, % shares	Δ Borrowing fee, %	Stock return, %
	(1)	(2)	(3)	(4)
Panel A: Fees below 50bps				
ΔBMI^{BoJ}	-0.223	-0.352**	-0.038	21.038**
	(-1.15)	(-2.40)	(-1.14)	(6.55)
Observations	5,108	5,108	5,108	5,108
Adjusted R-squared	0.114	0.149	0.181	0.477
Panel B: Fees between 50bps and 150bps				
ΔBMI^{BoJ}	0.227	0.280**	0.085	24.855***
	(1.06)	(2.07)	(1.32)	(6.44)
Observations	6,538	6,538	6,538	6,538
Adjusted R-squared	0.098	0.032	0.078	0.344
Panel C: Fees above 150bps				
ΔBMI^{BoJ}	1.056***	1.002***	0.550***	35.481***
	(3.96)	(4.26)	(3.02)	(8.87)
Observations	4,789	4,789	4,789	4,789
Adjusted R-squared	0.068	-0.011	0.028	0.319

This table reports the estimates of the sensitivity of spot and lending market variables to changes in BMI due to the BoJ's purchases in the panel of TOPIX constituents across 13 policy periods. The specification is the same as (20), except, rather than using the interaction with specialness, estimation is done in subsamples. Specialness definition follows the levels outlined by the JSDA, as in, for example, `https://www.fsb.org/wp-content/uploads/JSDA-on-1411DEG.pdf`, and is based on the fee averaged over one trading month prior to the start of the policy period. Panel A presents estimation results in the subsample with fees below 50bps, panel B in the subsample with fees between 50bps and 150ps, and panel C in the subsample with fees above 150bps. ΔBMI^{BoJ} is a shock to BMI in a given policy period, as defined in (19). Changes in lending market variables are computed as differences between the end of the current policy period and the preceding one; see details in Appendix A.3. All regressions include date and stock fixed effects. t-statistics based on standard errors clustered by stock and period are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

A.23 Shorting demand for Japanese stocks

In my main tests, I use short value on loan as computed by S&P (Markit). This is the total value on loan cleaned from nondirectional transactions. As Figure A9 shows, the total value on loan has a strong seasonality around ex-dividend dates for Japanese stocks and the short value on loan exhibits some of it as well (potentially because S&P's cleaning algorithm yields only an approximation). Nondirectional transactions around ex-dividend dates are driven by the so-called "tax arbitrage," as the tax rate applied to dividend payments is different. As Saffi and Sigurdsson (2011) discuss, fees around dividend dates are also not representative of a general borrowing cost for a given security. Thornock (2013) shows that dividend taxation restricts lending supply and affects shorting volumes around ex-dividend dates. This motivates removing dividend observations around the ex-dividend date in my baseline analyses. Robustness tests with respect to this filter are reported in Appendix A.20.

Figure A9: ETF assets and shorting demand in Japan



This figure plots the total assets under management (AUM) of the ETFs purchased by the BoJ, cumulative purchases, and the value on loan for Japanese stocks (in trillion yen).

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 $U(W^D)$:

$$\max_{\theta_D} E_0[-\exp\{-\gamma W^D\}]. \tag{28}$$

To evaluate the expectation in (28), 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

$$Ee^{\alpha x'Y} = e^{\alpha x' E[Y] + \frac{\alpha^2}{2} x' Var[Y] x}. \tag{29}$$

Substituting in the terminal wealth $W^D = W_0^D + \theta_D(\bar{D} - p)$ and using property (29), 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 (29), 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

$$\max_{\theta_H} E_0[-\exp\{-\gamma(W_0^H + e\bar{D} + \theta_H(\bar{D} - p + \Delta\mathbf{1}_{\theta_H<0}))\}]. \tag{30}$$

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 (29), I can rewrite (30) 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

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):

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

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

$$p - l\Delta = \mu + \frac{1}{l\lambda_M/(a+b)+\lambda_H}\left[(1-l)\lambda_H\Delta + \gamma\sigma l\lambda_M b/(a+b)\omega - \gamma\sigma\lambda_H e\right]. \tag{31}$$

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

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

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

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

Subtract (32) from (31) and rearrange:

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

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

Next, rearrange (32) to get

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

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.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 benchmarking intensity is always less likely to be on special.

B.4 Slack in the lending market

B.4.1 Equilibrium prices and fees

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.4.2 Supply and demand sensitivity to benchmarking intensity

Using the new equilibrium price, I can get shorting supply and demand sensitivities to benchmarking intensity ω_λ. The general equilibrium response of the shorting demand is

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

The index effect implies that the shorting demand is positively related to benchmarking intensity 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

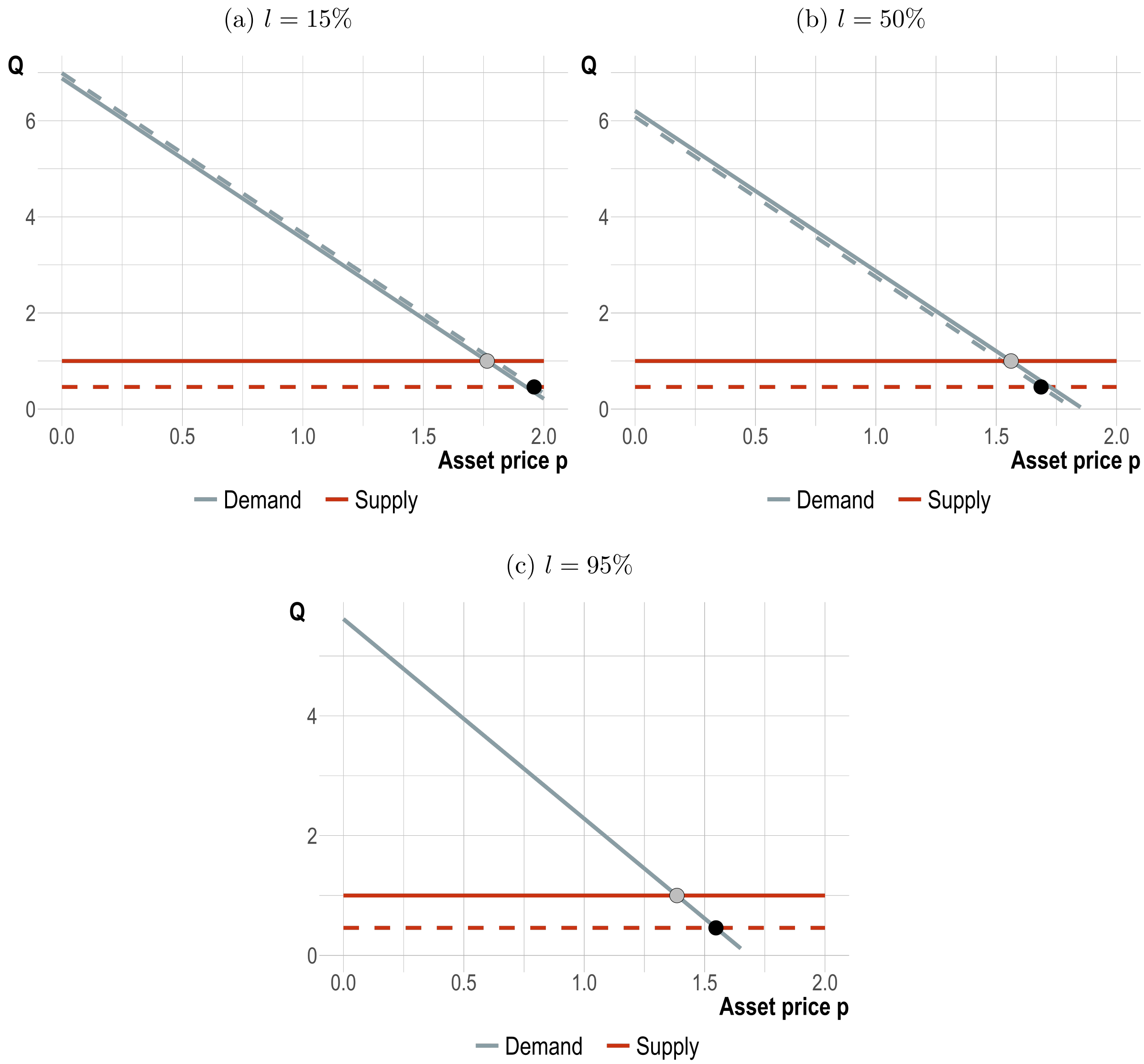
$$\begin{aligned}
\frac{dQ^s}{d\omega_\lambda} =& \frac{\partial Q^s}{\partial \omega_\lambda} - \frac{l\lambda_M}{\gamma\sigma(a+b)}\frac{\partial p}{\partial \omega_\lambda}\\
=& l\left(1 - \frac{\frac{\lambda_M}{(a+b)}}{\frac{\lambda_M}{(a+b)} + \lambda_D + \lambda_H}\right)\\
=& l\frac{\lambda_D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

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.

B.4.3 Benchmarking intensity and price elasticity of demand

For a general collateral asset, because there is no feedback from the lending market, a change in benchmarking intensity can be used to measure the slope of the aggregate demand curve in the asset market. In the model, this slope is represented by the coefficient on price, appropriately weighted from the optimal portfolio demands of all four types of investors. As panel

Figure A10: Demand and supply in the cash market



This figure plots demand and supply curves in the cash 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 (zero ω_λ), whereas dashed lines correspond to an identical asset that belongs to the benchmark index. The black (grey) dot marks the equilibrium for the (not) benchmarked asset. The fee is fixed at the equilibrium levels for the purposes of illustration. Appendix B.4.4 details all parameter values.

(c) of Figure A10 illustrates, an increase in BMI is equivalent to a reduction in asset supply. Therefore, a change in BMI coupled with the observed change in price can help recover the true elasticity from the data.

It is not the same for an asset on special, which is illustrated in panels (a) and (b) in Figure A10. A change in BMI also affects the equilibrium borrowing fee, which drives a shift in the aggregate demand curve in the long market. This shift is outward if the demand effect of benchmarking dominates (panel (a)) and inward if the supply effect dominates (panel (b)). Therefore, the observed change in prices may not lie on the same demand curve, introducing a bias to the (simplified) elasticity estimate $-(P_2 - P_1)/(BMI_2 - BMI_1)$. Panel (b) shows that the bias is downward if the supply effect dominates, as the observed $P_2 - P_1$ is smaller than without the demand shift. Analogously, the bias is upward if the demand effect dominates.

Despite this theoretical complication, it is unlikely that this bias is considerable in the US data. First, as I discuss in Section 5.2, the elasticity estimates are inflated because of how I weigh active funds' assets in BMI and because my time window underestimates the shift in price. Second, for the demand effect of benchmarking (prevalent in the data) to depress the estimates in line with panel (a) in Figure A10, the sensitivity of fund managers to fees has to be strong enough. In other words, fund managers have to significantly overweigh securities with large fees (see their demand in (3)). Johnson and Weitzner (Forthcoming) show that only a fraction of funds with securities lending programs do so. Moreover, lending decisions may be centralized at a fund family level, with funds getting loan allocations simply in proportion to their assets (see suggestive evidence in Section 5.3.1 and in Honkanen (2020)). Third, in my model, hedgers also have demand that is elastic with respect to borrowing fees. The higher the fee is, the less they short, which contributes to the outward shift in demand in the asset market. They have to be large enough in the data relative to all long investors to meaningfully contribute to the bias. Overall, it is unlikely that the demand shift due to benchmarking is large enough to significantly sway the elasticity estimates for special stocks, but the reader should be careful if using the reported values.

B.4.4 Numerical illustration

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

$$
\begin{aligned}
\mu =& 2,\\
\gamma =& 2,\\
\sigma =& 0.15,\\
a =& 0.1,\\
b =& 0.9,\\
\lambda_M =& 0.6,\\
\lambda_D =& 0.25,\\
\lambda_H =& 0.15,\\
e =& 7,\\
\bar{\theta} =& 1,\\
\omega =& 1 \quad \text{(for a benchmark asset)},\\
\omega =& 0 \quad \text{(for an off-benchmark asset)}.
\end{aligned}
$$

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.

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:

$$\theta_D = \frac{1}{\gamma}\Sigma^{-1}(\mu - p), \tag{34}$$

$$\text{i.e.} \qquad \theta_D = \frac{1}{\gamma}\begin{pmatrix} A\sigma_2^2 & -A\sigma_{12} \\ -A\sigma_{12} & A\sigma_1^2 \end{pmatrix}\begin{pmatrix} \mu_1 - p_1 \\ \mu_2 - p_2 \end{pmatrix},$$

$$\begin{pmatrix} \theta_{D1} \\ \theta_{D2} \end{pmatrix} = \frac{1}{\gamma}\begin{pmatrix} A\sigma_2^2(\mu_1 - p_1) - A\sigma_{12}(\mu_2 - p_2) \\ -A\sigma_{12}(\mu_1 - p_1) + A\sigma_1^2(\mu_2 - p_2) \end{pmatrix}$$

Fund managers' demand is given by

$$\theta_M = \frac{1}{\gamma(a+b)}\Sigma^{-1}(l\Delta + \mu - p) + \frac{b}{a+b}\omega, \tag{35}$$

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

$$\begin{pmatrix} \theta_{M1} \\ \theta_{M2} \end{pmatrix} = \frac{1}{\gamma(a+b)}\begin{pmatrix} A\sigma_2^2(l\Delta_1 + \mu_1 - p_1) - A\sigma_{12}(\mu_2 - p_2) \\ -A\sigma_{12}(l\Delta_1 + \mu_1 - p_1) + A\sigma_1^2(\mu_2 - p_2) \end{pmatrix} + \frac{b}{a+b}\begin{pmatrix} \omega_1 \\ \omega_2 \end{pmatrix}$$

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

Lastly, hedgers' demand function is

$$\theta_H = \frac{1}{\gamma}\Sigma^{-1}(\mu - p + \Delta) - e, \tag{36}$$

$$\begin{pmatrix} \theta_{H1} \\ \theta_{H2} \end{pmatrix} = \frac{1}{\gamma}\begin{pmatrix} A\sigma_2^2(\Delta_1 + \mu_1 - p_1) - A\sigma_{12}(\mu_2 - p_2) \\ -A\sigma_{12}(\Delta_1 + \mu_1 - p_1) + A\sigma_1^2(\mu_2 - p_2) \end{pmatrix} - \begin{pmatrix} e_1 \\ e_2 \end{pmatrix}$$

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 securities lending fees

I use the market clearing conditions (5) and (6) as well as the optimal portfolio choice of the investors (34)–(36) to solve for the equilibrium asset prices and the borrowing fee of asset 1. To solve for the price of asset 2, I use only the asset market clearing (5) and set the fee to zero.

The expression for the equilibrium borrowing fee for asset 1 is

$$\Delta_1 = \frac{\gamma}{\sigma_2^2 A}\bar{B}\left(C_e e_1 - C_\theta \bar{\theta}_1 + C_\omega \omega_{\lambda 1}\right), \tag{37}$$

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 (37), 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

$$p_2 = \mu_2 + \bar{C}\frac{\gamma}{A}\left[\omega_{\lambda 2} - \bar{\theta}_2 - \lambda_H e_2 - \frac{\sigma_{12}}{\sigma_2^2}\left(\lambda_H e_1 + \bar{\theta}_1 - \omega_{\lambda 1}\right)\right], \tag{38}$$

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 (38) 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.

$$p_1 = \mu_1 + \frac{\gamma}{\sigma_2^2 A}\left[D_e e_1 - D_\theta \bar{\theta}_1 + D_\omega \omega_{\lambda 1} + \sigma_{12}\bar{C}\left(\omega_{\lambda 2} - \bar{\theta}_2 - \lambda_H e_2\right)\right], \tag{39}$$

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 benchmarking intensity, as well as the benchmarking intensity 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 (34)–(36) to solve for the equilibrium asset price and borrowing fee (in vector forms).

The expression for the equilibrium borrowing fee Δ is

$$\Delta = \gamma \Sigma \bar{B} \left(C_e e - C_\theta \bar{\theta} + C_\omega \omega_\lambda \right), \tag{40}$$

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

$$p = \mu + \gamma \Sigma \bar{B} (B_e e - B_\theta \bar{\theta} + B_\omega \omega_\lambda), \tag{41}$$

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,

$$\Delta = \gamma\sigma\bar{B}\left(C_e e - C_\theta\bar{\theta} + C_\omega\omega_\lambda\right), \tag{42}$$

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,

$$p = \mu + \gamma\sigma(B_e e - B_\theta \bar{\theta} + B_\omega \omega_\lambda), \tag{43}$$

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 benchmarking intensity. 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 elastic lenders are present and benchmarked investors are allowed to lend.

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 benchmarking intensity 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 elastic lenders relaxes the market clearing condition in the lending market.

D.2 Full lending by benchmarked lenders

In this section, I consider the case when benchmarked investors do not have a limit on lending, that is, when $l = 1$.

Scalars defined above are then simplified to

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

Under full lending, C_ω is always negative, so the supply effect of benchmarking on borrowing fee always dominates. This is also because $B_\omega < 0$, hence the index effect is negative.

D.3 No lending by benchmarked lenders

In this section, I consider the case when benchmarked investors are not allowed to lend, that is, $l = 0$. In contrast to no-lending case of the baseline model, the lending market can clear because the supply is now provided by direct investors.

Scalars defined above are then simplified to

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

Thus, if benchmarked investors are not allowed to lend, $C_\omega > 0$ and, naturally, only the demand effect of benchmarking on borrowing fee is present. At the same time, $B_\omega > 0$, hence the index effect is positive, as in the baseline model. Shorting demand goes up with price, pushing the fee up.

What happens to lending supply? Higher price discourages holdings by direct investors while higher fee incentivizes them. Lending supply is $Q^s = \varphi\lambda_D\theta_D = \frac{1}{\gamma\sigma}\varphi\lambda_D(\mu - p + \varphi\Delta)$, and its sensitivity to benchmarking intensity is

$$\begin{aligned}\frac{dQ^s}{d\omega_\lambda} =& \frac{1}{\gamma\sigma}\varphi\lambda_D(\varphi\frac{\partial\Delta}{\partial\omega_\lambda} - \frac{\partial p}{\partial\omega_\lambda}) \\ =& -\varphi\lambda_D\left(\frac{\lambda_M}{a+b}(\varphi^2\lambda_D + \lambda_H) + \lambda_H(\lambda_D + \lambda_H - \varphi) + \varphi^2\lambda_D(\lambda_H + \lambda_D - 1)\right),\end{aligned}$$

which can be positive or negative.

D.4 Restricted lending by benchmarked lenders

In the case when benchmarked investors' lending limit is more lenient 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.

E Economy with costly lending by lenders

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:

$$\max_{\theta_M, l} \quad E_0[-\exp\{-\gamma((a+b)\theta_M(l\Delta + \bar{D} - p - c(l)) - b\omega(\bar{D} - p))\}]. \tag{44}$$

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

$$\theta_M = \frac{1}{\gamma\sigma(a+b)}(\mu - p) + \frac{b}{a+b}\omega + \frac{1}{\gamma\sigma(a+b)}(l\Delta - c(l)). \tag{45}$$

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

The chosen fraction of lending has to simply satisfy

$$\Delta = c'(l), \tag{46}$$

where the marginal increase in lending fraction 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,

$$l = \frac{\Delta}{\kappa}. \tag{47}$$

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 (45) to solve for the equilibrium asset price and borrowing fee. First, substitute the demand functions (45) and (4) into the market clearing condition in the lending market (6),

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

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

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

$$p - l\Delta = \mu + \frac{1}{l\lambda_M/(a+b) + \lambda_H}\left[(1-l)\lambda_H\Delta + \gamma\sigma l\lambda_M b/(a+b)\omega - \gamma\sigma\lambda_H e - \frac{l\lambda_M}{a+b}c(l)\right]. \quad (48)$$

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 (45) into the expression above yields another expression for $p - l\Delta$,

$$p - l\Delta = \mu - \frac{1}{(1-l)\lambda_M/(a+b) + \lambda_D}\left[\lambda_D l\Delta + (1-l)\frac{\lambda_M}{a+b}c(l) + \gamma\sigma\bar{\theta} - \gamma\sigma(1-l)\lambda_M b/(a+b)\omega\right]. \quad (49)$$

Subtract (49) from (48) and rearrange to get the expression for the equilibrium borrowing fee Δ,

$$\Delta = \gamma\sigma\bar{B}\left(C_e e - C_\theta\bar{\theta} + C_\omega\omega_\lambda\right) - \bar{B}C_\omega\frac{\lambda_M}{a+b}c(l), \quad (50)$$

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 (50) 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 (49) 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

$$\begin{aligned} \max_{l,\theta_H} \quad & lE_0[-\exp\{-\gamma(W_0^H + e\bar{D} + \theta_H(\bar{D} - p + \Delta\mathbf{1}_{\theta_H<0}))\}] \\ & + (1-l)E_0[-\exp\{-\gamma(W_0^H + e\bar{D})\}] - c(l), \end{aligned} \tag{51}$$

or, equivalently,

$$\begin{aligned} \max_{l,\theta_H} \quad & -l\exp\{-\gamma[W_0^H + e\mu + \theta_H(\mu - p + \Delta) - \frac{\gamma}{2}\sigma(e+\theta_H)^2]\} \\ & -(1-l)\exp\{-\gamma(W_0^H + e\mu - \frac{\gamma}{2}\sigma e^2)\} - c(l). \end{aligned} \tag{52}$$

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

$$\begin{aligned} \max_{\theta_1^M,\theta_0^M} \quad & lE_0[-\exp\{-\gamma((a+b)\theta_1^M(\Delta + \bar{D} - p) - b\omega(\bar{D} - p))\}] \\ & + (1-l)E_0[-\exp\{-\gamma((a+b)\theta_0^M(\bar{D} - p) - b\omega(\bar{D} - p))\}]. \end{aligned} \tag{53}$$

The market clearing condition in the asset market becomes

$$\lambda_D\theta_D + l(\lambda^M\theta_1^M + \lambda_H\theta_H) + (1-l)\lambda^M\theta_0^M = \bar{\theta}. \tag{54}$$

The lending market clearing condition is

$$l(\lambda^M\theta_1^M + \lambda_H\theta_H) \geq 0. \tag{55}$$

F.2 Portfolio choice

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

$$\theta_1^M = \frac{1}{\gamma\sigma(a+b)}(\mu - p) + \frac{b}{a+b}\omega + \frac{1}{\gamma\sigma(a+b)}\Delta \tag{56}$$

if they meet a hedger and

$$\theta_0^M = \frac{1}{\gamma\sigma(a+b)}(\mu - p) + \frac{b}{a+b}\omega, \tag{57}$$

if they do not.

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

$$\theta_H = \frac{1}{\gamma\sigma}(\mu - p + \Delta) - e. \tag{58}$$

The search intensity is a unique solution to

$$-\exp\{-\gamma[W_0^H + e\mu + \theta_H(\mu - p + \Delta) - \frac{\gamma}{2}\sigma(e+\theta_H)^2]\} + \exp\{-\gamma(W_0^H + e\mu - \frac{\gamma}{2}\sigma e^2)\} = c'(l). \tag{59}$$

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 (54) 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.

$$\lambda_H \theta_H = -\lambda^M \theta_1^M,$$

$$\lambda_H \left[\frac{1}{\gamma\sigma} (\mu - p + \Delta) - e \right] = -\lambda^M \left[\frac{1}{\gamma\sigma(a+b)} (\mu - p) + \frac{b}{a+b} \omega + \frac{1}{\gamma\sigma(a+b)} \Delta \right],$$

$$\left(\lambda_H + \frac{\lambda^M}{a+b} \right) \Delta = \gamma\sigma\lambda_H e$$

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

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

$$\frac{\lambda_H - \lambda_D}{\lambda_H} > l. \tag{60}$$

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 (60). To do so, I plug the equilibrium quantities into (59)

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

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. I also find that, under admissible parameter values, condition (60) 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.