The Real Cost of Benchmarking*

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Abstract

Benchmark-linked capital flows increase firms' CAPM βs, thereby raising managers' perceived cost of equity and reducing investment. Using exogenous variation from Russell and S&P 500 reconstitutions, we show that inclusion in a benchmark stock index increases a stock's CAPM β. Managers interpret the higher β as a higher cost of equity and reduce investment. Consistent with this mechanism, benchmark inclusion also raises the perceived cost of equity among stock analysts and regulators. Industries with larger increases in βs due to benchmarking have accumulated less capital over the past two decades. Benchmark-induced changes in the cross-section of CAPM βs do not cancel out but affect aggregate investment because higher βs fall on many firms with high investment elasticities, while lower βs benefit a few large but inelastic firms.

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Keywords: Benchmarking, Capital Allocation, CAPM Beta, Passive Investing, Perceived Cost of Equity

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Why do we think that a 10% return is good? Well, you have to — whether we're creating shareholder value really goes to what's our cost of capital. [...] Most of you will bring back visions of business school. This is the ***capital asset pricing model****, right? Our cost of equity, about 10.7%.*

— CFO of LKQ Corp. (Q1 2016 Earnings Call)

1 Introduction

The U.S. economy has exhibited two concurrent trends over the past 25 years: weak firm investment relative to high equity valuations and a structural shift toward benchmark-linked capital allocation. The growth of passive mutual funds and ETFs and the evaluation of active managers against benchmarks mean that investors today allocate a large share of capital based on stocks' membership in benchmark indices, as opposed to fundamentals.[1] This inelastic demand affects asset prices, leading to price dislocations (Shleifer, 1986, Harris & Gurel, 1986), increased volatility (Greenwood & Thesmar, 2011, Ben-David et al., 2018), and excess comovement (Vijh, 1994, Barberis et al., 2005, Greenwood, 2008) for stocks in benchmark indices. Whether the asset pricing effects of benchmarking affect firm investment is not well understood.

Our paper documents a novel mechanism through which benchmarking affects firm behavior. We use exogenous variation in the fraction of a stock's market capitalization held by benchmarked funds to show that greater exposure to benchmark-linked capital flows increases the stock's CAPM β estimate (i.e., $\hat{\beta}$). Firm managers interpret this increase in $\hat{\beta}$ as a higher cost of equity and reduce investment. Importantly, changes in firm fundamentals do not drive this effect. Instead, we argue that managers rely on textbook guidance to set discount rates using the CAPM without accounting for the effects of benchmarking on asset prices. By increasing the *perceived* cost of equity, benchmarking lowers investment at the firm, industry, and aggregate level. Our study thus provides new insights into how benchmark-linked ownership affects real outcomes.

We illustrate the mechanism by introducing two frictions into a textbook model of firm investment. First, benchmarking affects asset prices in a way that creates wedges in firms' discount rates. The inelastic demand of benchmarked funds for benchmark constituent stocks raises their price, but also increases their comovement. These forces have opposing effects on the discount rate: the increased stock price lowers the implied discount rate and incentivizes investment, while greater comovement increases exposure to market risk and discourages investment. As such, the

[1] In 2023, \$17.9 trillion in assets were benchmarked to S&P Dow Jones' and \$10.5 trillion to FTSE-Russell's U.S. indices. The Investment Company Institute (2024) reports that passive funds held 18% of the U.S. stock market in 2023. Chinco & Sammon (2024) put the total passive share at twice that number, accounting for institutions with internally managed index portfolios and quasi-indexing active managers (see also Cremers & Petajisto, 2009).

total effect of benchmarking on discount rates and optimal investment is ambiguous. Second, we assume that managers are boundedly rational and behave exactly as they are taught to in corporate finance textbooks and MBA classrooms: they use the weighted average cost of capital (WACC) implied by the CAPM to discount cash flows.

The assumption that managers practice what textbooks teach is key to our mechanism.[2] Managers who set discount rates using their stocks' CAPM $\hat{\beta}$ observe an increase in comovement after benchmark inclusion and infer that their cost of equity has increased. However, the price effect does not enter the CAPM-implied discount rate they compute. The failure to fully internalize the effects of benchmarking leads managers to perceive an increase in their cost of equity. Consequently, benchmark-linked ownership has an unambiguously negative effect on firm investment.

Managers may have strong incentives to behave in this manner since changes in their firm's CAPM $\hat{\beta}$ can directly affect their compensation through capital efficiency targets. Compensation plans frequently award stock or option grants when the firm's return on invested capital (ROIC) exceeds the CAPM-implied cost of capital. This creates high-powered incentives for managers to adjust investment in response to changes in their firm's CAPM $\hat{\beta}$. In 2010, 41% of Russell 3000 firms used capital efficiency targets in long-term incentive plans and 28% used them in short-term plans (Reda & Tonello, 2015). Appendix Figure A1 provides examples from proxy statements.

We test our model's predictions using Pavlova & Sikorskaya's (2023) benchmarking intensity (BMI) measure. BMI is the share of a stock's market capitalization held by funds benchmarked to an index of which the stock is a constituent. BMI covers around 90% of mutual fund and ETF assets and captures the heterogeneous inelastic demand that a stock attracts from those funds because of its benchmark membership. We combine BMI with CAPM $\hat{\beta}$s, market data from CRSP, accounting data from Compustat, and data on managers' perceived cost of capital from Gormsen & Huber (2025a) for the period from 1998 to 2018. The combined data allow us to answer three questions: Does benchmarking affect CAPM $\hat{\beta}$s? Do benchmarking-induced changes in $\hat{\beta}$s affect managers' perceived cost of equity? Do benchmarking-induced changes in $\hat{\beta}$s affect firm investment?

We start by establishing three novel stylized facts about U.S. stocks included in benchmark indices. First, BMI positively correlates with CAPM $\hat{\beta}$ estimates. From 1998 to 2018, CAPM $\hat{\beta}$s and BMI increased in lockstep. The average stock's BMI increased by around 10 p.p., while the *equal-weighted* average $\hat{\beta}$ rose by around 0.36. Importantly, changes in fundamental risk or leverage cannot explain the $\hat{\beta}$ increase. Instead, we find systematic differences in $\hat{\beta}$s across market capitalization ranks used in the construction of benchmark indices. Second, BMI negatively correlates

[2] For example, corporate finance textbooks by Brealey et al. (2023), Berk & DeMarzo (2023), and Ross et al. (2016).

with investment rates. In the cross-section, firms with higher BMI invest less. In the time series, average investment rates have declined, with the decline more pronounced for firms that experienced larger increases in $\hat{\beta}$s and BMI. Third, BMI negatively correlates with net equity issuance rates. In the cross-section, firms with higher BMI issue less equity. In the time series, average net equity issuance has fallen, with the decline more pronounced for firms that saw larger increases in BMI. These facts suggest that the growth of benchmark-linked ownership and the institutional design of benchmark indices impact firms' real and financial decisions.

Next, we link exogenous changes in BMI to changes in CAPM $\hat{\beta}$ using a difference-in-differences design around Russell reconstitution. The Russell indices are widely used equity benchmarks and reconstitute annually based on market capitalization ranks. Changes in Russell benchmark membership around inclusion cutoffs create exogenous variation in BMI (Pavlova & Sikorskaya, 2023). Our baseline specifications address potential threats to the validity of the Russell identification strategy discussed in the literature. We use end-of-May, not June, market capitalization to avoid selection bias (Chang et al., 2015, Appel et al., 2024). To approximate Russell's proprietary market caps, we follow Ben-David et al. (2019) and use publicly available data which allow us to accurately predict benchmark assignment and mitigate mismeasurement concerns (Glossner, 2024). We restrict our sample to stocks within 300 ranks around the Russell benchmark cutoffs to ensure we capture changes in BMI due to reconstitution (Pavlova & Sikorskaya, 2023). We include controls for the banding policy introduced by Russell after 2007 (Appel et al., 2019). We additionally control for stocks' momentum and liquidity. We include high-dimensional industry-by-time fixed effects that remove time-varying unobserved heterogeneity to ensure that our estimates are well-identified. Lastly, we conduct a series of exclusion restriction tests. We find no evidence that changes in BMI correlate with changes in fundamental risk exposure, access to debt markets, governance scores, or the likelihood of facing an activist investor.

An exogenous 10 percentage points (p.p.) increase in BMI raises CAPM $\hat{\beta}$s by 0.25, on average. Using 21-day $\hat{\beta}$s, we find that the increase occurs immediately after index reconstitution, consistent with excess comovement rather than changing fundamentals. When using longer-horizon rolling-window $\hat{\beta}$s, for example, 252 days or 156 weeks, the effect gradually builds up as older data points leave the sample window and might go unnoticed for a substantial amount of time.

The effects are symmetric, with stocks experiencing a decrease in BMI showing a corresponding decrease in $\hat{\beta}$ of similar magnitude. We find similar magnitudes in panel regressions where we regress CAPM $\hat{\beta}$ on BMI in levels. Notably, we find no effect of the institutional ownership ratio (IOR) on $\hat{\beta}$s, suggesting that the effect is specific to benchmark-linked ownership.

The increase in CAPM $\hat{\beta}$ arises from heterogeneous exposure to benchmark-linked *passive* flows. Cross-sectional changes in $\hat{\beta}$s correlate with net flows into passive mutual funds and ETFs, but not with net flows into active mutual funds. Stocks that transition from the Russell 1000 to the Russell 2000 index further support this conclusion: prior work shows the Russell 1000/2000 transition shifts ownership from active to passive funds without changing overall institutional ownership (Chang et al., 2015, Appel et al., 2016). Benchmark-linked capital flows affect CAPM $\hat{\beta}$s because of the cross-sectional dispersion in BMI. The institutional design of benchmark indices segments the market (e.g., Russell 1000 vs. Russell 2000, value vs. growth), creating unequal ownership by benchmarked mutual funds and ETFs, and in turn, unequal exposure to correlated flows (Buffa & Hodor, 2023, Pavlova & Sikorskaya, 2023). If all funds were to index to a single comprehensive market benchmark, such as the CRSP value-weighted index, BMI would be uniform across stocks. In this case, index trading would affect stocks proportional to their market weight, and we would not observe heterogeneous changes in $\hat{\beta}$ tied to rank cutoffs or style categories.

The effect of increased exposure to benchmark-linked capital flows on the CAPM-implied cost of equity is large and persistent. Our baseline results imply an initial increase of 150 bps, assuming an equity risk premium of 6%. Even after six years, we find that the cost of equity is still more than 50 bps higher than before the exogenous BMI increase. The long-run persistence reflects both sticky benchmark membership[3] as well as the slow decay of rolling-window $\hat{\beta}$ estimates. If managers rely on the CAPM to set hurdle rates and allocate capital, this persistent change in $\hat{\beta}$s may have long-lasting effects on investment (Gormsen & Huber, 2025a).

In contrast, the effect of an exogenous BMI increase on the implied cost of capital (ICC) derived from stock prices is small and short-lived.[4] We observe an initial decrease of 21 bps in the ICC, equivalent to a 3.0% price increase, close to estimates of Pavlova & Sikorskaya (2023) and Chang et al. (2015). However, we find that the price effect reverts within six months. We also find no evidence that firms exploit the short-term price dislocations by issuing equity, likely because investors view equity issuance as a negative signal. Consistent with this interpretation, we provide qualitative evidence from earnings call transcripts that managers view benchmark inclusion as a corporate milestone for investor relations, not as a mechanism that lowers the cost of equity or as an opportunity to alter the capital structure. This evidence suggests that benchmarking primarily impacts managers' perceived cost of equity through persistent changes in CAPM $\hat{\beta}$s rather than through short-term stock price dislocation.

Consistent with managers using the CAPM, we find that an exogenous increase in BMI results in

[3]Online Appendix Figure C11 shows that transitions from the Russell 1000 to the Russell 2000 are highly persistent.
[4]The ICC is the internal rate of return that equates a stock's price to the present value of expected cash flows.

higher perceived costs of capital and hurdle rates by managers in the Gormsen & Huber (2025a) data. We use changes in BMI around Russell benchmark reconstitution as an instrumental variable (IV) to identify the effect of changes in CAPM $\hat{\beta}$ on a firm's perceived cost of capital. Our IV estimates imply a perceived equity risk premium of around 3.3%, close to the average equity risk premium of 3.6% reported by CFOs in the survey of Graham & Harvey (2018). We provide ancillary evidence from earnings calls supporting this mechanism, as managers explicitly state that they use the CAPM to determine their cost of equity.

We provide corroborating evidence that benchmarking-induced changes in CAPM $\hat{\beta}$ change the perceived cost of equity in five additional datasets: Independent stock analysts of Morningstar and Value Line, as well as sell-side analysts covered by I/B/E/S, all report a higher perceived cost of equity after an exogenous increase in BMI. Similarly, the authorized cost of equity of regulated monopolies such as public utilities and railroads rises when their BMI increases. Across these additional datasets, perceived equity risk premia range from 4% to 12% per year.

Our second set of results investigates how managers and firms react to increases in their stock's BMI and CAPM $\hat{\beta}$. For a manager who follows textbook guidance to set investment policies using the WACC implied by the CAPM, an increase in $\hat{\beta}$ raises the cost of capital and should lead to declining investment. Consistent with this, a higher BMI predicts lower investment rates in panel regressions: A 10 p.p. higher BMI is associated with a 12.5% lower investment rate relative to the sample mean. This negative association holds after including time-by-industry and firm fixed effects, as well as controls for size, leverage, cash flow, firm age, and Tobin's q.

The dynamic response of investment to a year-on-year increase in BMI is quantitatively consistent with a perceived cost of equity increase. We use Jordà's (2005) local projections (LP) to estimate the impulse response of investment rates to a year-on-year increase in BMI. A 10 p.p. year-on-year increase in BMI gradually lowers investment by a cumulative 7.8% over the next 10 years. The implied semi-elasticity of investment with respect to the cost of capital is −6.4, close to estimates of −5 in Koby & Wolf (2020) and −7.2 in Zwick & Mahon (2017). We find that the negative investment response is significantly larger for firms that use more equity financing and for firms with higher asset duration. A placebo test using changes in institutional ownership ratio (IOR) yields a small positive effect on investment. Because IOR does not affect $\hat{\beta}$s, this result suggests the negative investment effect is specific to benchmark-linked ownership by mutual funds and ETFs, rather than institutional ownership generally.

Using exogenous variation in BMI from Russell reconstitution, we instrument for the effect of CAPM $\hat{\beta}$ on investment in local projections. A benchmarking-induced 100 bps increase in the

CAPM-implied cost of capital reduces capital expenditures by a cumulative 10.2% over six years. The effects are robust to alternative bandwidths around the Russell 2000 cutoff, momentum controls that address "fallen angels" concerns, granular industry fixed effects, and alternative definitions of the investment rate. Firms also reduce intangible investment and acquisitions, consistent with a higher cost of equity. The investment response is stronger for firms that rely more on equity financing, and we find no evidence that firms offset the shock to the cost of equity by substituting toward debt.

We provide additional evidence for the mechanism that increases in BMI raise managers' perceived cost of equity and hurdle rates by increasing CAPM $\hat{\beta}$s, with capital efficiency targets in executive compensation plans as a key amplification channel. Capital efficiency targets are common in pay contracts and reward managers for accounting returns (e.g., ROIC) relative to WACC (Reda & Tonello, 2015). A higher $\hat{\beta}$ raises the CAPM-implied cost of equity and tightens the spread between ROIC and WACC, making marginal projects less attractive. Using ISS Incentive Lab data, we show that ROIC targets are tightly linked to CAPM $\hat{\beta}$s and increase systematically with BMI. Moreover, investment responds more strongly to exogenous BMI increases at firms having capital efficiency targets, with effects about 2.5 times larger and materializing faster.

Our second natural experiment studies additions to the S&P 500 in a difference-in-differences framework. We find that firms added to the S&P 500 see a similar increase in $\hat{\beta}$. Moreover, we find that inclusion leads to a gradual but significant decline in investment, alongside a sharp and sustained increase in net payouts. Initially funded from cash reserves, firms increasingly sustain the payouts by reducing investment. These results corroborate our central hypothesis: increases in CAPM $\hat{\beta}$s due to benchmarking raise firms' perceived cost of equity, leading managers to reduce investment and increase shareholder distributions.

To test whether these firm-level effects aggregate, we conduct an industry level analysis using long-difference IV regressions on over 100 manufacturing industries from the NBER-CES dataset. We instrument the change in industry level CAPM $\hat{\beta}$s with the corresponding change in BMI. We find that from 1998 to 2016, higher benchmarking-induced $\hat{\beta}$s reduced capital accumulation by 9.8%, or about 0.5% annually. A key feature of this approach is that it nets out intra-industry reallocations such as business stealing. The significant net effect suggests industry-wide spillovers, consistent with managers learning from the asset prices of other firms in their industry (Foucault & Fresard, 2014, Dessaint et al., 2019, Goldstein et al., 2021, Kim et al., 2024). The results are robust to controls for industry pre-trends, exposure to Chinese import competition, and sectoral fixed effects that identify effects from within-sector variation.

Lastly, we show that the effects of cross-sectional changes in CAPM $\hat{\beta}$ on aggregate investment do not cancel out, even though the value-weighted β is one by construction. The intuition that they should cancel rests on two assumptions the data reject. First, firms' shares in aggregate investment must mirror their market capitalization weights. Empirically, they differ substantially: the financial sector averages 17.3% of U.S. market capitalization yet only 3.5% of capital expenditures. Second, the elasticity of investment with respect to the cost of capital must be uniform across firms. A large literature shows that large firms' investment is relatively inelastic to financing costs, while smaller firms' investment is highly elastic (Gertler & Gilchrist, 1994, Zwick & Mahon, 2017, Crouzet & Mehrotra, 2020, Best et al., 2024). The aggregate effect depends on the covariance between firms' investment elasticities and the distribution of $\hat{\beta}$ shocks. A few large firms receive a subsidy through lower $\hat{\beta}$, while most face higher $\hat{\beta}$. Because large firms adjust little, their subsidy cannot offset the contraction of smaller firms, and aggregate investment falls.

We organize the paper as follows. The remainder of this section discusses the related literature. Section 2 describes the data. Section 3 documents several new facts about the cross-section of benchmark stocks. Section 4 illustrates our mechanism in an MBA-textbook model of firm investment. Section 5 establishes a link between benchmarking, CAPM $\hat{\beta}$s, and the perceived cost of equity. Section 6 tests whether benchmarking-induced changes in $\hat{\beta}$ affect real outcomes at the firm level. Section 7 tests for industry-wide effects of benchmarking on investment. Section 8 examines whether benchmarking affects aggregate investment. Section 9 concludes.

Related Literature While the inelastic demand associated with benchmark-linked ownership is often viewed as lowering firms' financing costs and thus as beneficial for the real economy, we uncover a more nuanced and, for many firms, adverse effect. Our contribution is threefold.

First, we show that benchmark-linked ownership alters the covariance structure of returns in a way that systematically affects CAPM $\hat{\beta}$s, holding fundamentals, leverage, and cash-flow risk constant. This advances the index-inclusion and comovement literature that finds price dislocations (Shleifer, 1986, Chang et al., 2015, Pavlova & Sikorskaya, 2023), higher volatility (Ben-David et al., 2018), and excess comovement around benchmark events (Vijh, 1994, Barberis et al., 2005, Greenwood, 2008).[5] We differ from this literature in three respects. We extend event-time studies to a long-horizon and cross-sectional analysis of CAPM $\hat{\beta}$s. We document that measured $\hat{\beta}$s rose in lockstep with BMI over the past 25 years, with most stocks experiencing a rise and only a small number of the largest firms exhibiting a decline. We find that net flows into *passive* mutual funds

[5] See also Veldkamp (2006), Boyer (2011), Basak & Pavlova (2013), Wahal & Yavuz (2013), Claessens & Yafeh (2013), Antón & Polk (2014), Da & Shive (2018), Jylhä et al. (2018), Buffa & Hodor (2023), Fang et al. (2024), Kim (2025).

and ETFs drive these changes.[6] We thus provide evidence for theories that posit excess comovement due to the shift to passive investing (Basak & Pavlova, 2013, Chabakauri & Rytchkov, 2021, Baruch & Zhang, 2022, Bond & Garcia, 2022, Davies, 2024).[7]

Second, we show that these benchmark-linked $\hat{\beta}$ increases affect the real economy because practitioners set discount rates using the CAPM.[8] We provide evidence that higher BMI raises the perceived cost of equity and lowers investment. Relative to Kashyap et al. (2021), who predict more investment due to the price effect of inelastic demand for benchmark stocks, we identify a behavioral channel: managers follow textbook guidance to use the CAPM and fail to internalize the full effect of benchmarking on asset prices. This bounded rationality may arise because managers believe markets are efficient and ignore the effects of non-fundamental demand on prices, use sparse models that focus on variables perceived to be of first-order importance (Gabaix, 2014), or face limited information-processing capacity (Sims, 2003).[9] By linking passive flows to how practitioners use the CAPM, we shift the passive investing debate from statistical price efficiency to revelatory efficiency (Bond et al., 2012). Benchmarking degrades the informativeness of covariance signals that guide real allocation, complementing recent evidence on information production and arbitrage frictions associated with benchmark-linked ownership (Brogaard et al., 2019, Coles et al., 2022, Sammon, 2024, Sikorskaya, 2024).[10]

The empirical literature finds mixed effects of benchmark inclusion on firm investment. On the negative side, Cremers et al. (2020) show that micro-cap stocks joining the Russell 2000 from below reduce R&D expenditures *if* ownership by short-term, high-turnover institutions increases after inclusion. Their mechanism is distinct from ours: *active* short-termist investors pressure managers to act myopically, whereas our mechanism posits that benchmark-linked ownership raises the perceived cost of equity through higher CAPM $\hat{\beta}$s. Bennett et al. (2023) similarly document a decline in investment following S&P 500 inclusion, emphasizing peer effects and categorical thinking as compensation peer groups expand to include more S&P 500 firms. We propose a

[6]On the importance of institutional flows, see Gabaix et al. (2006), Coval & Stafford (2007), Basak et al. (2007), Chen et al. (2010), Greenwood & Thesmar (2011), Lou (2012), Chien et al. (2012), Gabaix & Koijen (2021).

[7]For other theories of passive investing, see Stambaugh (2014), Malikov (2019), Brown et al. (2021), Gârleanu & Pedersen (2022), Schmalz & Zame (2024), Cong et al. (2024), Haddad et al. (2025), Jiang et al. (2025).

[8]For evidence on this, see Graham & Harvey (2001), Da et al. (2012), Jacobs & Shivdasani (2012), Krüger et al. (2015), Berk & Van Binsbergen (2016), Barber et al. (2016), Jagannathan et al. (2016), Dessaint et al. (2020), Mukhlynina & Nyborg (2020), Graham (2022), Cho & Salarkia (2022), Décaire & Graham (2024), Jensen (2024), Kontz (2025).

[9]For evidence that behavioral biases of managers influence firm investment, see research on overconfidence (Malmendier & Tate, 2005, Landier & Thesmar, 2008), overprecision and miscalibration (Ben-David et al., 2013, Barrero, 2022, Boutros et al., 2025), overreaction (Dessaint & Matray, 2017), lifetime experiences (Malmendier et al., 2011, Dittmar & Duchin, 2016, Schoar & Zuo, 2017), and education (Bertrand & Schoar, 2003, Custódio & Metzger, 2014).

[10]ETF investing may increase price informativeness about industry-wide factors while reducing idiosyncratic or private information (Bhattacharya & O'Hara, 2018, Cong et al., 2024, Antoniou et al., 2023).

complementary mechanism in which inclusion raises the perceived cost of equity by increasing CAPM $\hat{\beta}$s. In contrast, Bena et al. (2017) and Kacperczyk et al. (2021) find modest investment increases following inclusion in the MSCI ACWI. We reconcile our mechanism with the MSCI evidence by showing that MSCI inclusion reduces firms' CAPM $\hat{\beta}$ relative to the local market index, lowering the perceived cost of equity, consistent with a positive effect on investment. Using a sample of 251 consumer goods firms, Sharma (2026) finds that benchmark inclusion leads to market share gains through lower prices and increased trade credit and marketing expenditures.

Third, we establish aggregate implications and show that cross-sectional changes in investment do not cancel out, even though cross-sectional changes in the value-weighted CAPM βs sum to zero. The covariance between firms' investment elasticities and $\hat{\beta}$ shocks determines the aggregate effect. A few large firms receive a subsidy through lower $\hat{\beta}$, while most face higher $\hat{\beta}$. Because larger firms' investment is relatively inelastic to the CAPM-implied cost of capital, their subsidy cannot offset the contraction of smaller firms, and aggregate investment falls.

2 Data and Sample

We use four main data sources in our empirical analysis: (1) Pavlova & Sikorskaya's (2023) measure of benchmarking intensity, (2) U.S. stock market data from CRSP, (3) firm-level data from S&P's Compustat and other sources, and (4) data on the perceived cost of capital of managers, stock analysts, and regulators. Our sample covers 1998 to 2018, the period for which the BMI measure is available. In some cases, we extend the sample back to earlier years when data availability allows. Online Appendix K provides variable definitions and corresponding data sources.

Benchmarking Intensity Our measure of a stock's exposure to benchmark-linked capital flows is the monthly benchmarking intensity (BMI) measure of Pavlova & Sikorskaya (2023), available from 1998 to 2018. BMI captures the fraction of capital that is invested in a stock inelastically (i.e. without regard to a risk-return trade-off) due to the stock's inclusion in benchmark indices. Pavlova & Sikorskaya (2023) define the BMI for stock i in month t as

$$\text{BMI}_{i,t} = \sum_{j=1}^{J} \frac{\text{AUM benchmarked to index } j \text{ at time } t \times \text{weight of stock } i \text{ in index } j \text{ at time } t}{\text{Market capitalization of stock } i \text{ at time } t} \tag{1}$$

where AUM are assets under management of mutual funds and ETFs benchmarked to index j. Pavlova & Sikorskaya (2023) construct BMI from 34 indices that account for about 90% of mutual fund and ETF assets. The nine Russell indices are the primary driver of this measure, contributing about 73% of the average stock's BMI, followed by S&P (11%) and CRSP (8%) indices.

A key advantage of BMI over an index inclusion indicator is its granularity. BMI captures the total, heterogeneous change in benchmarked capital when a stock switches not only between broad market indices (e.g., Russell 1000/2000) but also between style indices (e.g., Value and Growth). As Pavlova & Sikorskaya (2023) note, a stock moving from the Russell 1000 Value to the Russell 2000 Value index experiences different flows than a stock moving between Growth indices.

Stock Market Data Our sample consists of common equities listed on the NYSE, AMEX, and NASDAQ. We obtain stock market data from the Center for Research in Security Prices (CRSP), additional asset pricing variables from Jensen et al. (2023), and estimates of stocks' implied cost of capital (ICC) from Eskildsen et al. (2024).[11] We primarily use CAPM β estimates from Welch (2022). The estimates are based on exponentially weighted least squares regressions of a firm's winsorized daily excess return on the market excess return, estimated on an expanding window. We additionally estimate rolling-window $\hat{\beta}$s using 21 daily, 252 daily, 156 weekly, or 36 monthly returns against the CRSP value-weighted index. We explicitly state when we use these alternative estimates in place of the primary Welch (2022) $\hat{\beta}$s. Appendix Table A2 reports summary statistics for the monthly BMI-CAPM $\hat{\beta}$ panel covering 1998m1 to 2018m8.

Firm-level Data We use annual Compustat data for publicly listed companies incorporated and located in the U.S. from 1998 to 2018. In the Compustat sample, we exclude financial firms (SIC codes 6000-6999) and firms in regulated industries (4900-4999), as well as firms with less than \$50m in total assets or less than \$10m in sales (in 2017 dollars). Firms must have at least five years of consecutive data such that we can estimate long-term effects.[12] We winsorize the data at the 2.5% and 97.5% levels. We use additional firm or industry level data in specific analyses and state the source upon its first appearance. Appendix Table A5 reports summary statistics for the annual Compustat investment panel covering 1998 to 2018.

Data on Perceived Cost of Equity We source data on managers' perceived cost of capital and hurdle rates from the public database of Gormsen & Huber (2025a). We additionally obtain stock analysts' perceived cost of equity from Morningstar Direct, perceived riskiness of stocks from Value Line, subjective return expectations from I/B/E/S, and data on regulators' authorized cost of equity for utilities and railroads (for details, see Online Appendix G).

[11] Using these measures, Eskildsen et al. (2024) estimate a positive green convenience yield in equities. Similarly, Kontz (2023) estimates a green convenience yield in senior tranches of automobile asset-backed securities.

[12] We verify that these restrictions do not materially affect our results, cf. Table 4 and Online Appendix Table B4.

3 Novel Stylized Facts About Benchmark Stocks

We establish three novel stylized facts about U.S. stocks in benchmark indices. First, BMI is positively associated with CAPM $\hat{\beta}$ estimates. From 1998 to 2018, $\hat{\beta}$s and BMI rose in lockstep: the average stock's BMI increased by about 10 p.p., while the equal-weighted average $\hat{\beta}$ increased by about 0.36. Second, BMI is negatively associated with investment. Firms with higher BMI invest less, both in the cross-section and over time. Third, BMI is negatively associated with net equity issuance. Firms with higher BMI issue less equity, both in the cross-section and over time. Together, these facts suggest that benchmark-linked ownership and benchmark design affect firms' financing and investment decisions.

To visualize these facts across market capitalization ranks, we mirror the construction of the Russell indices in our empirical design. We fix each stock's market capitalization rank at the end of May and plot variables of interest over the following year. This timing isolates the effects of Russell benchmark membership, since end-of-May ranks have no other inherent economic meaning. We group stocks into bins of roughly 100 consecutive ranks and compute equal-weighted means of BMI, CAPM $\hat{\beta}$, investment, and net equity issuance. Absorbing time fixed effects isolates the cross-sectional relationship between these variables and firm rank within each period.

To visualize the cross-sectional relationship between BMI and each outcome, we additionally plot binned scatters of the following regression in Figure 2:

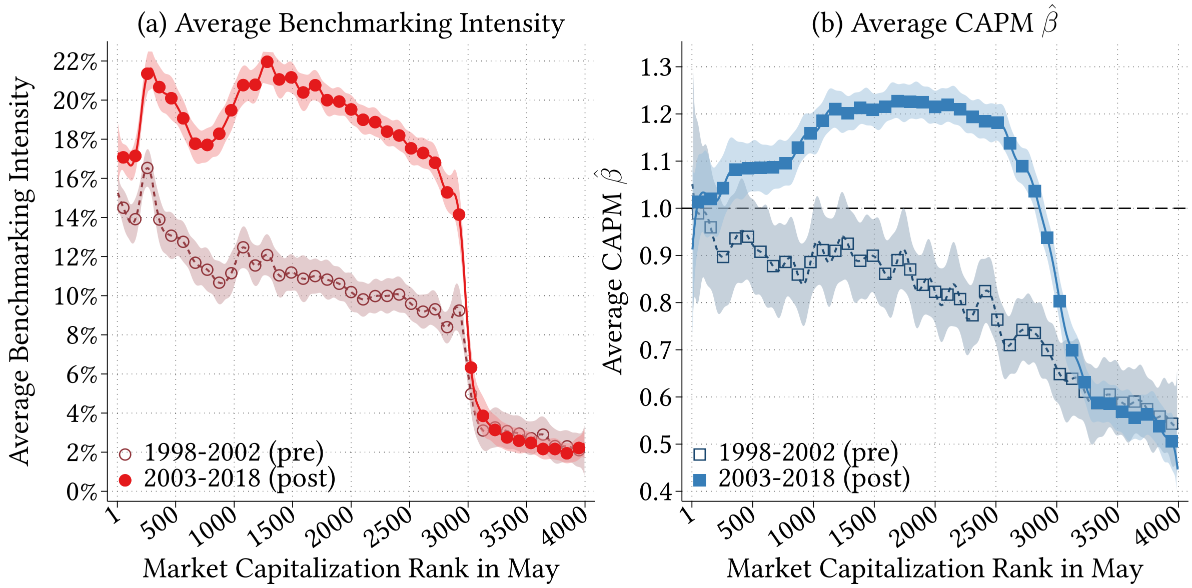
$$\text{Outcome}_{i,t+1} = \alpha_{t,\text{Rank Bucket}} + \gamma \,\text{BMI}_{i,t} + \varepsilon_{i,t+1},$$

where $\alpha_{t,\text{Rank Bucket}}$ are time fixed effects interacted with rank buckets defined every 250 market capitalization ranks. This specification flexibly controls for time-varying differences across the market capitalization spectrum, ensuring that firm size does not drive the results.

Fact 1: Benchmarking Intensity positively correlates with CAPM β estimates. Figure 1 plots BMI and $\hat{\beta}$s across market capitalization ranks in May, separately for the pre-2003 and post-2002 periods. We split the sample in 2003 when BMI increases substantially, coinciding with tax reforms that caused large net flows into mutual funds (Mainardi, 2025).

Two patterns emerge. First, both BMI and $\hat{\beta}$s increased after 2002 across nearly the entire market capitalization spectrum. For Russell 2000 stocks (ranks 1000–3000), average BMI almost doubled from 9.7% to 17.8%, while the average $\hat{\beta}$ rose 46%, from 0.81 to 1.18. Changes in BMI and $\hat{\beta}$s are highly correlated (ρ=0.92) across market capitalization ranks (Appendix Figure A3). Second,

Figure 1: Benchmarking Intensity and CAPM $\hat{\beta}$ vs. Market Capitalization Ranks in May



Notes: This figure plots binned scatters of BMI and CAPM $\hat{\beta}$ against May market capitalization ranks. Each bin reflects the equal-weighted average of 100 ranks. We identify the conditional means from cross-sectional variation by absorbing year-month fixed effects. Outlined bins use 1998-2002 data; filled bins use 2003-2018. Shaded areas show 95% confidence bands with standard errors clustered by stock and year-month.

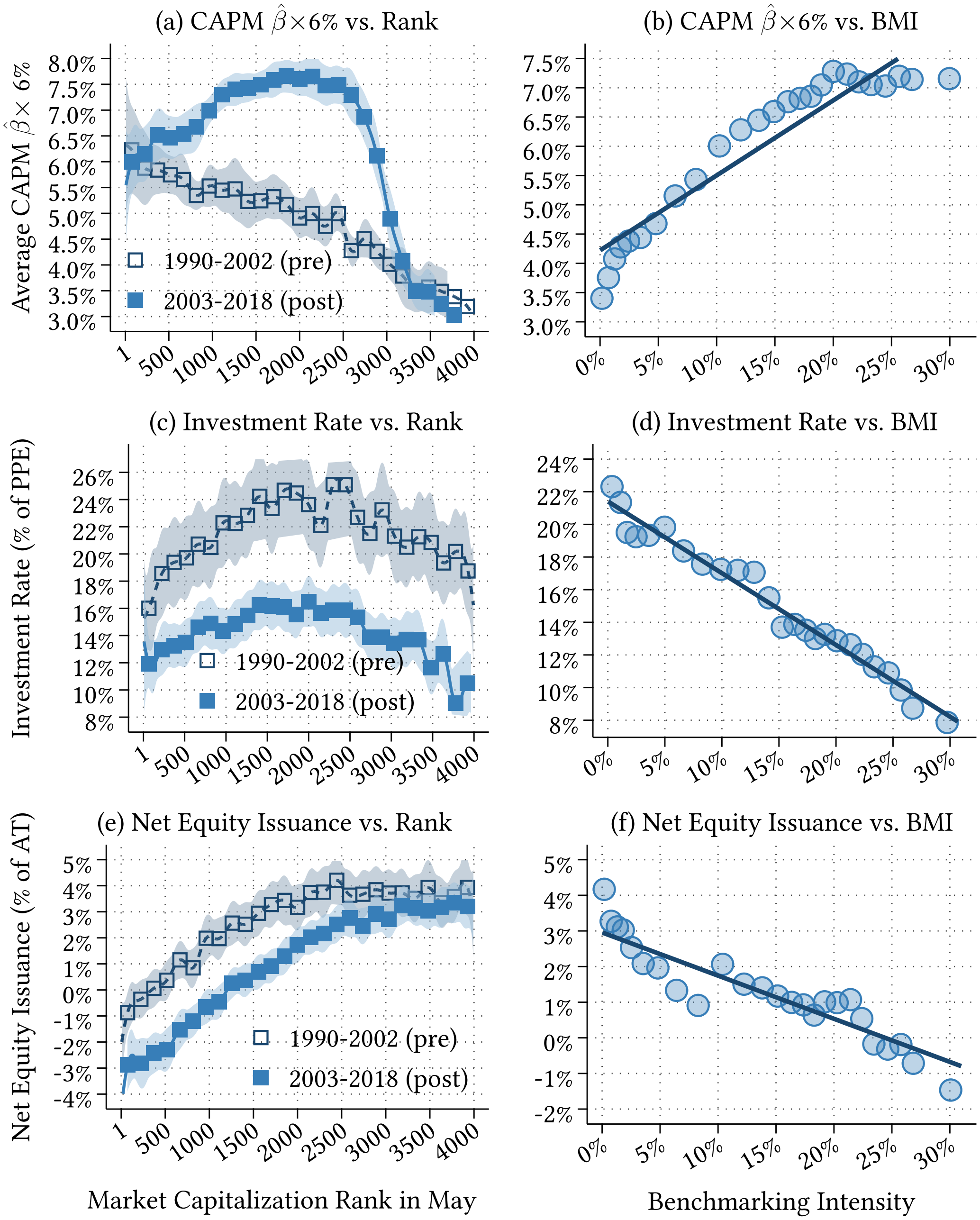
both series display discontinuities aligned with Russell benchmark construction rules. Average BMI and $\hat{\beta}$s increase around the 1000th rank, the threshold between the Russell 1000 and 2000. Both series then decline near the Russell 3000 cutoff. These patterns suggest that the institutional design of benchmark indices affects stocks' estimated market risk.

The widespread increase in individual $\hat{\beta}$s does not imply that the value-weighted market β changes, which equals 1 by construction. An Olley-Pakes decomposition shows that the increase in the equal-weighted average $\hat{\beta}$ above 1 is offset by a shift in the covariance between market-cap weights and $\hat{\beta}$s from positive to negative.[13] This reflects a structural inversion: whereas larger stocks historically had higher CAPM $\hat{\beta}$s, smaller stocks now exhibit higher $\hat{\beta}$s. Firms that experienced $\hat{\beta}$ increases account for over 70% of capital expenditures in Compustat and saw a weighted average $\hat{\beta}$ increase of around 0.1, corresponding to a 60 bps higher CAPM-implied expected return. The few large firms whose $\hat{\beta}$s declined hold sufficient market weight to offset the increase in the equal-weighted average $\hat{\beta}$ but represent a much smaller share of real investment.

Greater BMI is associated with an increase of up to 300 bps in the CAPM-implied cost of eq-

[13] The value-weighted β decomposes as $\sum_i \omega_{i,t}\hat{\beta}_{i,t} = \bar{\beta}_t + \text{cov}(\omega_{i,t}, \hat{\beta}_{i,t}) = 1$. Since the equal-weighted average $\bar{\beta}_t$ rose above 1 (see Appendix Figure A2), the covariance term turned negative. Appendix Table A1 shows that the average $\hat{\beta}$ of the 50 largest firms declined from 1.07 to 0.94 after 2002, while $\hat{\beta}$s of smaller firms rose above 1.

Figure 2: New Facts About the Cross-Section of Benchmark Stocks



Notes: This figure plots binned scatters of CAPM $\hat{\beta}$s multiplied by a 6% equity risk premium, investment rate (capital expenditure scaled by lagged gross property, plant, and equipment), and net equity issuance (scaled by lagged total assets), against market capitalization ranks and benchmarking intensity (BMI). Panels (a), (c), and (e) show bins of approx. 150 ranks; outlined bins use 1990–2002 data, filled bins use 2003-2018. Shaded regions denote 95% confidence bands with standard errors clustered by stock and year. Panels (b), (d), and (f) show 25 quantile-spaced bins, constructed after absorbing year-by-rank-bucket fixed effects, with buckets defined every 250 market capitalization ranks, using the 1998-2018 sample for which BMI is available.

uity. Panel (a) of Figure 2 translates $\hat{\beta}$s into excess return space by multiplying by an equity risk premium of 6%. The implied cost of equity increases especially for small- and mid-cap firms. Panel (b) shows that $\hat{\beta}$s correlate with BMI in the cross-section. A 10 p.p. higher BMI predicts a $\hat{\beta}$ increase of 0.25, corresponding to 150 bps higher cost of equity. The estimation includes year-month-by-rank-bucket fixed effects to ensure the correlation is not driven by firm size.

Changes in capital structure do not explain the rise in CAPM $\hat{\beta}$s. If leverage were the driver, unlevered asset $\hat{\beta}$s would remain stable. Instead, asset $\hat{\beta}$s mirror equity $\hat{\beta}$s: for Russell 2000 stocks, the average asset $\hat{\beta}$ rose by 0.29 (Appendix Figure A4). The increase is robust to daily, weekly, or monthly estimation frequencies (Appendix Figure A2). Nor does the increase reflect greater cash flow risk: accounting-based cash flow βs (Cohen et al., 2009) and consumption growth βs (Kim et al., 2024) show no corresponding change (Appendix Figure A4; Online Appendix Figure B4). Higher $\hat{\beta}$s thus reflect a market-based shift rather than changes in fundamentals.

Fact 2: Benchmarking intensity negatively correlates with investment. Panels (c) and (d) of Figure 2 show that firms more exposed to benchmarking invest less. We measure investment as annual capital expenditures scaled by lagged gross property, plant, and equipment. Panel (c) shows a broad-based decline in investment rates since the 2000s. The decline is most pronounced for Russell 2000 firms, whose average investment rate fell by 8.5 p.p. (from 24.1% to 15.6%), compared to 3.6 p.p. for the 100 largest firms. Panel (d) displays a strong negative cross-sectional correlation between investment rates and BMI, with year-by-rank-bucket fixed effects ensuring the relationship is not driven by firm size. This negative correlation suggests that the growth of benchmarking contributes to the aggregate decline in investment (Gutiérrez & Philippon, 2017).[14]

Fact 3: Benchmarking intensity negatively correlates with net equity issuance. Panels (e) and (f) of Figure 2 show that firms more exposed to benchmarking issue less equity. We measure net equity issuance as equity issued minus equity repurchased, scaled by lagged total assets. Panel (e) plots net issuance by market capitalization rank and shows that the post-2002 decline is broad-based, affecting large-, mid-, and small-cap firms alike. Panel (f) shows that net equity issuance and BMI are negatively correlated in the cross-section. Firms in the highest BMI bins are, on average, net repurchasers of their own equity, while those with low BMI remain net issuers. The estimation includes year-by-rank-bucket fixed effects to ensure the relationship is not driven by firm size. This finding adds a cross-sectional dimension to the well-documented shift from dividends toward buybacks (see, e.g., Grullon & Michaely, 2002).

[14] Online Appendix Figure B3 confirms robustness to alternative investment rate definitions.

4 A Stylized Model of Firm Investment with Benchmarking

With these facts in hand, we present a stylized model that illustrates how benchmarking, through its effect on CAPM-implied discount rates, affects firm investment. We model the effects here in a stylized fashion as wedges in firms' discount rates. We formally derive these wedges in a three-period setting with (boundedly rational) managers in Online Appendix D.

Textbook Investment Policy Corporate finance textbooks instruct managers to adopt an investment policy that maximizes firm value by accepting only projects with positive net present value (NPV). Formally, consider a one-period project that requires an upfront cost C and delivers a random cash flow Y in the next period. The project has positive NPV if its present value exceeds its cost: NPV $= \mathbb{E}[MY] - C > 0$, where M is the one-period stochastic discount factor. In standard textbook implementations, managers approximate valuation by discounting expected cash flows at a constant required return. Let r_A denote the required one-period expected return for the project, i.e., the "asset" or "project" cost of capital. Then the decision rule is $E[Y]/(1 + r_A) > C$. Textbooks often operationalize r_A using the CAPM:

$$r_A = r_f + \beta^A ERP, \qquad \beta^A = \frac{\text{Cov}(R_A, R_m)}{\text{Var}(R_m)}, \tag{2}$$

where r_f is the risk-free rate, $ERP = \mathbb{E}[R_m] - r_f$ is the equity risk premium, and β^A is the project's β with the market. When projects are similar to the firm's existing assets and the firm maintains a stable target leverage, managers commonly proxy the project discount rate with the firm's weighted average cost of capital, $r_{\text{WACC}} = \frac{E}{D+E} r_E + \frac{D}{D+E} r_D(1-\tau)$, with the cost of equity computed via the CAPM, $r_E = r_f + \beta^E ERP$. Under the additional approximation that debt is close to risk-free (so $\beta_D \approx 0$), the project (asset) β can be inferred from the equity β using the standard unlevering relation (in market values),

$$\beta^A \approx \frac{\beta^E}{1 + (1-\tau)D/E}.$$

Accordingly, a manager can form an empirical hurdle rate $\hat{r}_A = r_f + \hat{\beta}^A ERP$ from an estimated equity $\hat{\beta}^E$ and invest when $\mathbb{E}[Y]/(1 + \hat{r}_A) > C$.

The Presence of Benchmarked Funds Affects Asset Prices Benchmarked funds' inelastic demand increases the prices of benchmark constituents and thereby lowers their implied discount rates (Kashyap et al., 2021). However, benchmark membership also induces excess comovement between constituents unrelated to the aggregate risk exposure of the firm's cash flows. The excess comovement increases $\hat{\beta}^E$ and thus raises the discount rate in proportion to the equity risk premium. We illustrate these two opposing forces in reduced form by postulating two discount rate wedges as functions of a stock's benchmarking intensity (BMI). The price pressure from benchmark inclusion reduces the implied discount rate by $\Delta_P(BMI)$. At the same time, β^E increases to $\hat{\beta}^E = \beta^E + \Delta_\beta(BMI)$. Both $\Delta_P(BMI)$ and $\Delta_\beta(BMI)$ monotonically increase in BMI and satisfy $\Delta_P(0) = \Delta_\beta(0) = 0$. The discount rate, adjusted for benchmarking, is

$$\widetilde{r}_A = r_f + \frac{\beta^E + \Delta_\beta(BMI)}{1 + (1-\tau)\frac{D}{E}} ERP - \Delta_P(BMI). \tag{3}$$

CAPM Investment Policy with Benchmarking Whether the benchmarking-induced changes to the discount rate in (3) incentivize managers to invest more or less is ambiguous: the price effect, $\Delta_P(BMI)$, encourages investment, whereas the increase in $\hat{\beta}$, $\Delta_\beta(BMI)$, discourages it. What if managers fail to fully internalize the asset pricing effects of benchmark-linked ownership but continue to follow textbook guidance and use the CAPM-implied cost of capital in Eq. (2) to evaluate investment opportunities? In this case, the presence of benchmarked funds has an unambiguously negative effect on investment for benchmark constituents. A boundedly rational manager observes an increase in their stock's β^E to $\tilde{\beta}^E = \beta^E + \Delta_\beta(BMI)$ and infers an increase in the firm's cost of equity. The manager now invests only in projects that satisfy

$$\mathbb{E}[Y]/(1+\widetilde{r}_A^\star) = \frac{\mathbb{E}[Y]}{1 + r_f + (\beta^E + \Delta_\beta(BMI))\left(1 + (1-\tau)\frac{D}{E}\right)^{-1} ERP} > C.$$

All else equal, a firm inside a benchmark index invests less than the same firm outside it.

Testable Hypotheses Our mechanism rests on the assumption that managers follow textbook guidance and form a weighted average cost of capital using their firm's CAPM $\hat{\beta}$s without internalizing the effects of benchmarking on asset prices. Benchmarking-induced comovement biases CAPM $\hat{\beta}$s upward, raising the perceived cost of equity and leading benchmark constituents to underinvest. This yields three testable hypotheses. All else equal,

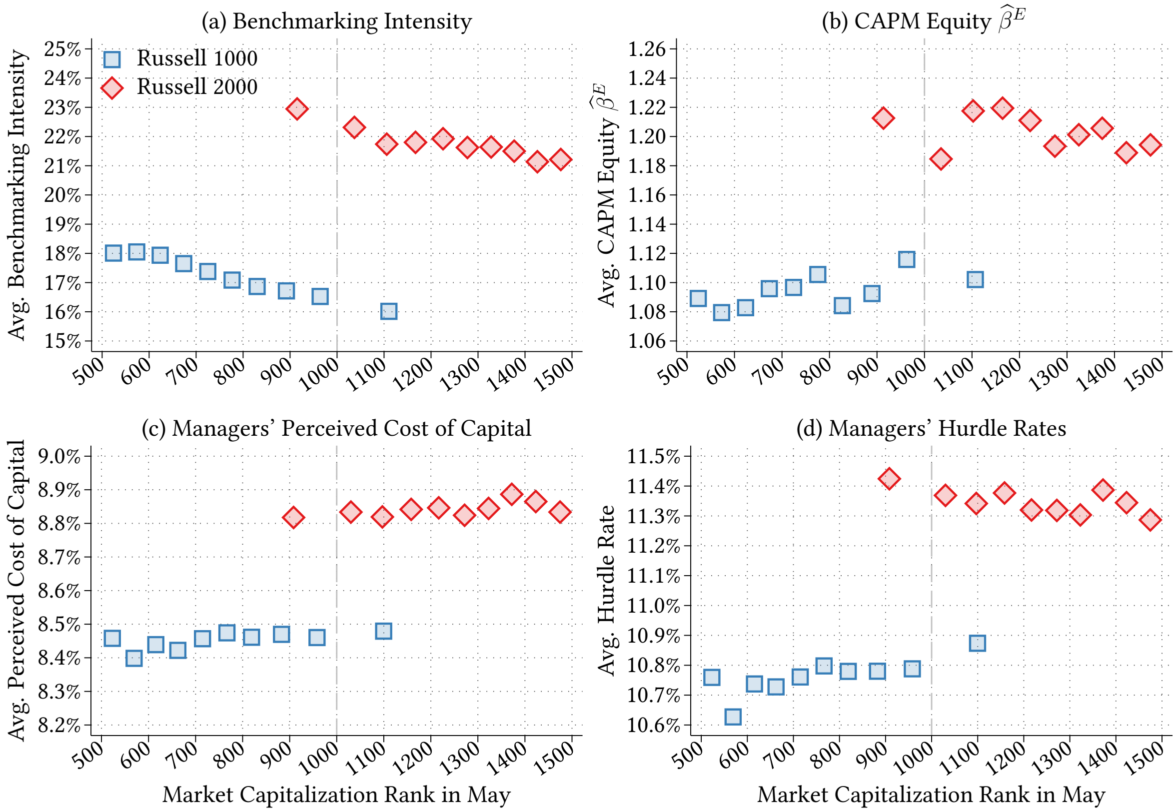
(i) an increase in BMI raises a firm's CAPM $\hat{\beta}^E$,

(ii) an increase in BMI raises the firm's perceived cost of equity, and

(iii) an increase in BMI leads to a decline in investment.

5 The Effects of Benchmarking Intensity on CAPM $\hat{\beta}$s and Managers' Perceived Cost of Capital

Figure 3: BMI, CAPM $\hat{\beta}$s, Perceived Cost of Capital, and Hurdle Rates Around Russell 1000 Cutoff



Notes: This figure shows binned scatters of (a) benchmarking intensity, (b) CAPM $\hat{\beta}$s, (c) managers' perceived cost of capital, and (d) hurdle rates against May market capitalization ranks. We plot conditional means for stocks in the Russell 1000 (blue squares) and Russell 2000 (red diamonds). We estimate conditional means using year-month and stock fixed effects. Single bins across the cutoff reflect the banding policy introduced in 2007.

We begin by documenting a striking set of discontinuities around the Russell 1000/2000 index cutoff in Figure 3. After absorbing year-month and stock fixed effects, a clear jump emerges at the rank-1000 threshold. Panel (a) shows that as firms move from just inside the Russell 1000 to just inside the Russell 2000, average BMI jumps from approximately 17% to 23%. Panel (b) shows that this increase in BMI coincides with an increase in average CAPM $\hat{\beta}$ from 1.09 to 1.21. Managers' own assessments mirror these patterns: Panels (c) and (d) show that average perceived cost of capital and hurdle rates also jump at the cutoff. While consistent with our hypothesis, these discontinuities are suggestive; other factors, such as liquidity effects or unobserved differences between the largest small-cap and smallest mid-cap firms, might also influence $\hat{\beta}$s and the perceived cost of capital at the cutoff. The banding policy introduced by Russell in 2007 precludes regression discontinuity designs (see Appel et al., 2024, for details).

To establish that these discontinuities stem from changes in BMI, we exploit quasi-exogenous variation induced by Russell reconstitution in a difference-in-differences design. We compare the evolution of $\hat{\beta}$s for stocks that experience BMI changes around reconstitution dates to control stocks that do not. A 1 p.p. increase in BMI raises $\hat{\beta}$ by around 0.025. This increase in $\hat{\beta}$ directly affects managers' perceived cost of capital. Using the BMI change as an instrument for the change in $\hat{\beta}$, our IV estimates imply that a 0.2 increase in $\hat{\beta}$ raises the perceived cost of capital by 70 bps. We corroborate this pass-through in five additional datasets: stock analysts as well as state and federal regulators also incorporate benchmarking-induced $\hat{\beta}$ increases into their cost of equity estimates, implying perceived equity risk premia between 4% and 12%.

5.1 Difference-in-differences Strategy to Identify the Effect of Changes in Benchmarking Intensity on CAPM $\hat{\beta}$s

We analyze the *short-run* effects of an exogenous increase in BMI on a firm's CAPM $\hat{\beta}$ by estimating a series of continuous difference-in-differences specifications of the form:

$$\text{CAPM } \hat{\beta}_{i,t} \times 6\% = \theta_{i,c} + \theta_{t,c} + \sum_{k=-6,k\neq-1}^{12} \gamma_k \left(\Delta \text{ BMI} \times \mathbb{1}\{t - T_i = k\}\right) + X_{i,t}'\psi + \varepsilon_{i,t} \tag{4}$$

for firm i in month t, where $X_{i,t}$ is a vector of controls. The parameters $\{\gamma_k\}_{k=-6}^{12}$ measure the dynamic effects of changes in BMI around Russell benchmark reconstitution on CAPM $\hat{\beta}$. We multiply $\hat{\beta}$ by a constant equity risk premium of 6% to translate the effects into changes in the CAPM-implied cost of equity. To address the biases that can arise from staggered treatment timing with heterogeneous effects (De Chaisemartin & d'Haultfoeuille, 2023), we follow the recommendation of Baker et al. (2022) and stack yearly cohorts (c) and include both cohort-by-firm ($\theta_{i,c}$) and cohort-by-time ($\theta_{t,c}$) fixed effects. This ensures that $\{\gamma_k\}_{k=-6}^{12}$ is never estimated by comparing later-treated units with earlier-treated units.

Identification Strategy Our identification strategy exploits quasi-exogenous variation in BMI from the annual Russell benchmark reconstitution, using both the Russell 1000/2000 and 3000 cutoffs. Changes in BMI around the reconstitution date satisfy the relevance condition because they predict portfolio rebalancing by benchmarked investors. The exclusion restriction requires that index membership be conditionally exogenous. The literature finds this assumption valid after controlling for the market capitalization rank that determines index assignment (Pavlova &

Sikorskaya, 2023, Sikorskaya, 2024, Chaudhry, 2025). The key identifying assumption in Eq. (4) is parallel trends: conditional on fixed effects and controls, the CAPM $\hat{\beta}$s of firms experiencing BMI changes would have evolved similarly absent the treatment. Panel (a) of Figure 4 presents visual evidence supporting this assumption.

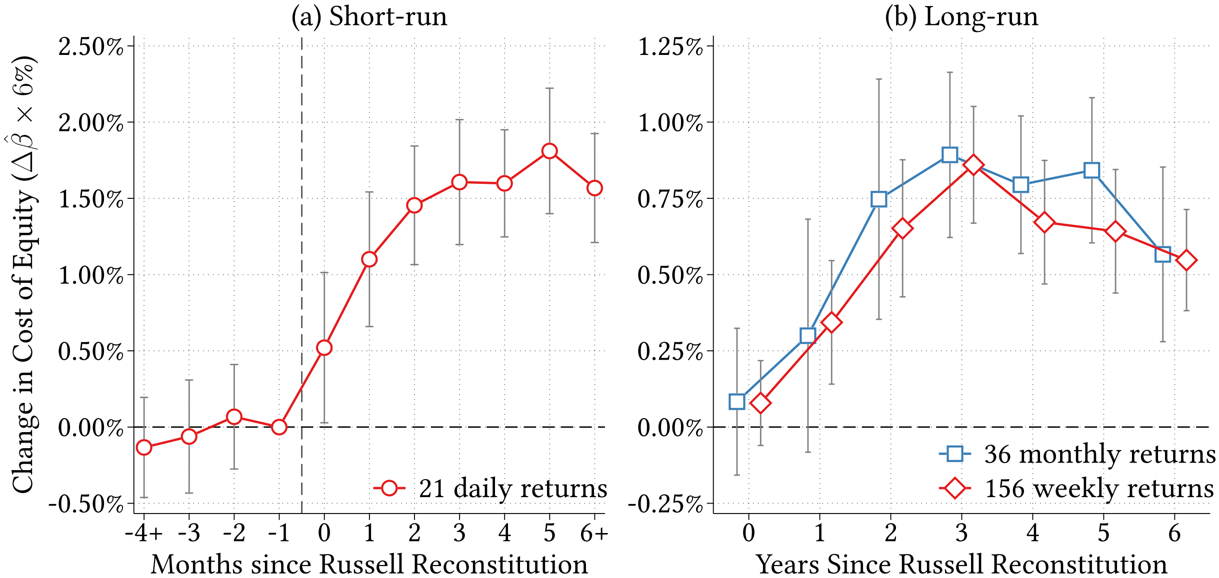
To approximate Russell's proprietary market capitalization ranking, we follow Ben-David et al. (2019) and use publicly available data that allow us to accurately predict index assignments and mitigate mismeasurement concerns (Glossner, 2024). Online Appendix Table C8 confirms that our constructed ranking variable predicts assignment into the Russell 1000 and 2000 with high accuracy. Online Appendix Table C9 shows that our proxy replicates the main result of Pavlova & Sikorskaya (2023) almost perfectly, despite slight differences in sample and variable construction. Following Appel et al. (2019), we account for Russell's banding policy introduced in 2007, which affects only the Russell 1000/2000 cutoff (see Online Appendix C for details on the Russell indices).

We address the main identification concern, that benchmark membership may be endogenous to firm characteristics that also affect CAPM $\hat{\beta}$, in several ways. First, following Pavlova & Sikorskaya (2023), we include log market capitalization as a proxy for Russell's ranking variable and add indicator variables for the banding policy (indicators for being in the band, for Russell 2000 membership in May, and their interaction) as suggested by Appel et al. (2019). Conditional on these baseline controls, the change in BMI due to reconstitution is exogenous. Second, we address potential endogeneity of ΔBMI to stock liquidity by including the logarithms of bid-ask spreads and Amihud illiquidity. Third, we control for momentum using the cumulative 12-month return. We interact all controls with cohort fixed effects. Lastly, we restrict the sample to firms within 300 ranks of the Russell cutoffs. This window captures large BMI changes for firms that cross the cutoff and smaller mechanical BMI changes for non-moving firms when benchmark weights are revised. The latter variation is even less likely to correlate with firm-specific news or fundamentals (Sikorskaya, 2024, Aghaee, 2024).

Persistence and Long-run Effects We investigate whether benchmarking creates persistent, *long-run* changes in the CAPM-implied cost of equity. Our short-run difference-in-differences specification in Eq. (4) analyzes BMI-induced changes in CAPM $\hat{\beta}$s up to 12 months. If changes in the CAPM-implied cost of equity fade after a year, long-term effects on investment are unlikely. We thus extend our analysis to test for long-run effects of exogenous BMI changes on $\hat{\beta}$s over a six-year horizon using the following specification:

$$\text{CAPM } \hat{\beta}_{i,t+h} \times 6\% = \delta^h_{t,s} + \gamma^h \Delta\text{BMI}_{i,t} + X'_{i,t}\zeta^h + \epsilon_{i,t+h}, \quad h = 0, \ldots, 6. \tag{5}$$

Figure 4: Russell Reconstitution Event Study of Changes in BMI on CAPM-implied Cost of Equity



Notes: This figure shows the dynamic effects of a 10 p.p. increase in BMI on CAPM $\hat{\beta} \times 6\%$ around Russell reconstitution using both the Russell 1000/2000 and 3000 cutoffs. The left panel reports *monthly* estimates of Eq. (4) using rolling-window $\hat{\beta}$s based on 21 daily returns. The right panel reports *yearly* estimates of Eq. (5) using rolling-window $\hat{\beta}$s based on 156 weekly returns (red diamonds) and 36 monthly returns (blue squares). The sample is restricted to stocks within 300 ranks of each cutoff. Controls include market capitalization, bid-ask spread, Amihud illiquidity, momentum, and banding variables. Pointwise 95% confidence intervals use double-clustered standard errors.

for firm i in industry s in year $t+h$. The coefficients of interest, $\{\gamma^h\}_{h=0}^6$, summarize the long-run effects of a BMI increase on CAPM $\hat{\beta}$s after h years, respectively. The vector $X_{i,t}$ contains the log market capitalization, bid-ask spread, Amihud illiquidity, momentum, lagged BMI, lagged $\hat{\beta}$, and banding variables. We restrict the sample to within 300 ranks around the cutoffs and absorb year-by-industry fixed effects to account for unobserved time-varying industry shocks.

Results Figure 4 shows the short- and long-run effect of an exogenous BMI increase on a firm's CAPM $\hat{\beta}$. We scale the results so that the coefficients represent the effect of a 10 p.p. increase in BMI. Panel (a) presents the results from our short-run difference-in-differences event study. We use a rolling window of 21 daily returns to highlight the immediate change after Russell reconstitution. Panel (b) shows the long-run effects of BMI changes on CAPM $\hat{\beta}$s up to six years after reconstitution using $\hat{\beta}$s estimated from 156 weekly or 36 monthly returns.

Several results are worth noting. First, Panel (a) of Figure 4 supports our identification strategy. In the months leading up to the reconstitution in June (time 0), the coefficients are statistically indistinguishable from zero. The lack of a differential pre-trend supports the parallel trends assumption underlying our design. Second, using a short-term 21-day $\hat{\beta}$, we find a large and immediate jump in $\hat{\beta}$ in the months after reconstitution. This immediate jump shows that the economic effect is instantaneous. For a 10 p.p. increase in BMI, the CAPM-implied cost of equity rises by approximately 150 basis points.

Third, Panel (b) of Figure 4 shows that the BMI-induced increases in CAPM $\hat{\beta}$s persist for at least six years. The high persistence of the effect suggests that benchmarking creates a long-lasting increase in the CAPM-implied cost of equity, which can have significant implications for long-term investment decisions. The long-run persistence reflects both sticky benchmark membership as well as the slow decay of rolling-window $\hat{\beta}$ estimates.[15] Fourth, comparing Panel (a) and (b) highlights a crucial measurement issue: Using longer-horizon estimators, BMI changes increase CAPM $\hat{\beta}$ only gradually as pre-treatment observations have to leave the sampling window and are thus only detectable at long horizons. This measurement delay has practical implications, as managers or analysts using common estimation methods may not even recognize the benchmarking-induced change in their firm's cost of equity for months or even years after it occurs. This measurement issue makes it unlikely that managers and analysts connect the $\hat{\beta}$ increase to benchmark inclusion.

Appendix Table A3 reports the average post-treatment effect of a 1 p.p. BMI increase on CAPM $\hat{\beta}$ of Eq. (4). The magnitudes are economically significant and consistent with Figures 1, 2, and 3. Moreover, we find similar effect sizes in Appendix Table A4, which reports panel regressions of CAPM $\hat{\beta}$ on BMI levels. Across six specifications with increasingly stringent fixed effects, the coefficient on BMI is stable and highly significant. The level of BMI explains between 17% and 29% of residual variation in $\hat{\beta}$ after absorbing fixed effects. Notably, the institutional ownership ratio (IOR) has no discernible effect on $\hat{\beta}$ when included alongside BMI, suggesting that the observed relationship is specific to *benchmark-linked* ownership.

A higher BMI-induced $\hat{\beta}$ also raises the CAPM's explanatory power (see Online Appendix Figure B6). Note that the increase in $\hat{\beta}$s and R^2 of the CAPM does not imply that investors receive compensation for increased market risk. Pavlova & Sikorskaya (2023) find *lower* realized returns after an exogenous increase in BMI. This finding is consistent with the negatively sloped security market line reported by Baker et al. (2011) and their argument that benchmarking introduces limits to arbitrage that prevent institutional investors from exploiting the "beta anomaly." However, consistent with Jylhä et al. (2018), our evidence indicates that causality runs from benchmark-linked ownership to CAPM $\hat{\beta}$s, rather than the reverse.

[15] Online Appendix Figure C11 shows that, after the introduction of the banding policy in 2007, firms transitioning from the Russell 1000 to the Russell 2000 have a 76% probability of remaining in the Russell 2000 for six years.

Additional Evidence From S&P 500 Additions We examine stocks added to the S&P 500 to provide additional evidence on the effect of benchmark-linked ownership on CAPM $\hat{\beta}$s, following Vijh (1994) and Barberis et al. (2005). Appendix Figure A7 shows that stocks joining the S&P 500 exhibit a relative increase in $\hat{\beta}$s of 0.14, on average. The event study coefficients show similar patterns to those of the Russell reconstitution, suggesting that the effect of benchmarking on $\hat{\beta}$s generalizes beyond the Russell setting. Joining the S&P 500 increases a stock's BMI by 8.6 p.p., from 14.1% to 22.7%, on average. This change implies that $\hat{\beta}$ increases by approximately 0.016 per 1 p.p. increase in BMI, somewhat smaller but similar to the estimate from Russell reconstitution in Table A3. However, we note that stocks added to the S&P 500 are typically larger, more liquid, and enter with higher initial BMI and $\hat{\beta}$ than firms affected by Russell reconstitution.

Alternative CAPM β Estimators We test the relationship between BMI and several alternative β estimators to confirm that our results do not depend on a specific estimator. Online Appendix Table B1 shows that BMI is a statistically significant predictor of $\hat{\beta}$ across several estimators, including those proposed by Blume (1975), Dimson (1979), and Welch (2022). Furthermore, we decompose the increase and find that it is due to a rise in correlations, not volatility. This increase in correlation distinguishes our finding from Ben-David et al. (2018) who show that the arbitrage activity between ETFs and the underlying stocks increases stock volatility.

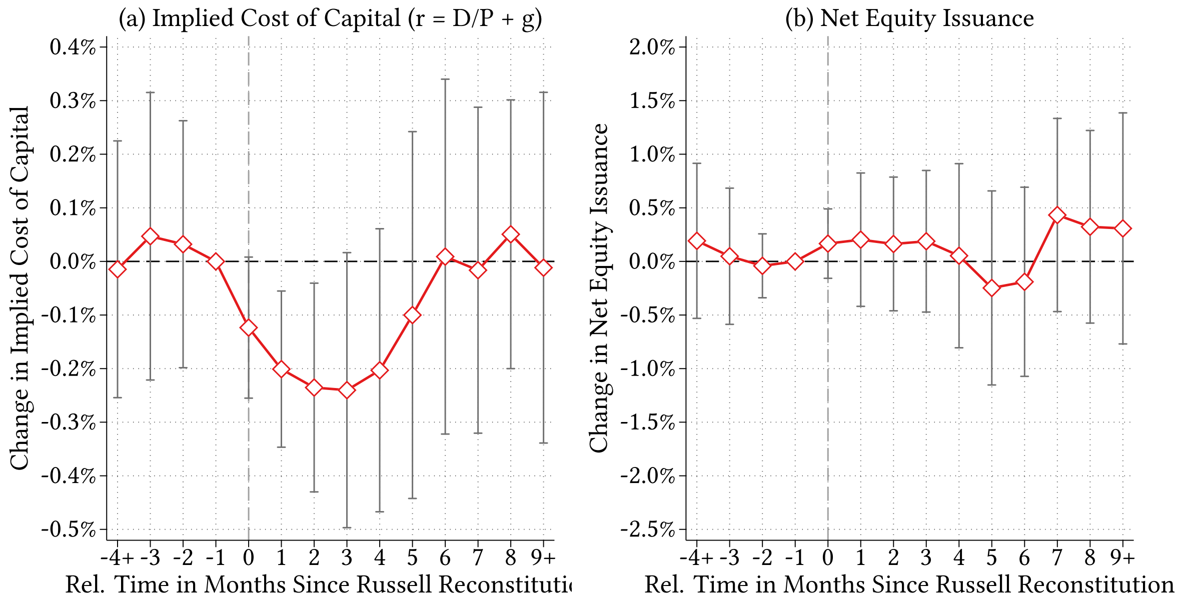
Long-Run Estimates via Cointegration To estimate the long-run impact of BMI on $\hat{\beta}$s, we test for cointegration between the aggregate time series of average BMI and average CAPM $\hat{\beta}$. As shown in Online Appendix Table B2, we strongly reject the null hypothesis of no cointegration. This test validates our use of Dynamic OLS (DOLS) to estimate the long-run relationship. The DOLS estimation yields a long-run coefficient of approximately 0.03 in $\hat{\beta}$ per 1 p.p. increase in average BMI. This effect size is consistent with our difference-in-differences estimates, indicating that the effects of BMI on $\hat{\beta}$ are persistent.

5.1.1 Price Effects of Benchmark Inclusion on the Implied Cost of Capital

We assume that managers use the CAPM to set discount rates and do not account for the full effects of benchmarking on asset prices. Alternatively, managers might infer their discount rate from stock prices and expected cash flows. We test whether BMI changes at benchmark reconstitution influence the implied cost of capital (ICC) that managers can infer from stock prices. The ICC is the internal rate of return that equates the current stock price with the present value of expected cash flows under a Gordon growth–style model.[16]

[16]We calculate the ICC by averaging the dividend discount models of Easton (2004) and Ohlson & Juettner-Nauroth (2005) and the residual income models of Gebhardt et al. (2001) and Claus & Thomas (2001).

Figure 5: Event Study of Changes in BMI on Implied Cost of Capital and Net Equity Issuance



Notes: This figure shows the dynamic effects of a 10 p.p. increase in BMI on the implied cost of capital (r = D/P+g) and net equity issuance over lagged total assets. Controls include market capitalization, bid-ask spread, Amihud illiquidity, momentum, and banding variables. We restrict the estimation sample to stocks within 300 ranks around the Russell 1000/2000 index cutoff. Pointwise confidence intervals (95%) are based on double-clustered standard errors.

Figure 5 plots difference-in-differences event study coefficients of BMI changes on the implied cost of capital and net equity issuance. The event study coefficients show no pre-trends, supporting the parallel trends assumption. Panel (a) shows that the implied cost of capital falls by 0.21% in the month following the exogenous 10 p.p. increase in BMI. To translate this into a stock return, we use Gordon's growth model and assume that the expected dividend, D, and expected dividend growth rate, g, remain constant when BMI changes. We set r to the pre-period average ICC of 8.9% and g to the long-run average real dividend growth of U.S. stocks of 1.6% (from Robert Shiller's website). The 21 bps decrease in ICC at $t+1$ corresponds to a price increase of:

$$\frac{P^{Post}}{P^{Pre}} - 1 = \frac{-\Delta r}{r^{Pre} + \Delta r - g} = \frac{0.21\%}{8.9\% - 0.21\% - 1.6\%} = \underset{(1.2)}{3.0^{**}}\%$$

Our estimate of 3.0% aligns with the 2.7% stock price increase per 10 p.p. BMI change reported by Pavlova & Sikorskaya (2023). The 95% confidence interval, obtained using the delta method, similarly covers the 5% average price effect found by Chang et al. (2015).

However, this price effect is temporary, reverting within six months. The small, short-lived price impact makes it unlikely that increased benchmarking affects investment through a price-level channel. Our results are consistent with Harris & Gurel (1986), Petajisto (2011), Patel & Welch (2017), and Chaudhry (2025), who similarly show that price effects of benchmark inclusion revert over time.

We find no significant change in net equity issuance, implying firms do not exploit the temporary price dislocation. Firms likely do not issue because the costs exceed the potential benefits. First, investors may perceive equity issuance as a negative signal about firm quality (Myers & Majluf, 1984), a concern particularly salient for Russell 1000 firms moving into the less-prestigious Russell 2000. Second, beyond signaling, the direct transaction and underwriting costs of an offering may render it unprofitable given the modest price increases. Third, any buyer of the newly issued shares would bear the benchmarking-induced $\hat{\beta}$ increase without receiving a commensurate increase in expected return.[17]

Qualitative evidence from earnings call transcripts indicates that managers do not view Russell benchmark inclusion as a financing event. In Online Appendix F.1, we analyze 163 earnings call transcripts of firms added to the Russell benchmark indices from 2008 to 2024. Only five of the 163 transcripts link inclusion to equity offerings, two of which are from REITs that issue equity frequently as part of their business model.[18] In over 60% of transcripts, executives announce inclusion without elaboration. The rest briefly discuss expected gains in visibility (21%) or in trading liquidity and volume (16%). Executives view benchmark inclusion as a corporate milestone for investor relations, not as a mechanism for lowering the cost of equity or altering capital structure.

5.2 Effect of Flows Into Passive Mutual Funds and ETFs on CAPM $\hat{\beta}$

Our difference-in-differences results establish a direct link from BMI to CAPM $\hat{\beta}$s. We posit that the underlying economic driver is the inelastic and *correlated* demand from passive index funds for benchmark constituents. This hypothesis is consistent with the fact that there is no increase in institutional ownership at the Russell 1000 cutoff, but rather a shift from active to passive ownership (Pavlova & Sikorskaya, 2023).

We test this hypothesis using data on net flows into active and passive mutual funds from Morningstar. Panel regressions show that net inflows into passive funds are significantly associated with increases in $\hat{\beta}$s, particularly for smaller stocks where passive ownership is more concentrated. In contrast, net flows into active funds have a modest effect limited to the early part of

[17] Earlier work suggests that firms exploit sentiment-driven overvaluation (e.g., Morck et al., 1990, Stein, 1996, Baker & Wurgler, 2000, Shleifer & Vishny, 2003). However, Warusawitharana & Whited (2016) show that while misvaluation affects firm behavior, its impact is much stronger on financial decisions than on real investment.

[18] REITs must distribute at least 90% of taxable income to retain REIT status, leaving little internal cash for growth.

the sample, likely reflecting the quasi-indexing behavior of active managers.

A simulation in Online Appendix E provides more structural support. We construct a parsimonious two-factor model in which stock returns depend on a fundamental factor and a flow factor. Calibrating the flow factor to observed passive fund flows, with exposures proxied by BMI, the model replicates the cross-sectional and time-series evolution of CAPM $\hat{\beta}$s from 1998 to 2018. A calibration using active fund flows fails to match these patterns.

Together, the panel and simulation evidence indicates that the structural shift toward passive index investing drives the increase in CAPM $\hat{\beta}$s.[19] These findings lend direct empirical support to recent theories positing that the shift to passive, benchmark-linked ownership increases asset price comovement (e.g., Bond & Garcia, 2022).

Mutual Fund Flow Data We use monthly total net assets and flows of active and passive mutual funds and ETFs from Morningstar Direct. We exclude feeder funds and funds of funds. The net flows into mutual funds in month t, $F_t^{(\iota)}$, do not include any valuation effects from price changes, distributions, or reinvested dividends (Morningstar Direct, 2024). Rather, these net flows present the net amount that investors put into or withdraw from mutual funds and ETFs.

We estimate the following panel regression at the monthly frequency (using end of month $\hat{\beta}$s):

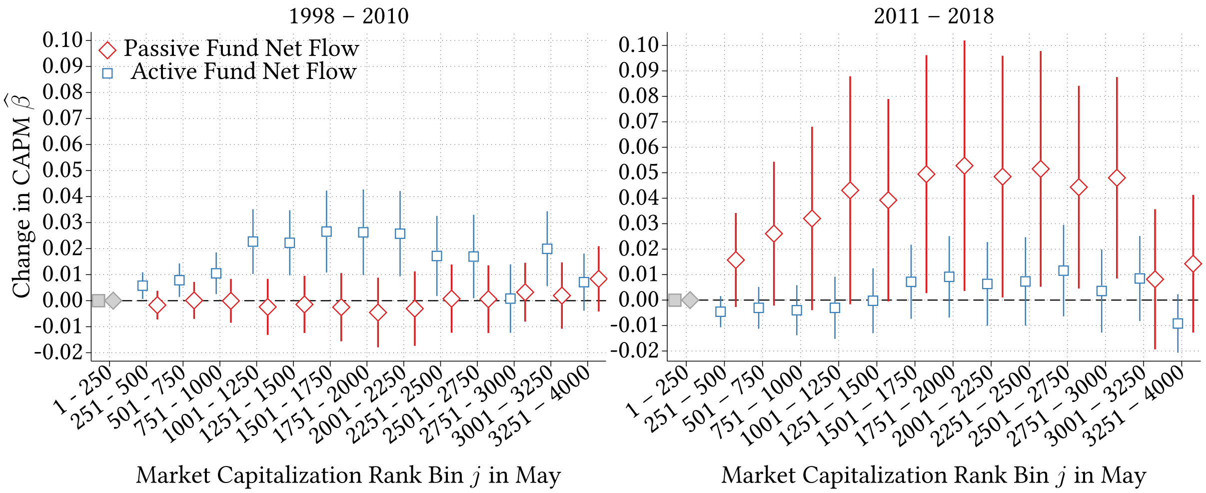
$$\begin{aligned}\text{CAPM } \hat{\beta}_{i,t} = &\sum_{j \notin \{250\}} \gamma_j^A \, \mathbb{1}\{i \in \text{Bin } j\} \times F_t^A / A_{t-1}^A + \sum_{j \notin \{250\}} \gamma_j^P \, \mathbb{1}\{i \in \text{Bin } j\} \times F_t^P / A_{t-1}^P \\ &+ \alpha_i + \alpha_t + \rho \text{ CAPM } \hat{\beta}_{i,t-1} + X_{i,t}' \zeta + \varepsilon_{i,t} \end{aligned} \tag{6}$$

where F_t^A and F_t^P are net flows into active and passive funds. The model includes stock fixed effects (α_i) and year-month fixed effects (α_t). Time fixed effects absorb the average market-wide effect of fund flows; the coefficients of interest, γ_j^ι, are identified from the differential impact of flows across market-capitalization-rank bins. We control for the lagged dependent variable, so the γ coefficients capture the effect of flows on changes in $\hat{\beta}$. $X_{i,t}$ includes controls for size, bid-ask spread, Amihud illiquidity, and momentum. The γ_j^P coefficients are identified relative to the first bin (the largest 250 stocks), so each measures the change in $\hat{\beta}$ for stocks in bin j relative to top-250 stocks after a net passive fund inflow.

Figure 6 plots the estimated γ_j^A and γ_j^P coefficients, scaled to reflect the effect of a two standard deviation net inflow ($\approx 1\%$ of A_{t-1}). Panel (a) covers 1998–2010. In this period, a 2 sd inflow into

[19] This trend culminated in 2024, when assets in U.S. passive mutual funds and ETFs surpassed those in active funds (Morningstar Direct, 2025). Online Appendix Figure B7 shows that cumulative net flows into passive funds have surpassed those into active funds by more than $10 trillion since 1998.

Figure 6: Impact of Net Flows into Passive and Active Mutual Funds and ETFs on CAPM $\hat{\beta}$



Notes: This figure shows estimates of γ_j^A and γ_j^P from the monthly panel regression:
CAPM $\hat{\beta}_{i,t} = \alpha_i + \alpha_t + \sum_{j \notin \{250\}} \gamma_j^A \, \mathbb{1}\{i \in \text{Bin } j\} \times F_t^A / A_{t-1}^A + \sum_{j \notin \{250\}} \gamma_j^P \, \mathbb{1}\{i \in \text{Bin } j\} \times F_t^P / A_{t-1}^P + X'_{i,t}\xi + \varepsilon_{i,t}$.
We normalize the coefficients relative to the first bin (ranks 1-250) and scale estimates to a 2 standard deviation net inflow ($\approx 1\%$ of A_{t-1}). Controls include market capitalization, bid-ask spread, Amihud illiquidity, momentum, and lagged $\hat{\beta}$. Pointwise confidence intervals (95%) are based on double-clustered standard errors.

active funds raises the $\hat{\beta}$ of small-cap stocks by about 0.02, while passive flows have no significant effect. Panel (b) covers 2011–2018. Passive flows now dominate: a 2 sd inflow increases $\hat{\beta}$s of mid- and small-cap stocks by 0.02 to 0.05, with effects statistically significant throughout. Active flows have no measurable impact after 2010.

The cross-sectional pattern aligns with differences in BMI. Stocks below the Russell 1000 cutoff, particularly small caps, show the strongest response to passive flows, consistent with their higher BMI. Micro-caps below the Russell 3000 cutoff show no effect, consistent with their near-zero BMI. Importantly, BMI does not enter this regression directly. Instead, size-sorted bins proxy for differential exposure to passive demand. This design provides a BMI-free validation of our mechanism: stocks with higher implicit BMI exhibit larger $\hat{\beta}$ responses to flows.

Figure 6 suggests that flows affected $\hat{\beta}$s through different channels over time, with active flows dominating before 2010 and passive flows afterward. We argue that both periods reflect the influence of quasi-passive demand for benchmark stocks. Official data show large passive inflows only after 2010, yet Chinco & Sammon (2024) find large inflows into quasi-passive strategies before then that were not recorded as passive.

Since BMI assumes active portfolios scale with benchmark weights (Pavlova & Sikorskaya, 2023), it provides a consistent proxy for benchmark-driven demand across both periods. We interact

Table 1: Benchmarking Intensity and Net Flows into Active and Passive Mutual Funds

	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent variable: CAPM $\hat{\beta}$					
$\text{BMI}_{i,t-1}$ (as fraction of ME)	0.723***	0.824***	0.502***	0.809***	0.584***	1.223***
	(0.098)	(0.100)	(0.143)	(0.097)	(0.165)	(0.135)
$\text{BMI}_{i,t-1} \times F_t/A_{t-1}$ (Pooled)	0.203***	0.105*	0.221**			
	(0.057)	(0.059)	(0.100)			
$\text{BMI}_{i,t-1} \times F_t^P/A_{t-1}^P$ (Passive)				0.029	0.318*	0.056
				(0.062)	(0.181)	(0.077)
$\text{BMI}_{i,t-1} \times F_t^A/A_{t-1}^A$ (Active)				0.115*	0.076	0.070
				(0.063)	(0.120)	(0.073)
$\text{BMI}_{i,t-1} \times F_t^P/A_{t-1}^P$ (Passive) $\times$ Trend						0.005***
						(0.001)
$\text{BMI}_{i,t-1} \times F_t^A/A_{t-1}^A$ (Active) $\times$ Trend						-0.005***
						(0.001)
Sample	1998 – 2018	1998 – 2010	2011 – 2018	1998 – 2010	2011 – 2018	1998 – 2018
Controls	✓	✓	✓	✓	✓	✓
Stock Fixed Effects	✓	✓	✓	✓	✓	✓
Year-Month Fixed Effects	✓	✓	✓	✓	✓	
Adj. R^2	0.32	0.39	0.25	0.39	0.25	0.36
Observations	804,598	510,559	294,039	510,559	294,039	804,469

Notes: This table reports coefficients for panel regressions: CAPM $\hat{\beta}_{i,t} = \alpha_i + \alpha_t + \gamma \text{BMI}_{i,t-1} + \psi \text{BMI}_{i,t-1} \times F_t/A_{t-1} + X'_{i,t}\xi + \varepsilon_{i,t}$ where F_t are net flows and $A_{i,t}$ total net assets of mutual funds and ETFs from Morningstar Direct. F_t/A_{t-1} is standardized to have zero mean and unit variance. Observations are weighted by market capitalization. Specifications with a time trend include all interactions; some are omitted for brevity. Time trend is mean zero in July 2008. Standard errors clustered at the stock and year-month level in parentheses. * p<0.10, ** p<0.05, *** p<0.01

flows with BMI to test this channel formally, splitting the sample in 2010:

$$\text{CAPM } \hat{\beta}_{i,t} = \alpha_i + \alpha_t + \psi_0 \text{BMI}_{i,t-1} + \psi_1 \text{BMI}_{i,t-1} \times F_t^A/A_{t-1}^A + \psi_2 \text{BMI}_{i,t-1} \times F_t^P/A_{t-1}^P + X'_{i,t}\xi + \varepsilon_{i,t}.$$

Table 1 shows that before 2010, a positive and significant interaction between BMI and active flows drove variation in $\hat{\beta}$s, indicating quasi-indexing by active managers. After 2010, the pattern reverses: the BMI–passive flow interaction becomes positive and highly significant, while the BMI–active flow interaction becomes negligible. The BMI–passive flow effect post-2010 (column 5) is nearly three times larger than the BMI–active flow effect pre-2010 (column 4). This difference is not mechanical because both flows are standardized to mean zero and unit variance. It suggests that up to a third of active flows were quasi-indexing before 2010, consistent with Cremers & Petajisto (2009). Column 6 shows the result is robust to including a time trend and estimating across the full sample. Simulation evidence in Online Appendix E corroborates this: BMI–active flow interactions explain the early in-sample distribution of $\hat{\beta}$s but fail from 2004 onward. One interpretation is that quasi-indexing declined as explicitly passive products became widely available, consistent with Cremers et al. (2016), who find that the expansion of low-cost passive products intensifies competition and erodes the market share of quasi-indexers.

5.3 Impact on Managers' Perceived Costs of Capital and Hurdle Rates

Next, we show that benchmark-linked capital flows through their impact on CAPM $\hat{\beta}$s affect managers' perceived cost of capital and hurdle rates. Managers frequently reference the CAPM when discussing their cost of equity and capital budgeting decisions in earnings calls. For example,[20]

> *If you use some of the tools I learned in my MBA class, like the **capital asset pricing model**, they did teach that back in the 80s by the way, so it's been around for a while. I think our cost of equity is around 10%.*
>
> — CFO, Qorvo Inc. (Q4 2015)

Empirical Strategy We use the perceived cost of capital and hurdle rate data from Gormsen & Huber (2025a). We estimate how BMI-induced changes in CAPM $\hat{\beta}$ in year t pass through to managers' perceived cost of capital in year $t+1$ and hurdle rates in year $t+3$. We estimate a series of instrumental variable (IV) regressions with the following form:

$$\text{CAPM } \hat{\beta}_{i,t+1} = \delta^{(1)}_{j,t} + \theta \, \Delta \, \text{BMI}_{i,t} + X'_{i,t}\xi^{(1)} + \varepsilon^{(1)}_{i,t} \tag{7}$$

$$\text{Perceived Cost of Capital}_{i,t+1} = \delta^{(2)}_{j,t} + \lambda^{(2)} \, \widehat{\text{CAPM } \beta_{i,t+1}} + X'_{i,t}\xi^{(2)} + \varepsilon^{(2)}_{i,t+1} \tag{8}$$

$$\text{Managers' Hurdle Rate}_{i,t+3} = \delta^{(3)}_{j,t} + \lambda^{(3)} \, \widehat{\text{CAPM } \beta_{i,t+1}} + X'_{i,t}\xi^{(3)} + \varepsilon^{(3)}_{i,t+3} \tag{9}$$

where $X_{i,t}$ is a vector of control variables designed to ensure the conditional exogeneity of ΔBMI. This vector includes log market capitalization, the Russell May ranking variable constructed following Ben-David et al. (2019), and controls for the index banding rules per Appel et al. (2019) (as discussed in Section 5.1). We augment this specification with additional controls for stock liquidity and momentum. To restrict identifying variation to within-industry comparisons, we also include a full set of industry-by-year fixed effects, $\delta^{(\iota)}_{j,t}$. We directly account for the transmission lag from perceived cost of capital to hurdle rates that Gormsen & Huber (2025a) document by using changes in BMI in year t to predict hurdle rates in year $t+3$. We estimate the IV regressions using equity $\hat{\beta}$s and scale the resulting $\lambda^{(i)}$ estimates by the average equity-to-capital ratio around the index cutoffs such that the estimate can be interpreted as the effect of the asset $\hat{\beta}$ on the perceived cost of capital and hurdle rates.

Table 2 reports the effect of changes in CAPM $\hat{\beta}$ on managers' perceived cost of capital and hurdle rates. The reduced-form estimates in Columns (1) and (2) show that increases in BMI raise

[20]Online Appendix F.2 provides further examples of executives citing the CAPM during cost of equity discussions.

Table 2: Effect of Δ BMI on Managers' Perceived Cost of Capital and Hurdle Rates

	Perceived Cost of Capital$_{t+1}$ (in p.p.)				Managers' Hurdle Rate$_{t+3}$ (in p.p.)			
	RF		IV		RF		IV	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Δ Benchmarking Intensity$_t$ (in p.p.)	0.016**	0.014**			0.025**	0.025**		
	(0.007)	(0.005)			(0.010)	(0.009)		
$\widehat{\text{CAPM } \beta^A_{t+1}}$			3.422**	3.282**			5.232**	5.489**
			(1.307)	(1.183)			(2.318)	(2.252)
Baseline Controls	✓	✓	✓	✓	✓	✓	✓	✓
Additional Controls		✓		✓		✓		✓
Fixed Effects								
Year	✓		✓		✓		✓	
Year × Industry		✓		✓		✓		✓
FS F-stat.			12.89	16.36			12.86	16.88
Adj. R^2	0.32	0.52			0.07	0.34		
Observations	7,733	7,696	7,733	7,696	6,684	6,649	6,684	6,649

Notes: This table reports estimates of reduced form (RF) and instrumental variable (IV) regressions of managers' perceived cost of capital and hurdle rates on CAPM $\hat{\beta}$s, identified using exogenous changes in BMI around Russell reconstitution. Perceived cost of capital is measured in year $t+1$ after reconstitution, and hurdle rates are in year $t+3$. Baseline controls include log market capitalization, and controls for banding rules. Additional controls account for liquidity and momentum. IV estimated via LIML. We restrict the estimation sample to stocks within 300 ranks around Russell index cutoffs. Sample from 2002 to 2018 due to data availability of managers' perceived cost of capital and hurdle rates. Standard errors in parentheses are clustered by year. * p<0.10, ** p<0.05, *** p<0.01.

managers' perceived cost of capital one year after reconstitution. The coefficient is stable across specifications, and adding controls for liquidity and momentum together with industry-by-year fixed effects does not materially alter the coefficients. This stability, combined with a significant increase in the adjusted R^2 from 0.32 to 0.52, addresses concerns about omitted variable bias and unobserved heterogeneity (Oster, 2017). Columns (5) and (6) show that BMI-driven increases in $\hat{\beta}$ also translate into higher managerial hurdle rates three years after reconstitution.

The IV specifications in Columns (3)–(4) and (7)–(8) allow us to interpret the coefficients on $\hat{\beta}$ as perceived prices of risk. Under the CAPM, these coefficients correspond to the slope of the subjective security market line, i.e., the perceived equity risk premium. The IV estimates for the perceived cost of capital (Columns 3–4) imply an average perceived equity risk premium of about 3.3%, close to but below the 3.6% average equity risk premium reported by CFOs in the Graham & Harvey (2018) survey. By contrast, the IV estimates for managers' hurdle rates (Columns 7–8) suggest an equity risk premium around 5.3%. The gap between these two sets of estimates is consistent with the interpretation that hurdle rates embed an additional buffer reflecting managerial risk aversion (Gormsen & Huber, 2025a).

These findings provide a specific mechanism for how benchmarking through managers' perceptions of the cost of capital affects real economic activity. Recent work by Gormsen & Huber

Table 3: Benchmarking Intensity and Stock Analysts' Perceived Cost of Equity

	Δ Morningstar Cost of Equity (in p.p.)				Value Line Safety Rank $\times$ 1.5 p.p.				Δ I/B/E/S Expected Return (in p.p.)			
	RF		IV		RF		IV		RF		IV	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Δ BMI	0.023***	0.020**			0.030**	0.029**			0.101*	0.084*		
	(0.008)	(0.009)			(0.010)	(0.011)			(0.055)	(0.045)		
$\widehat{\Delta \text{ CAPM } \beta}$			4.867**	4.117**			4.425**	3.953*			12.336*	10.402*
			(2.276)	(1.976)			(1.673)	(1.956)			(6.243)	(5.189)
Baseline Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Additional Controls		✓		✓		✓		✓		✓		✓
Fixed Effects												
Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
FS F-stat.			9.9	11.9			25.1	18.1			87.3	88.4
Observations	5,721	5,381	5,514	5,389	1,866	1,866	1,809	1,809	4,692	4,692	4,692	4,692

Notes: This table reports estimates for specifications of the form: Δ Perceived Cost of Equity$_{i,t} = \alpha_t + \lambda \widehat{\Delta \text{ CAPM } \beta}_{i,t} + X'_{i,t}\xi + \varepsilon_{i,t}$ for IV regressions where the instrument is Δ BMI between May and June for stock i in year t. RF columns report reduced form and IV report instrumental variable estimates. Change in Morningstar cost of equity from Q4 to Q4. We convert Value Line's safety rank to a required return on equity by multiplying it by 1.5 (p.p.) (Eskildsen et al., 2024). Value Line sample is from 1998 to 2006 due to limited data availability. Change in I/B/E/S expected return from Q2 to Q4 based on consensus price and dividend forecast over the next 12 months. Estimation samples are restricted to stocks within 400 ranks around Russell index cutoffs. Baseline controls are log of market capitalization on the rank day in May and banding controls. Additional controls include log of bid-ask spread, log of Amihud illiquidity, and momentum. IV estimated via LIML. Standard errors in parentheses are clustered at the year-level. * p<0.10, ** p<0.05, *** p<0.01.

(2025b) establishes that the perceived cost of capital shapes long-run investment and that excess dispersion in it can cause misallocation. Building on this, Gormsen & Huber (2025a) show that higher hurdle rates, a direct output of these perceptions, depress future firm investment. We contribute by showing that exogenous increases in BMI directly influence these perceptions, raising managers' hurdle rates and, consequently, reducing real capital investment.

5.3.1 Other Perceived Cost of Equity Measures

We corroborate the pass-through from BMI to perceived cost of equity in three additional datasets: (1) Morningstar's cost of equity, which reflects Morningstar's qualitative assessment of systematic risk, (2) Value Line's safety rank, a subjective rating from 1 (safest) to 5 (riskiest) that we convert to a required return on equity by multiplying by 1.5 p.p. following Eskildsen et al. (2024), and (3) subjective return expectations derived from I/B/E/S consensus price targets and dividend forecasts. Online Appendix G provides further details.

We estimate specifications of the form

$$\Delta \text{ Perceived Cost of Equity}_{i,t} = \alpha_t + \lambda \widehat{\Delta \text{ CAPM } \beta}_{i,t} + X'_{i,t}\xi + \varepsilon_{i,t} \tag{10}$$

where we instrument changes in CAPM $\hat{\beta}$ with changes in BMI due to Russell reconstitution between May and June within a narrow window around index cutoffs. The vector $X_{i,t}$ contains our baseline controls: log market capitalization on the rank day in May and banding controls.

We additionally control for the log bid-ask spread, log Amihud illiquidity, and momentum. The year fixed effect α_t ensures that λ is identified from cross-sectional variation.

Table 3 shows that exogenous increases in BMI raise analysts' perceived risk and return expectations. The IV estimates of Eq. (10) imply perceived equity risk premia between 3.95% and 12.3% across the three datasets. The Morningstar estimates are close to the 4.5% equity risk premium that Morningstar (2022, page 4f) reports using internally. The estimates are robust to controlling for liquidity and momentum. The I/B/E/S-implied premium is larger and less precise. This estimate may reflect either genuinely higher perceived equity risk or an artifact of BMI affecting analysts' growth expectations. Evidence from the literature supports the latter: analysts adjust expectations in response to temporary index-inclusion price effects (Chaudhry, 2025) or to reconcile a flat security market line (Jylha & Ungeheuer, 2021).

Additional Evidence from Regulated Monopolies Online Appendix G.2 provides corroborating evidence from the regulatory rate-setting of public utilities and railroads. Regulators commonly use the CAPM to set an "authorized" cost of equity that monopolies pass on to consumers (Kontz, 2025). For public utilities, a 10 p.p. increase in BMI raises the authorized cost of equity by 70 bps, implying a perceived equity risk premium of 6.1%. Results from the railroad industry corroborate this finding: our IV-implied premium of 6.4% is statistically indistinguishable from the 6.85% average premium regulators actually applied. The estimates are stable to the inclusion of a control for the DCF-implied risk premium, mitigating concerns about unobserved confounders (Oster, 2017). A falsification test yields no effect of BMI on the authorized cost of debt, supporting the exclusion restriction. Together, these results show that benchmarking-induced changes in CAPM $\hat{\beta}$ directly translate into higher, government-sanctioned costs of equity.

6 Effects of Benchmarking on Investment at the Firm Level

For a manager who follows textbook guidance and sets investment policies using the CAPM, an increase in $\hat{\beta}$ raises the cost of capital and should lead to a decline in investment. We find that managers react to BMI-induced changes in $\hat{\beta}$ by reducing investment. We show this in panel regressions, instrumental variable regressions around Russell benchmark reconstitutions, and a difference-in-differences event study using additions to the S&P 500. The results are robust to controls for cash flow, leverage, firm size, and Tobin's q.

Table 4: Panel Regressions of Firm Investment on Benchmarking Intensity

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Dependent variable: CAPX_{t+1} / PPE_t (in %)						
BMI (in %)	-0.233***	-0.300***	-0.205***	-0.111***	-0.107***	-0.130***	-0.203***
	(0.051)	(0.038)	(0.041)	(0.022)	(0.025)	(0.029)	(0.042)
IOR (in %)				0.006	0.005	0.005	0.005
				(0.006)	(0.006)	(0.006)	(0.007)
Linear Time Trend	-0.433***						
	(0.078)						
Tobin's q^{tot}				2.881***	2.822***	2.814***	
				(0.186)	(0.182)	(0.182)	
Additional Controls				✓	✓	✓	✓
Fixed Effects							
Firm FE	✓		✓	✓	✓	✓	✓
Year × Rank FE		✓	✓	✓			
Ind. × Year × Rank FE					✓	✓	✓
Russell 2000 Index FE						✓	✓
Adj. R^2	0.42	0.08	0.45	0.51	0.59	0.59	0.54
Mean Dep. Var.	15.0	15.0	15.0	15.0	15.0	15.0	15.0
SD BMI	9.4	9.4	9.4	9.3	9.2	9.2	9.2
Observations	36,787	36,843	36,782	35,851	34,574	34,574	34,576

Notes: This table reports estimates for panel regressions of the form: $\frac{\text{CAPX}_{i,t+1}}{\text{PPE}_{i,t}} = \alpha_{t,bin} + \alpha_i + \gamma\,\text{BMI}_{i,t} + X'_{i,t}\xi + \varepsilon_{i,t}$, where $\alpha_{t,bin}$ is a year-by-rank-bin fixed effect with bins defined every 250 market capitalization ranks in May. Controls include institutional ownership ratio (IOR), Tobin's q (Peters & Taylor, 2017), leverage, cash flow to PPE, current ratio, log of market capitalization, and firm age. Standard errors in parentheses are clustered at the year- and firm-level. * p<0.10, ** p<0.05, *** p<0.01.

6.1 Panel Regressions of Firm Investment on Benchmarking Intensity

We document the reduced-form relationship between BMI and investment in panel regressions:

$$\frac{\text{CAPX}_{i,t+1}}{\text{PPE}_{i,t}} = \alpha_i + \alpha_{t,bin} + \gamma\,\text{BMI}_{i,t} + X'_{i,t}\xi + \varepsilon_{i,t+1}$$

for firm i in year $t+1$. Controls $X_{i,t}$ include a proxy for marginal Tobin's q inclusive of intangible capital (Peters & Taylor, 2017), cash flow, leverage, current ratio, log market capitalization, and firm age. Firm fixed effects α_i absorb time-invariant heterogeneity. Year-by-rank-bin fixed effects $\alpha_{t,bin}$ identify γ from variation among firms of similar size within the same year.

Table 4 shows that the coefficient on BMI is negative and statistically significant across all specifications. The estimate in column (3) implies that a one standard deviation increase in BMI corresponds to a 12.5% reduction in the investment rate relative to the sample mean. Column (1) includes firm fixed effects and a linear time trend. Column (2) uses year-by-rank-bin fixed effects, ensuring comparisons among similarly sized firms within the same year. Column (3) includes both firm and year fixed effects. Across these specifications, the BMI coefficient ranges from −0.21 to −0.30.

Including Tobin's q in columns (4) through (6) attenuates the BMI coefficient by approximately 50%, though it remains significant at the 1% level. Excluding Tobin's q in column (7), the coefficient reverts to a magnitude comparable to column (3). This attenuation reflects a negative correlation between BMI and Tobin's q: firms with higher BMI tend to have lower q, consistent with a higher perceived cost of capital. In theory, marginal q equals the present value of future marginal profits discounted at the market's required return. If benchmarking increases priced systematic risk, the discount rate rises and marginal q falls.

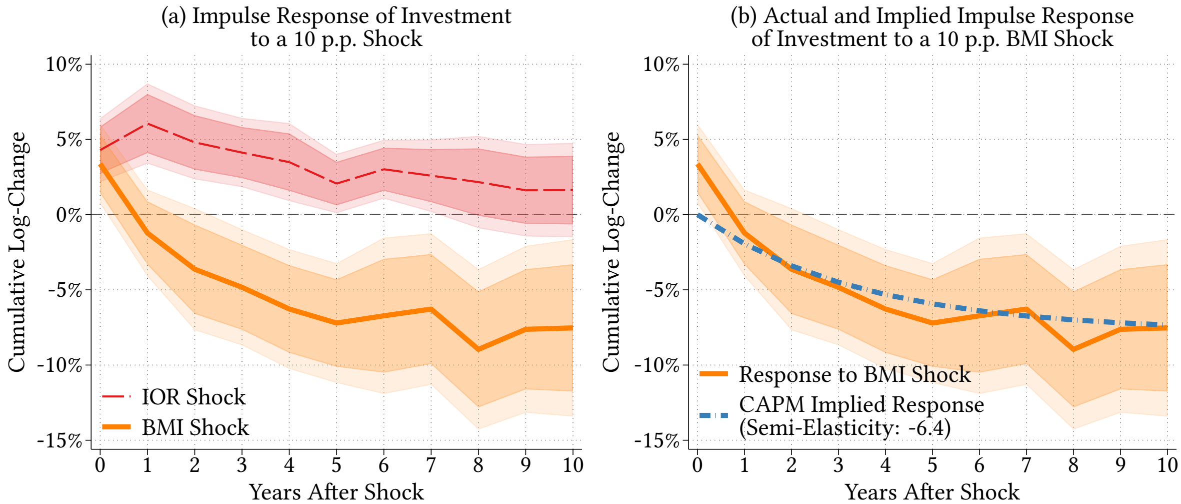
BMI remains a significant predictor of investment even after controlling for Tobin's q, suggesting two non-exclusive interpretations. First, our proxy for the unobservable marginal q is imperfect, and the residual significance of BMI may capture the portion of its effect on true marginal q that our proxy fails to measure. Online Appendix Table B3 shows that BMI remains economically and statistically significant after adjusting for measurement error in Tobin's q (Erickson & Whited, 2012). Second, the residual effect may reflect a divergence between the discount rate managers use for capital budgeting and the discount rate investors price into Tobin's q. If managers perceive a steeper security market line than what markets price, their subjective discount rate for new projects exceeds the market rate, and they invest less than the level prescribed by q. In this case, BMI captures the incremental effect of managerial risk perception on investment, beyond what is priced into the firm's q.

To distinguish the effect of benchmarking from general institutional ownership, columns (4) through (7) include IOR as a control. The coefficient on IOR is not statistically different from zero, while the coefficient on BMI remains negative and significant. This result indicates that the investment effect is specific to benchmark-linked ownership.

6.2 Dynamic Effects of Benchmarking on Firm Investment

We explore the dynamic effects of an increase in BMI on investment through impulse response functions, which we estimate using Jordà's Local Projections (LPs). LPs estimate impulse response functions by regressing future values of a variable on current shocks and controls. The sequence of horizon-specific coefficients describes how the conditional expectation of a variable responds at different leads, and hence how shocks propagate across horizons. Specifically, we

Figure 7: Impulse Response Function of Investment to a 10 p.p. year-on-year Increase in BMI



Notes: This figure shows coefficient estimates of γ^h from local projection panel regressions of the form: $\log\left(Inv_{i,t+h}\right) - \log\left(Inv_{i,t-1}\right) = \alpha^h_{t,j} + \gamma^h\left(\text{BMI}_{i,t} - \text{BMI}_{i,t-1}\right) + X'_{i,t}\xi^h + \varepsilon_{i,t+h}$, scaled to a 10 p.p. year-on-year increase in BMI. $X_{i,t}$ includes log of market equity, Tobin's q, leverage, cash flow, current ratio, and firm age. Panel (a) plots the cumulative percentage change in the investment rate (CAPX/PPE) in response to a 10 p.p. increase in benchmarking intensity (BMI) and institutional ownership ratio (IOR). In panel (b), we also plot the implied investment response under a gradual adjustment of hurdle rates (dashed line). We assume that 25% of the perceived cost of capital is incorporated into the hurdle rate each year, starting from an initial increase implied by $\Delta\hat{\beta}$=0.27, with a 6% equity risk premium, a 75% equity share, and an investment semi-elasticity with respect to the cost of capital of -6.4. Shaded regions are pointwise confidence intervals (90% and 95%) based on clustered standard errors.

estimate cumulative impulse response functions using OLS panel regressions of the form:

$$\log\left(Inv_{i,t+h}\right) - \log\left(Inv_{i,t-1}\right) = \alpha^h_{t,j} + \gamma^h\left(\text{BMI}_{i,t} - \text{BMI}_{i,t-1}\right) + X'_{i,t}\xi^h + \varepsilon_{i,t+h} \tag{11}$$

where $Inv_{i,t}$ is the investment rate and $\left(\text{BMI}_{i,t} - \text{BMI}_{i,t-1}\right)$ is the year-on-year change in BMI for firm i in industry j in year t. We include industry-by-year fixed effects $\alpha_{j,t}$ to control for time-varying unobserved heterogeneity across industries, such as industry level business cycles, which may correlate with firm outcomes. The vector $X_{i,t}$ contains the same set of time-varying controls as in the panel regressions above: a proxy for Tobin's q, cash flow, leverage, log market equity, current ratio, and firm age. The coefficients of interest, $\left\{\gamma^h\right\}_{h=0}^{10}$, provide cumulative effects in % after h years, scaled to a 10 p.p. year-on-year change in BMI. We stress that the estimates are reduced-form correlations and not causal estimates. However, they provide useful insights into the dynamic response of investment to changes in BMI.

Panel (a) of Figure 7 shows that the investment rate falls by a cumulative 7.8% over the subsequent 10 years following a 10 p.p. year-on-year increase in BMI. The impact response is initially positive but turns negative after one year and continues to decline over the next five years. It then stabilizes at a 7.8% lower level and exhibits no mean reversion over the remaining horizon, consistent with $\hat{\beta}$ remaining permanently higher (see Figure 4).

We next ask whether the investment response is quantitatively consistent with a cost of capital channel. We assess this (a) by estimating the implied semi-elasticity of investment with respect to user cost of capital and (b) considering whether the dynamic path of investment is consistent with the gradual pass-through of the perceived cost of capital to hurdle rates documented by Graham (2022) and Gormsen & Huber (2025a).

To calculate the implied semi-elasticity, we divide the cumulative investment response at horizon $t + 10$ by the change in the user cost of capital implied by a 10 p.p. increase in BMI, assuming a 6% ERP and 75% equity financing. The change in $\hat{\beta}$ implied by our estimates in Table A3 for a 10 p.p. BMI increase is 0.27. With these parameters, the increase in the CAPM-implied WACC is 122 bps and the semi-elasticity of investment with respect to cost of capital thus

$$\begin{array}{c}\text{Semi-Elasticity of Inv.}\\ \text{to Cost of Capital}\end{array} = \frac{\partial Inv}{Inv}\frac{1}{\partial r} = \frac{\widehat{d\log Inv}_{t+10}}{\underset{75\%}{\text{E/(D+E)}} \times \underset{6\%}{\text{ERP}} \times \underset{0.27}{\Delta\hat{\beta}}} \approx \underset{(1.5)}{-6.4}$$

The response of the investment rate after a 10 p.p. shock in BMI implies a semi-elasticity of −6.4. This estimate is large but consistent with evidence from Zwick & Mahon (2017) and Koby & Wolf (2020) who use tax changes to estimate a semi-elasticity of −7.2 and −5, respectively.

Gormsen & Huber (2025a) document that pass-through from the perceived cost of capital to the hurdle rates that managers use is gradual. We model this gradual pass-through by assuming that the perceived cost of capital increases immediately with the change in $\hat{\beta}$, but that managers adjust their hurdle rates only gradually, by 25% a year.[21] Panel (b) of Figure 7 plots the implied response under gradual updating of hurdle rates and the actual investment response. The implied response lies close to or within the confidence interval of the actual response at all horizons. In summary, the investment response is quantitatively consistent with a perceived cost of equity increase and gradual pass-through to hurdle rates.

Placebo Test We conduct a placebo test using the institutional ownership ratio (IOR). Because IOR does not affect CAPM $\hat{\beta}$ (see Table A4), it should not influence investment through the perceived cost of equity channel. We replace the year-on-year increase in BMI in equation (11) with a year-on-year increase in IOR and re-estimate the local projections.

[21]Specifically, we model pass-through after t years as exponential saturation $y(t) = 1 - (1 - \lambda)^t$ with $\lambda = 0.25$.

Panel (a) of Figure 7 shows the investment response to a 10 p.p. increase in IOR. In contrast to the negative response to BMI, the investment rate rises by approximately 5% at impact and remains elevated before gradually converging to zero over 10 years. This positive response supports the interpretation that the negative investment effect is specific to benchmark-linked ownership, not institutional ownership broadly. It also mitigates concerns that omitted variables associated with higher institutional ownership, such as changes in corporate governance, drive our results.

Cross-sectional Heterogeneity in Firms' Investment Response If BMI shocks affect investment through the perceived cost of equity, their impact should be larger for firms more reliant on equity financing and for firms with longer-lived assets. We test both predictions by adding interaction terms to the cumulative impulse responses in Eq. (11), comparing firms in the top versus bottom terciles of equity share of capital and of asset maturity, measured as the inverse of the capital depreciation rate (Hubert De Fraisse, 2024).[22]

Appendix Figure A5 confirms both predictions. The investment response to a positive BMI shock is significantly more negative for firms that rely more on equity financing and for firms with high asset maturity. Firms in the bottom terciles of both measures also experience investment declines, but of smaller magnitude. These cross-sectional patterns support the perceived cost of equity channel: the investment response to BMI is strongest precisely where sensitivity to the cost of equity is highest.

Summary Our panel regression and local projection results show that higher BMI correlates with lower firm level investment. The magnitude and dynamics of the investment response are consistent with an increase in the perceived cost of equity, suggesting that managers adjust investment in response to benchmarking-induced changes in CAPM $\hat{\beta}$. However, the level of BMI and year-on-year changes in BMI may be correlated with omitted variables. We next turn to natural experiments that provide plausibly exogenous variation in BMI.

6.3 Natural Experiment 1: Annual Russell Benchmark Reconstitution

Our first natural experiment exploits exogenous variation in BMI generated by the annual Russell benchmark reconstitution. We use an instrumental variable (IV) local projections (LP) strategy where we instrument changes in CAPM $\hat{\beta}$ with changes in BMI due to Russell benchmark reconstitution to identify the effects of benchmarking on investment and other firm outcomes.

[22] In a model with fixed adjustment cost and marginal product of capital $\alpha k^{\alpha-1}$, the semi-elasticity of investment with respect to the discount rate r is $\frac{\partial i/i}{\partial r} = -\frac{1}{\delta}\frac{1}{1-\alpha}\left(\frac{1+r}{r+\delta}\right)$ where δ is the depreciation rate (Winberry, 2021).

We estimate a series of LP-IV regressions of the following form:

$$\Delta\text{CAPM } \hat{\beta}_{i,t} = \delta_{j,t} + \theta \Delta\text{BMI}_{i,t} + \psi \log\left(\text{Market Cap.}\right)_{i,t} + \text{Banding Vars.}_{i,t} + \zeta X_{i,t} + \epsilon_{i,t} \tag{12}$$

$$\log\left(Y_{i,t+h}\right) - \log\left(Y_{i,t-1}\right) = \alpha^h_{j,t} + \gamma^h \widehat{\Delta\text{CAPM } \beta}_{i,t} + \phi^h \log\left(\text{Market Cap.}\right)_{i,t} + \text{Banding Vars.}_{i,t} + \xi^h X_{i,t} + \varepsilon_{i,t+h} \tag{13}$$

where $Y_{i,t}$ is the outcome (e.g., capital expenditures) and $\Delta\text{BMI}_{i,t}$ is the change in BMI between May and June for firm i in year t. The coefficients of interest, γ^h, provide cumulative local average treatment effects in % after $h = 0, 1, \ldots, 6$ years. We include 2-digit SIC industry-by-year fixed effects $\alpha^h_{j,t}$ and $\delta^h_{j,t}$ to absorb time-varying unobserved heterogeneity across industries.

Identifying Assumptions and Threats to Identification The exclusion restriction in a local projection setting requires that the instrument not be correlated with contemporaneous or future shocks to firm outcomes after conditioning on controls. In our case, changes in BMI must affect firm outcomes only through changes in CAPM $\hat{\beta}$.

To ensure that our estimates are well-identified, we follow three steps. First, we include a proxy for the Russell ranking variable: market capitalization at the end of May. We use end-of-May, not June, market capitalization to avoid selection bias (Chang et al., 2015, Appel et al., 2024). To approximate Russell's proprietary market caps, we follow Ben-David et al. (2019) and use publicly available data that accurately predict benchmark assignment and mitigate mismeasurement concerns (Glossner, 2024). We restrict the sample to stocks within 300 ranks of the Russell cutoffs to capture changes in BMI due to reconstitution (Pavlova & Sikorskaya, 2023), and include controls for the banding policy introduced after 2007 (Appel et al., 2019). Second, we saturate the estimator with industry-by-year fixed effects to remove time-varying unobserved heterogeneity. Third, we control for Tobin's q, cash flow, the cumulative 12-month return (momentum), log bid-ask spreads, and log Amihud illiquidity in $X_{i,t}$.

A remaining concern is that other factors, such as risk exposure, access to debt markets, or governance, could change alongside CAPM $\hat{\beta}$s when BMI changes. In Online Appendix H, we test whether changes in BMI correlate with changes in firm risk, financial frictions, or governance, and find no evidence that they do. Column (1) of Online Appendix Table H16 shows that changes in BMI do not correlate with firm statements about delaying investments.

Reduced Form Results Table 5 reports reduced-form effects of BMI changes due to Russell reconstitution on investment and net payouts. Panel A shows that a 1 p.p. exogenous increase

Table 5: Reduced Form Effect of Russell Reconstitution BMI Shock on Investment and Payouts

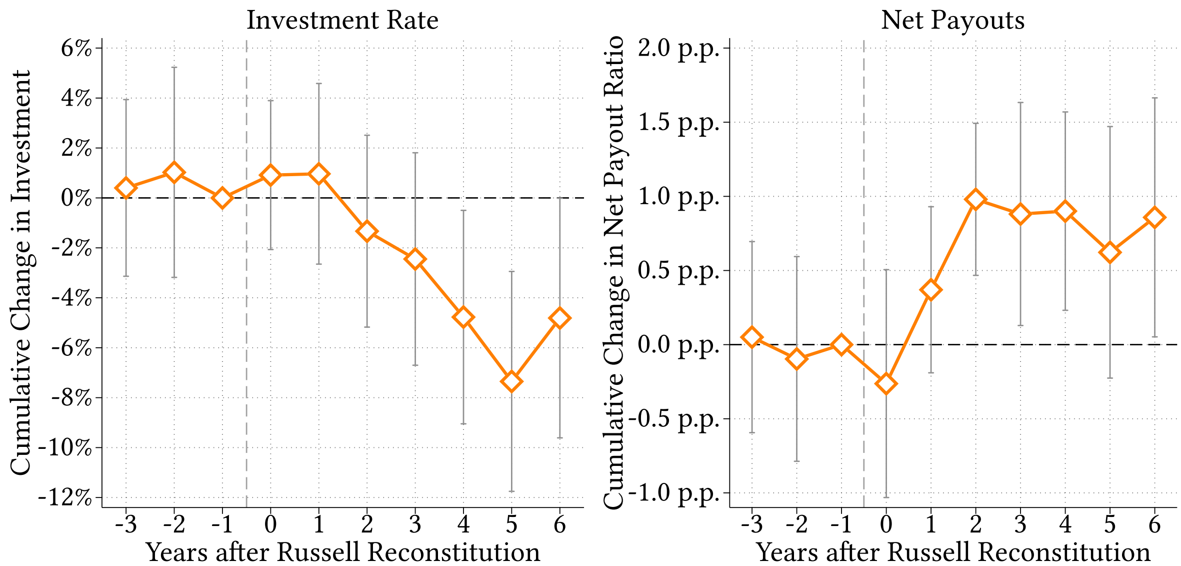
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Dep. var.: Cum. log change in investment $100 \times (\log(Inv_{i,t+h}) - \log(Inv_{i,t-1}))$							
Horizon $t+h$:	$t+0$	$t+1$	$t+2$	$t+3$	$t+4$	$t+5$	$t+6$
Δ BMI	-0.077	0.102	-0.318	-0.582	-0.841**	-0.926**	-0.723*
	(0.265)	(0.316)	(0.346)	(0.374)	(0.382)	(0.390)	(0.394)
Log(Mkt. Cap) and Log(Bid-Ask Spread)	✓	✓	✓	✓	✓	✓	✓
Banding Variables	✓	✓	✓	✓	✓	✓	✓
Window width around Russell 1000 cutoff	300	300	300	300	300	300	300
Adj. R^2	0.06	0.10	0.11	0.10	0.08	0.07	0.07
Observations	8,593	8,261	7,909	7,571	7,251	6,535	5,869
Panel B: Dep. var.: Cum. change in net payout ratio $100 \times (\text{Net Payout Ratio}_{i,t+h} - \text{Net Payout Ratio}_{i,t-1})$							
Horizon $t+h$:	$t+0$	$t+1$	$t+2$	$t+3$	$t+4$	$t+5$	$t+6$
Δ BMI	0.006	0.072	0.158**	0.170**	0.164*	0.206**	0.137
	(0.066)	(0.079)	(0.074)	(0.081)	(0.080)	(0.095)	(0.079)
Log(Mkt. Cap) and Log(Bid-Ask Spread)	✓	✓	✓	✓	✓	✓	✓
Banding Variables	✓	✓	✓	✓	✓	✓	✓
Window width around Russell 1000 cutoff	300	300	300	300	300	300	300
Adj. R^2	0.01	0.03	0.05	0.06	0.06	0.06	0.06
Observations	8,346	8,036	7,700	7,363	7,037	6,328	5,699

Notes: This table reports estimates for regressions of the form: $100 \times (\log(Inv_{i,t+h}) - \log(Inv_{i,t-1})) = \alpha_t^h + \gamma^h \Delta\, \text{BMI}_{i,t} + \rho^h \log(\text{Market Cap.})_{i,t} + \psi^h \log(\text{Bid-Ask-Spread})_{i,t} + \phi^h \text{Banding Variables}_{i,t} + \varepsilon_{i,t+h}$, where $Inv_{i,t+h} = \frac{\text{CAPX}_{i,t+h}}{\text{PPE}_{i,t+h-1}}$ in Panel A and $100 \times (\text{Net Payout Ratio}_{i,t+h} - \text{Net Payout Ratio}_{i,t-1}) = \alpha_t^h + \gamma^h \Delta\, \text{BMI}_{i,t} + \rho^h \log(\text{Market Cap.})_{i,t} + \psi^h \log(\text{Bid-Ask-Spread})_{i,t} + \phi^h \text{Banding Variables}_{i,t} + \varepsilon_{i,t+h}$, where $\text{Net Payout Ratio}_{t+h} = \frac{\text{Dividends}_{i,t+h} + \text{Net Stock Repurchases}_{i,t+h}}{\text{Total Assets}_{i,t+h-1}}$ in Panel B. Market capitalization in May is measured using the methodology of Ben-David et al. (2019). We restrict the estimation sample to stocks within 300 ranks around Russell index cutoffs. Standard errors in parentheses are clustered at the year- and firm-level. * p<0.10, ** p<0.05, *** p<0.01.

in BMI lowers the investment rate by 0.723% after six years. The effect is negligible during the first three years but becomes increasingly negative from year $t+4$ onward. Panel B shows that firms respond to the BMI-induced increase in their perceived cost of equity by raising net payouts (dividends plus net stock repurchases). Figure 8 plots the results of Table 5 scaled to the average BMI change (≈ 6.7 p.p.) for stocks transitioning from the Russell 1000 to the Russell 2000.

Appendix Figure A6 shows robustness to alternative specifications and definitions of investment. Panel (a) shows that both intangible investment and acquisitions decline following an exogenous increase in BMI. The intangible investment rate falls by about 2.2 p.p., an 11% decline relative to the sample mean of 20.3%. Acquisitions scaled by total assets fall by about 0.4 p.p., a 9% decline relative to the sample mean of 4.2%. The relatively larger response of intangible investment is consistent with theories emphasizing that intangible assets have low pledgeability and liq-

Figure 8: Impulse Responses to a 6.7 p.p. increase in BMI around Russell Reconstitution



Notes: This figure shows local projection coefficient estimates for $100\times$ cumulative (log-)changes of outcome variables from regression of the form $\log(Y_{i,t+h}) - \log(Y_{i,t-1}) = \alpha^h_{j,t} + \gamma^h \Delta \text{BMI}_{i,t} + \phi^h \log(\text{Market Cap.})_{i,t} + \text{Banding Vars.}_{i,t} + \xi^h X_{i,t} + \varepsilon_{i,t+h}$, where the shock is scaled to the average increase in BMI for a stock transitioning from the Russell 1000 to the Russell 2000 ($\approx$ 6.7 p.p.). We restrict the estimation sample to stocks within 300 ranks around Russell index cutoffs. Standard errors are double clustered at the firm and year level.

uidation values, which tightens debt capacity and makes equity the marginal source of finance. Consequently, shocks that increase the cost of equity should transmit more strongly to intangible investment than to tangible investment (Hall, 2002). Panel (b) shows that firms do not substitute toward debt financing following an exogenous increase in BMI.

Panel (c) shows that varying the bandwidth around the Russell 2000 cutoff from 200 to 400 ranks leaves the investment rate point estimates and conclusions largely unchanged. Panel (d) shows that explicitly controlling for momentum (cumulative stock return over the prior 12 months) does not affect the results. This addresses concerns that firms moving from the Russell 1000 to the Russell 2000 are "fallen angels," with deteriorating fundamentals that mechanically drive both index assignment and investment. Once momentum is included, selection on recent performance is unlikely to explain the treatment effects. Momentum itself is a strong predictor of investment, but its variation is orthogonal to the incremental effect of BMI on investment.

Panel (e) tightens the baseline specification by including 4-digit NAICS industry fixed effects and adding controls for momentum, leverage, and Tobin's q; the estimates remain close to the baseline. Finally, panel (f) uses alternative definitions of the investment rate, CAPX/PPENT and CAPX/AT, and again yields results similar to the baseline definition, CAPX/PPEGT.

Second Stage Results We estimate the effects of BMI-induced changes in CAPM $\hat{\beta}$s on capital expenditures, capital stocks, employment, and payouts using LP-IV regressions. We calibrate the shock to correspond to a 100 bps increase in the CAPM-implied WACC, equivalent to a 10 p.p. increase in BMI under a 6% equity risk premium (100 bps $= 0.25 \times 6\% \times 2/3$).

Benchmarking-induced increases in CAPM $\hat{\beta}$s lead to large and persistent declines in investment. In response to a 100 bps increase in the CAPM-implied WACC, firms reduce capital expenditures by approximately 10.2% over six years. After six years, physical capital stocks decline by 4.0%, intangible capital stocks by 8.4%, and employment falls by 5.5%.

Online Appendix Figure B8 shows several additional patterns. First, firms respond gradually, with effects starting close to zero in the treatment year and growing over time; the cumulative impact becomes statistically and economically significant after about three years. This adjustment pattern likely reflects the gradual pass-through from managers' perceived cost of capital to hurdle rates documented by Gormsen & Huber (2025b). Second, cash holdings increase, consistent with firms self-insuring against increased exposure to benchmark-linked capital flows. Eventually, firms increase dividends and stock repurchases, providing indirect evidence that treated firms are not financially constrained.[23] Third, employment also declines, indicating that firms scale back labor alongside physical capital.

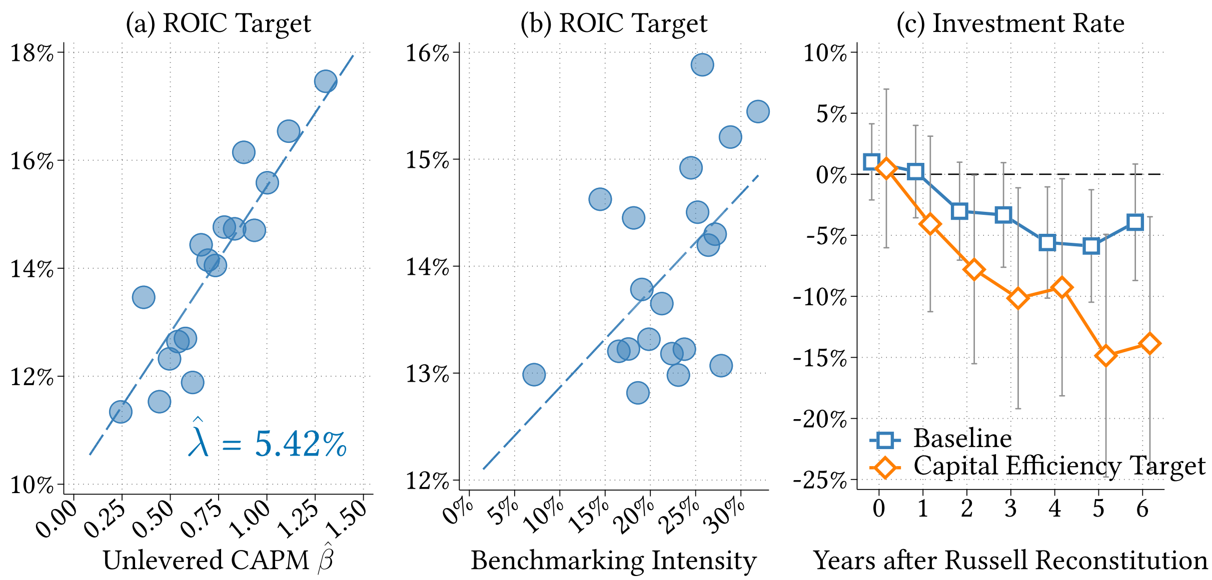
6.3.1 Mechanism: Managerial Incentive Contracts

A key institutional feature amplifying the effect of BMI on investment is the widespread use of capital efficiency targets in executive compensation. Capital efficiency targets reward managers for achieving accounting returns, such as return on invested capital (ROIC), in excess of WACC. When managers compute WACC using the CAPM, an increase in $\hat{\beta}$ mechanically raises the hurdle rate and compresses the ROIC-minus-WACC spread, making marginal projects appear value-destroying. Managers therefore rationally respond by reducing investment to preserve capital efficiency performance and compensation outcomes. In 2010, 41% of Russell 3000 firms used capital efficiency metrics in long-term incentive plans and 28% in short-term plans (Reda & Tonello, 2015). Appendix Figure A1 provides examples from proxy statements that explicitly link these targets to CAPM-based cost of capital calculations.

We test this channel using data from ISS Incentive Lab for the period 1998 to 2018. We classify a firm as using capital efficiency targets if such targets appear in its executive compensation con-

[23] In a broad class of macro-finance models, financially constrained firms do not distribute cash to shareholders (see, e.g., Begenau & Salomao 2019).

Figure 9: Capital Efficiency Targets, CAPM $\hat{\beta}$s, Benchmarking Intensity, and Investment



Notes: This figure shows the relationship between capital efficiency targets, CAPM $\hat{\beta}$, and firms' investment responses to benchmarking shocks. Panels (a) and (b) plot binned scatterplots of firms' ROIC targets against their stocks' unlevered CAPM $\hat{\beta}$ and benchmarking intensity (BMI), respectively, using 20 quantile-spaced bins after absorbing year and firm fixed effects. Panel (c) reports reduced form local projection estimates of the effect of changes in BMI on investment rates, allowing for differential responses by firms with capital efficiency targets (defined as having used such a target in the three years preceding Russell reconstitution).

tracts in the previous three years. We define capital efficiency targets to include ROIC, return on capital employed (ROCE), return on equity (ROE), and Economic Value Added (EVA). Appendix Table A6 shows that firms with capital efficiency targets achieve higher realized ROIC, ROCE, and ROE in the cross-section, and that ROIC targets significantly predict subsequent realized ROIC, consistent with these targets being binding and salient in managerial decision-making.

Panel (a) of Figure 9 shows that firms' ROIC targets are strongly correlated with unlevered CAPM $\hat{\beta}$. The slope implies a perceived equity risk premium of approximately 5.4%, closely aligned with the estimates in Table 2. This finding suggests that managers map CAPM-based discount rates into internal performance benchmarks. Panel (b) shows that ROIC targets also increase systematically with BMI: firms with greater exposure to benchmark-linked capital flows set higher internal hurdle rates, consistent with managers interpreting benchmark-induced increases in $\hat{\beta}$ as increases in the cost of equity. Panel (c) shows that investment at firms with capital efficiency targets responds more strongly to exogenous increases in BMI. The estimated coefficients are approximately 2.5 times larger than for firms without such targets. The effects materialize within two years, consistent with managers facing high-powered incentives to closely monitor CAPM-implied WACC and to adjust investment policies accordingly.

6.4 Natural Experiment 2: S&P 500 Benchmark Inclusion

Additions to the S&P 500 provide additional evidence that changes in BMI affect capital accumulation. We analyze 325 inclusions between 2000 and 2018 using a difference-in-differences event-study design. BMI rises sharply upon S&P 500 inclusion: on average, stocks experience an 8.6 p.p. increase in BMI in the month of addition, relative to a baseline of 14.1%.[24]

Unlike the mechanical annual reconstitution of the Russell indices, S&P 500 additions are discretionary. A selection committee determines inclusion based on criteria such as market capitalization, liquidity, sector classification, profitability, and listing history. This discretion raises endogeneity concerns, as the committee may select firms based on unobserved characteristics, such as growth opportunities or managerial quality, that also affect investment.

We use a difference-in-differences design comparing added firms with non-added firms in the same industry and year; identification requires that the timing of inclusion does not correlate with *time-varying* unobserved shocks to CAPM $\hat{\beta}$s and investment, rather than unobserved *level* differences. Appendix Figure A7 shows that S&P 500 inclusion increases CAPM $\hat{\beta}$s. The 21-day $\hat{\beta}$ rises by approximately 0.14 immediately after addition. The 252-day $\hat{\beta}$ increases gradually, reaching 0.10 after nine months. Included firms are, on average, 80% equity-financed, implying that the $\hat{\beta}$ increase raises the user cost of capital by 50–70 bps under a 6% equity risk premium.[25]

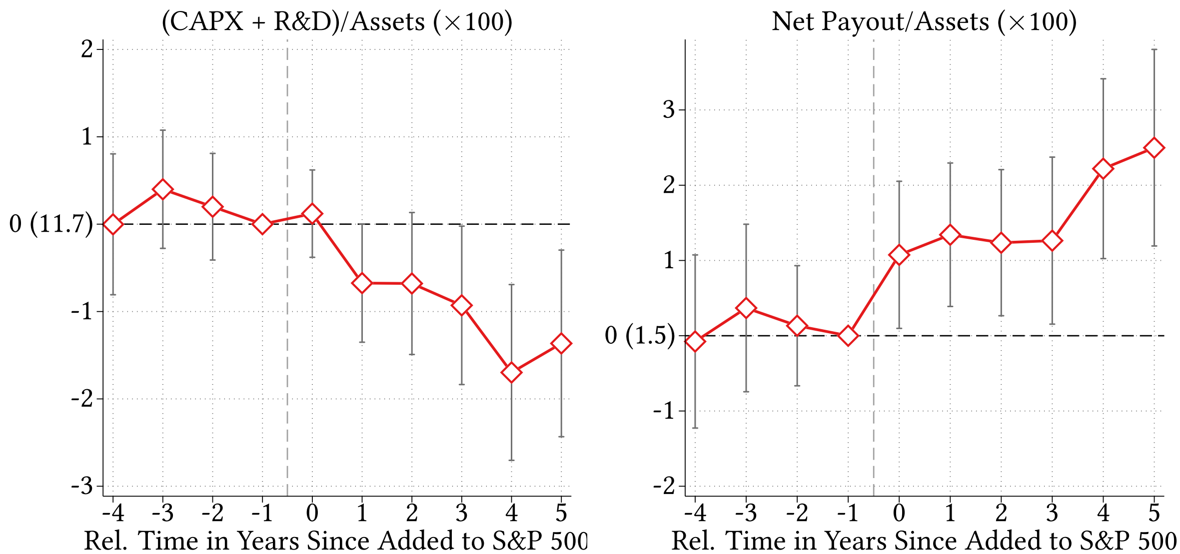
Turning to real outcomes, we estimate the impact on investment rates and net payout ratios at annual frequency, controlling for Tobin's q, cash flow, momentum, and industry-by-year fixed effects. Figure 10 shows that inclusion leads to a gradual decline in investment, alongside a sharp and sustained increase in net payouts. Investment rates bottom out four years post-inclusion, consistent with managerial discount rates updating slowly in response to a higher perceived cost of equity. Payouts respond faster, peaking at 2.5 p.p. above baseline after five years. Initially funded from cash reserves, payouts are increasingly sustained by reduced capital expenditures.

Our results align with Bennett et al. (2023), who also find a decline in investment following S&P 500 inclusion; we propose a complementary mechanism. Managers, perceiving themselves to be acting in shareholders' interests, reduce investment and increase payouts in response to a higher perceived cost of equity. Bennett et al. (2023) emphasize peer effects and categorical thinking, arguing that managers' incentives shift as compensation peer groups expand to include more

[24]We focus on additions, as most deletions stem from mergers or acquisitions, making it difficult to measure post-event real outcomes for the affected firms. Inclusion dates are drawn from Chinco & Sammon (2024).

[25]We find no significant effect on the ICC following S&P 500 inclusion, consistent with Patel & Welch (2017) and Greenwood & Sammon (2024), who document a disappearance of S&P 500 inclusion price effects.

Figure 10: Effects of S&P 500 Benchmark Inclusion on Investment and Net Payouts



Notes: This figure reports yearly difference-in-differences event-study estimates of changes in investment rate and net payout ratio for stocks added to the S&P 500. Effects are identified from within-industry-year variation. Controls include log market cap, Tobin's q, cash flow, and momentum. Pointwise confidence intervals (95%) are based on double-clustered standard errors.

S&P 500 firms and boards begin evaluating management relative to index peers. We note that these explanations are not mutually exclusive but leave disentangling them to future work.

6.5 Natural Experiment 3: MSCI ACWI Benchmark Inclusion

In an international setting, prior research finds that inclusion in the MSCI ACWI is associated with a modest increase in firm investment, attributed to foreign ownership disciplining entrenched managers (Bena et al., 2017) and enhancing price efficiency (Kacperczyk et al., 2021). We offer a complementary mechanism: MSCI ACWI inclusion reduces the perceived cost of equity by lowering a stock's CAPM $\hat{\beta}$ relative to its local market index. Inclusion shifts a stock's investor base from local to global benchmarked funds, reducing the stock's exposure to local demand shocks and thereby lowering its covariance with the domestic index. A lower local $\hat{\beta}$ reduces managers' perceived cost of capital, consistent with an investment increase. This interpretation assumes managers use local market $\hat{\beta}$ to estimate their cost of equity, in line with evidence that analysts favor home-country indices over international benchmarks (Décaire & Graham, 2024).

Online Appendix Figure B9 plots difference-in-differences event study coefficients confirming that local market $\hat{\beta}$ declines persistently after ACWI inclusion. The combination of a lower $\hat{\beta}$ to the local index and higher investment after ACWI addition is consistent with our perceived cost of equity channel and provides external validity to our U.S. findings.

6.6 Alternative Mechanisms

We interpret our findings as evidence that benchmarking reduces firm investment by increasing managers' perceived cost of equity. We examine three alternative mechanisms: (i) risk exposure, (ii) corporate governance, and (iii) the private information content of stock prices.

Risk Exposure We test whether firm-level risk exposure accounts for the investment effects of BMI. Appendix Table A7 adds proxies for high risk exposure as controls and interacts them with BMI. We use firms in the top tercile of firm-level risk and sentiment (Hassan et al., 2019) or firm-level exposure to economic policy uncertainty, oil price uncertainty, and exchange rate uncertainty (Alfaro et al., 2024). The BMI coefficient remains economically and statistically stable after including these risk proxies, suggesting that risk exposure does not confound the effect of BMI on investment. The interactions are also insignificant, indicating that the effect of BMI is homogeneous across high- and low-risk firms.

These findings are consistent with additional evidence on fundamental risk measures. Online Appendix Figure B4 shows that neither accounting-based βs (Cohen et al., 2009) nor consumption growth βs (Kim et al., 2024) exhibit significant changes in response to the increase in BMI over the past 25 years. In Online Appendix H, we test whether changes in BMI around Russell reconstitution correlate with changes in firm risk measures or the CAPM $\hat{\beta}$ of peer firms and find no evidence that they do.

Corporate Governance Next, we consider the role of corporate governance, focusing on the implications of common ownership. Theories of common ownership (e.g., Azar, 2012, Azar et al., 2018, Antón et al., 2023) predict outcomes consistent with our findings: a decrease in investment and an increase in payouts. Alternative theories regarding the impact of benchmark-linked ownership on governance are less clear, as their predictions depend on whether managers are ex-ante overinvesting (Jensen, 1986, Bebchuk, 2004) or underinvesting (Jensen & Meckling, 1976, Bertrand & Mullainathan, 2003), and on the specific governance effects of index fund ownership (Appel et al., 2019, Heath et al., 2021, Lewellen & Lewellen, 2022). In Online Appendix H, we additionally test whether changes in BMI correlate with changes in governance scores of several providers or the likelihood of facing an activist investor but find no evidence that they do.

Appendix Table A8 interacts BMI with proxies for high common ownership and low competition in investment rate regressions. Using several measures of common ownership at the NAICS 4-digit industry level from Koch et al. (2021), we find no evidence that the investment response to BMI differs in industries with high common ownership or in industries with high markups, estimated using the production function approach of De Ridder et al. (2025), or high price-cost margins. The common ownership measures themselves have mixed and insignificant main effects on investment, and the BMI coefficient remains stable after their inclusion, ruling out common ownership as a confounding channel. Common ownership thus neither moderates nor mediates the effect of BMI on investment.

Private Information If managers learn from stock prices (Dow & Gorton, 1997, Durnev et al., 2004) and prices of highly benchmarked stocks incorporate less private information, managers may reduce investment due to increased uncertainty about project values (Chen et al., 2007, Bakke & Whited, 2010). Consistent with this premise, Online Appendix Figure B6 shows that an exogenous increase in BMI raises the CAPM R^2 and that BMI explains a large share of the cross-sectional variation in R^2, suggesting that less firm-specific information is incorporated into the prices of highly benchmarked stocks. This finding is consistent with Sammon (2024), who shows that passive ownership reduces the extent to which stock prices anticipate future earnings.

To test whether this channel drives the investment response, we examine whether the effect of BMI on investment varies with the degree of private information in a firm's stock price. We use two proxies: price non-synchronicity (Chen et al., 2007) and the bid-ask spread, which captures market makers' compensation for adverse selection risk (Glosten & Milgrom, 1985). Appendix Table A9 shows that while firms with more private information (higher non-synchronicity or higher spreads) exhibit higher investment sensitivity to Tobin's q, this interaction does not absorb the negative effect of BMI on investment.

Summary Our tests do not support channels related to firm-level risk exposure or corporate governance. The governance finding is consistent with Koch et al. (2021), who document that common ownership is not associated with reductions in net capacity investment, even in concentrated industries (see also Lewellen & Lowry, 2021). Instead, benchmarking affects investment directly by increasing managers' perceived cost of equity, and may have an indirect effect by reducing the private information content of stock prices.

7 Effects of Benchmarking on Investment at the Industry Level

Industries with higher CAPM βs due to benchmarking have accumulated less capital over the past 25 years. The results are robust to industry pre-trends and sectoral fixed effects. Increases in CAPM $\hat{\beta}$ and BMI are strongly associated with lower capital accumulation, while changes in

Table 6: IV: Long-term Effects of Benchmarking on Capital Accumulation at the Industry level

	(1)	(2)	(3)	(4)	(5)
	Dependent variable: log (Real Capital Stock in 2016/Real Capital Stock in 1998)				
Δ CAPM β	-0.271*	-0.329**	-0.325*	-0.317**	-0.328**
(1998-2016)	(0.157)	(0.129)	(0.164)	(0.158)	(0.157)
Constant	0.243***	0.420**			
	(0.074)	(0.183)			
Industry controls in 1998		✓		✓	✓
Industry Pretrends 1980–1996					✓
NAICS-3 Subsector Fixed Effects			✓	✓	✓
Weights	VA_{1998}	VA_{1998}	VA_{1998}	VA_{1998}	VA_{1998}
Kleibergen–Paap F-statistic	12.95	13.79	17.60	17.37	17.07
Observations	103	103	103	103	103

Notes: This table reports coefficient estimates of IV regressions at the NAICS 5-digit industry level of the form: $\Delta \log\,(\text{Real Capital Stock})_i = \alpha_j + \gamma \Delta \text{CAPM}\ \hat{\beta}_i + X_i' \xi + \varepsilon_i$ where we instrument changes in CAPM $\hat{\beta}$ with changes in BMI from 1998 to 2016. BMI and CAPM $\hat{\beta}$ are market-value weighted averages of Compustat firms at the industry level. We exclude industries with fewer than 5 firms. Pre-trends measure log changes in variables from 1980 to 1996. Observations are weighted by industry value-added in 1998. We trim all variables at the 2% and 98% levels to remove outliers. Robust standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

the institutional ownership ratio have small positive but insignificant effects, supporting the interpretation that benchmarking-driven changes in the cost of equity, not institutional ownership broadly, reduce capital accumulation.

Data and Specifications We use the NBER-CES Manufacturing Industry database at the NAICS 5-digit level. Because the CES data on real capital stocks end in 2016, the analysis covers 1998–2016. We estimate IV long-difference regressions:

$$\Delta_{98}^{16}\ \text{CAPM}\ \hat{\beta}_i = \delta_j + \theta \Delta_{98}^{16}\ \text{BMI}_i + X_i' \zeta + \epsilon_i$$

$$\log\left(\text{Real Capital Stock}_i^{`16}/\text{Real Capital Stock}_i^{`98}\right) = \alpha_j + \gamma \widehat{\Delta_{98}^{16}\ \text{CAPM}\ \beta}_i + X_i' \xi + \varepsilon_i$$

where α_j are NAICS 3-digit subsector fixed effects, so coefficients are identified from variation across industries within the same subsector. Controls X_i include 1998 industry characteristics such as log employment and TFP. The change in CAPM $\hat{\beta}$ for industry i is the difference between the market-value-weighted average $\hat{\beta}$ in 2016 and 1998. We construct the change in BMI analogously, exclude industries with fewer than five firms, and weight observations by 1998 value-added shares. To address the concern that pre-existing growth paths confound the effects of benchmarking, we control for pre-trends in capital accumulation, employment, and wages from 1980 to 1996.

Results Table 6 reports the estimates. Across all specifications, increases in CAPM $\hat{\beta}$s have a statistically significant negative effect on long-term capital accumulation. The magnitudes are large: column (5) implies that a 0.3 increase in average CAPM $\hat{\beta}$ reduces the capital stock by 9.8% from 1998 to 2016, or about 0.55% annually. The results are robust to industry level controls and subsector fixed effects. Changes in BMI are strong instruments for changes in CAPM $\hat{\beta}$ even at the industry level, with first-stage F-statistics averaging 15.8 across columns.

A potential concern is that the secular rise in institutional ownership, rather than benchmarking-induced changes in $\hat{\beta}$, drives the results. Online Appendix Table B6 reports OLS and reduced-form estimates of the effects of changes in CAPM $\hat{\beta}$, BMI, and IOR on capital accumulation. Increases in $\hat{\beta}$ and BMI are associated with lower capital accumulation, while changes in IOR have a small, positive, and insignificant coefficient. This finding supports the interpretation that benchmarking-driven changes in the perceived cost of equity, not rising institutional ownership, drive the investment decline.

Robustness We replicate the analysis using BEA Fixed Asset Table 3.1, which covers all economic sectors at the 3-digit NAICS level. This broader coverage comes at the cost of reduced granularity: 38 industries at the 3-digit level compared to 103 at the 5-digit level in the NBER-CES data. Online Appendix Figure B7 confirms the negative relationship between changes in BMI and capital accumulation from 1998 to 2018. The estimates in column (4) imply that a 10 p.p. increase in BMI is associated with 16% lower capital accumulation over the sample period, or about −0.9% annually.

8 Aggregate Effects of Increased Benchmarking

In this last section, we assess whether the benchmarking-induced changes in CAPM $\hat{\beta}$s have consequences for aggregate investment. An effect on aggregate investment may seem unlikely, as the value-weighted market β must equal one, implying that any β increase for one firm is offset by a decrease for another. However, this intuition fails because it rests on two assumptions. First, it assumes that firms' shares in aggregate investment mirror their market capitalization weights. Second, it assumes that all firms respond identically to changes in their cost of capital.

The data reject both assumptions, creating a channel for aggregate effects. First, market capitalization weights and investment shares can differ markedly. For instance, the financial sector (NAICS 52) averages 17.3% of U.S. market capitalization yet only 3.5% of capital expenditures. Second, investment by smaller firms is more sensitive to financing costs than investment by larger firms (Gertler & Gilchrist, 1994, Zwick & Mahon, 2017). Benchmarking creates an aggregate investment decline because it provides a "β subsidy" to large, inelastic firms that do not adjust their investment, while imposing a "β penalty" on small, elastic firms that reduce their investment. Quantitatively, a back-of-the-envelope aggregation suggests that the rise in benchmarking reduces aggregate investment by 1.28% annually.

8.1 Aggregation of Firm Investment Across Market Capitalization Ranks

We derive the factors driving aggregate investment's response to changes in firms' CAPM βs. In the neoclassical investment model, capital stock and investment depend on the user cost of capital: $I = f(C)$. For firm i at time t, $C_{i,t} = (r_{i,t} + \delta)q_{i,t}$, where $r_{i,t}$ is the weighted average cost of capital, δ is depreciation, and $q_{i,t}$ is the relative price of capital goods. Managers set $r_{i,t}$ using the CAPM $r_{i,t} = (1-\mu_{i,t})(1-\tau_t)r^d_{i,t} + \mu_{i,t}\big(r^f_t + \beta_{i,t}\lambda_t\big)$, where $\mu_{i,t}$ is the equity share, $r^d_{i,t}$ the cost of debt, r^f_t the risk-free rate and λ_t the equity risk premium. The semi-elasticity of investment with respect to the user cost is then given by

$$\epsilon^C_{i,t} = \frac{1}{I_{i,t-1}}\frac{\partial I_{i,t}}{\partial C_{i,t}} = \frac{1}{I_{i,t-1}}\frac{1}{q_{i,t}\mu_{i,t}\lambda_t}\frac{\partial I_{i,t}}{\partial \beta_{i,t}}$$

since $\partial C_{i,t}/\partial \beta_{i,t} = q_{i,t}\mu_{i,t}\lambda_t$. The change in firm i's investment is to a first order approximation

$$\Delta I_{i,t} \approx I_{i,t-1}\,\epsilon^C_{i,t}\,\Delta C_{i,t} = \; I_{i,t-1}\,\epsilon^C_{i,t}\;\left(q_{i,t}\,\mu_{i,t}\,\Delta\beta_{i,t}\lambda_t\right).$$

That is, the change in firm i's investment depends on scale, $I_{i,t-1}$, and the firm's marginal propensity to invest in response to changes in the user cost of capital, $\epsilon^C_{i,t}$. The change in aggregate investment is the sum over all firms changing their investment. Assuming, for the moment, that all firms face the same relative price of capital, $q_{i,t} = q_t \; \forall \; i$, then

$$\frac{\Delta I_t}{I_{t-1}} \approx q_t\lambda_t \sum_i \pi_{i,t-1}\,\epsilon^C_{i,t}\,\mu_{i,t}\,\Delta\beta_{i,t} \tag{14}$$

Equation (14) shows that the aggregate investment response to changes in CAPM βs depends on the distributions of (i) investment shares $\pi_{i,t-1} = I_{i,t-1}/I_{t-1}$, (ii) semi-elasticities $\epsilon^C_{i,t}$, (iii) equity shares $\mu_{i,t}$, and (iv) changes in βs across firms. It also clarifies that market-cap weights aggregate investment correctly only when they match firms' shares of total investment.[26]

[26] Technically, using market-cap weights ω_i instead of investment-share weights π_i biases estimates in proportion to the covariance between $\omega_i - \pi_i$ and the firm-level shock x_i. This bias is zero only if the weights coincide.

Table 7: Covariance Decomposition of the Aggregate Investment Response

Component		Estimate	Std. Err.	Share
Average Firms' Response	$\mathbb{E}_\pi[\epsilon^C_{i,t}]\ \mathbb{E}_\pi[\mu_{i,t}]\ \mathbb{E}_\pi[\Delta\beta_{i,t}]$	-0.067	(0.096)	0.31
+ Sensitivity Sorting	$\text{Cov}_\pi(\epsilon^C_{i,t}, \Delta\beta_{i,t})\ \mathbb{E}_\pi[\mu_{i,t}]$	-0.149***	(0.033)	0.70
+ Equity-share Sorting	$\text{Cov}_\pi(\mu_{i,t}, \Delta\beta_{i,t})\ \mathbb{E}_\pi[\epsilon^C_{i,t}]$	0.003**	(0.001)	-0.01
+ Pass-through Sorting	$\text{Cov}_\pi(\epsilon^C_{i,t}, \mu_{i,t})\ \mathbb{E}_\pi[\Delta\beta_{i,t}]$	0.000	(0.000)	-0.00
× Equity Risk Premium	$\lambda_t = 0.06$			
× Relative Price of Capital	$q_t = 1$			
≈ Change in Aggregate Investment	$\Delta I_t / I_{t-1} \times 100$	-1.274*	0.662	

Notes: This table decomposes the change in aggregate investment into moments from Equation (15). $\mathbb{E}_\pi[\cdot]$ is the cross-sectional mean under investment-share weights π, and $\text{Cov}_\pi(\cdot,\cdot)$ the corresponding covariance. ϵ^C is the semi-elasticity of investment to the user cost, μ the equity share, $\Delta\beta$ the change in CAPM β, λ the equity premium, and q the relative price of capital. "Share" is each component's fraction of the total. Moments are jointly estimated by GMM with heteroskedasticity-robust standard errors. $^*p<0.10$, $^{**}p<0.05$, $^{***}p<0.01$.

A covariance decomposition of (14) provides further economic insights,

$$\frac{\Delta I_t}{I_{t-1}} \approx q_t \lambda_t \Bigg[\mathbb{E}_\pi[\epsilon^C_{i,t}]\ \mathbb{E}_\pi[\mu_{i,t}]\ \mathbb{E}_\pi[\Delta\beta_{i,t}] + \text{Cov}_\pi(\epsilon^C_{i,t}, \Delta\beta_{i,t})\ \mathbb{E}_\pi[\mu_{i,t}] + \text{Cov}_\pi(\mu_{i,t}, \Delta\beta_{i,t})\ \mathbb{E}_\pi[\epsilon^C_{i,t}] + \text{Cov}_\pi(\epsilon^C_{i,t}, \mu_{i,t})\ \mathbb{E}_\pi[\Delta\beta_{i,t}] \Bigg] \tag{15}$$

where all expectations and covariances are taken under π.[27]

The first product in brackets represents the average firm's investment response to a change in β. We can sign the expectations terms without further empirical analysis. The average investment semi-elasticity, $\mathbb{E}_\pi[\epsilon^C_{i,t}]$, is negative, while the average equity share, $\mathbb{E}_\pi[\mu_{i,t}]$, and the average investment-share weighted change in CAPM $\hat{\beta}$, $\mathbb{E}_\pi[\Delta\beta_{i,t}]$, are positive (see Table A1). Importantly, even if the average firm's investment does not respond, aggregate investment can still change due to reallocation effects that the covariance terms in (15) capture.

Our analysis focuses on the first covariance term, which proves most important. This term, $\text{Cov}_\pi(\epsilon^C, \Delta\beta)$, links investment sensitivities to the allocation of β shocks across firms. A negative covariance arises when larger β increases affect firms with more negative semi-elasticities. This condition creates a more contractionary aggregate response because the firms facing the biggest cost-of-capital shock are also those that cut investment most sharply. The high average equity share, $\mathbb{E}_\pi[\mu]$, amplifies this effect by increasing the pass-through from β to the user cost.

[27] We suppress a third-order term in the decomposition.

To compute the covariance term, we need estimates of investment semi-elasticities across firms. We estimate these by regressing investment rates on CAPM $\hat{\beta}$s within sales deciles. While OLS likely biases these estimates toward zero, their cross-sectional pattern aligns with well-identified estimates from the literature: smaller firms show more negative semi-elasticities (e.g., Zwick & Mahon, 2017). Online Appendix I details this estimation. We map decile-level semi-elasticities to market capitalization ranks and use GMM to jointly estimate the moments in Equation (15), using the empirical distributions of ϵ^C, π, μ, and $\Delta\beta$ (see Online Appendix Figure B10).

Table 7 shows that aggregate investment falls by 1.28%, all else equal. The average firm's response contributes about 31% of this decline. The covariance between $\Delta\beta_i$ and ϵ_i^C accounts for approximately 70%: this negative covariance generates a reallocation effect in which the firms most exposed to benchmarking-induced β increases are also the most investment-sensitive. The remaining two covariance terms in (15), linking financing patterns to risk exposure and investment flexibility, are negligible. Appendix Figure A8 shows the change in aggregate investment across market capitalization ranks under alternative weighting schemes and elasticity assumptions.

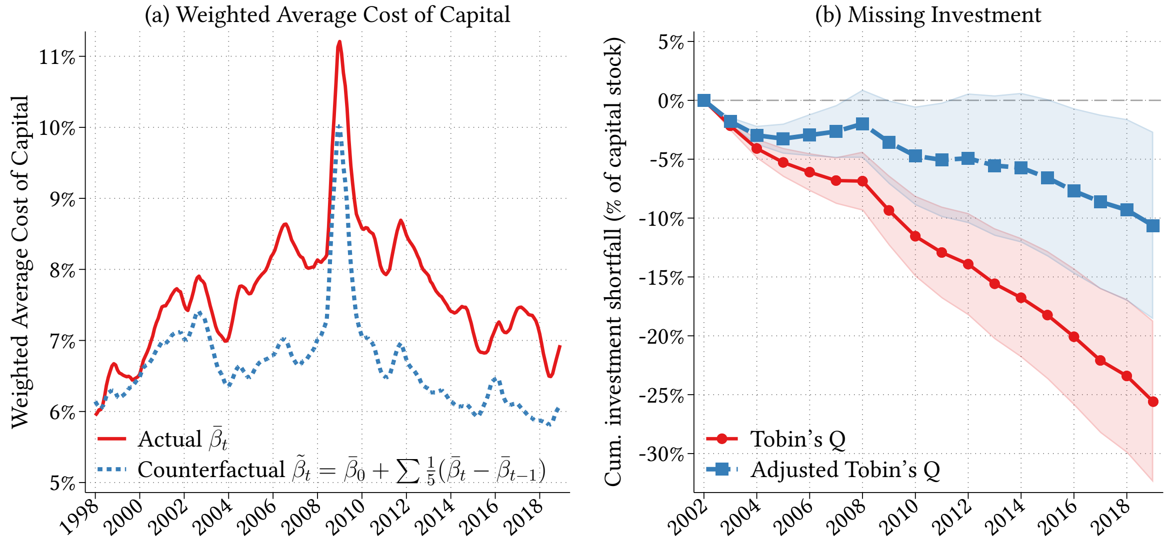
General Equilibrium Our preceding analysis provides clear intuition, but as a static partial equilibrium exercise, it abstracts from dynamic adjustments, non-linearities from capital adjustment costs, and general equilibrium feedback. To address these limitations, we embed the mechanism within a quantitative general equilibrium model detailed in Online Appendix J. The model features heterogeneous firms and capital adjustment costs, which allows us to evaluate the aggregate impact in a dynamic setting. We introduce the empirically observed changes in $\hat{\beta}$ as size-dependent shocks to firms' discount rates: the largest firms experience a decrease, while all other firms face an increase, consistent with our empirical results.

The general equilibrium model validates our back-of-the-envelope aggregation and predicts an aggregate investment decline of 1.8% in response to the $\hat{\beta}$ shock. The adverse shock to the cost of capital pushes small, high-growth firms to reduce investment. In contrast, large firms near their optimal scale show little response to the shock. While this richer model captures our mechanism, it abstracts from other margins like firm entry/exit and innovation, which represent promising avenues for future research (Gutiérrez et al., 2021, Bustamante & Zucchi, 2023).

8.2 Counterfactual WACC and the Missing Investment Puzzle

We construct a counterfactual WACC for the average firm by removing benchmarking-induced distortions from its CAPM $\hat{\beta}$ and test whether the resulting wedge is large enough to account

Figure 11: Actual and Counterfactual Weighted Average Cost of Capital and Missing Investment



Notes: Panel (a) plots the average firm's actual and counterfactual WACC, computed as $\text{WACC}_t = \mu_t r_t^e + (1-\mu_t)(1-\tau_t) r_t^d$, where $r_t^e = r_t^f + \beta \left(\mathbb{E}_t[r^{Mkt}] - r_t^f \right)$. The expected market return is $\mathbb{E}_t[r^{Mkt}] = 1/\text{CAPE}_t + 2\% + \mathbb{E}_t[\text{Inflation}]$, and r_t^d is the yield on the ICE-BofA HY Bond Index. The counterfactual assumes CAPM $\hat{\beta}$ increases by only 20% of the actual increase since 1998, with all other components varying as observed. Panel (b) plots the cumulative investment shortfall as a percentage of the capital stock. Following Gormsen & Huber (2025a), Tobin's Q is computed from Flow of Funds market value and BEA tangible plus intangible capital data. Adjusted Q corrects for the wedge between market discount rates and managers' perceived cost of capital (Eq. 16). The investment-Q relationship is estimated over 1990–2002. Post-2002 residuals are the difference between observed and predicted investment. Pointwise 95% confidence intervals use Newey-West standard errors with 5 lags.

for the missing investment puzzle documented by Gutiérrez & Philippon (2017).[28] Panel (a) of Figure 11 plots the average WACC from 1998 to 2019. The counterfactual assumes that the average firm's $\hat{\beta}$ increases by only 20% of the actual increase since 1998, while allowing all other WACC components to vary as observed.[29] The counterfactual implies that benchmarking has raised the average firm's WACC by over 120 bps after 2003, offsetting much of the decline in risk-free rates.

We follow Gutiérrez & Philippon (2017) and Gormsen & Huber (2025a) to construct the missing investment. Using data from 1990 to 2002, we estimate the relationship between aggregate investment and Tobin's Q, then predict post-2002 investment assuming that this relationship remained unchanged. The missing investment is the cumulative shortfall since 2002, reflecting the divergence between Tobin's Q and investment. As Gormsen & Huber (2025a) show, when a firm's perceived discount rate exceeds the market's discount rate, the firm undervalues the profits generated by its capital relative to the market. Following their approach, we adjust Tobin's Q for the

[28] See also Peters & Taylor (2017), Barkai (2020), Gutiérrez et al. (2021), Crouzet & Eberly (2023), Corhay et al. (2025).

[29] This is a conservative calibration. The dynamic OLS estimates in Online Appendix Table B2 imply that the rise in the average stock's BMI from 1998 to 2018 explains 88% (=14 p.p.×0.029/(1.09-0.63)) of the increase in the average CAPM $\hat{\beta}$. We cannot statistically reject that 100% of the increase is due to the increase in BMI.

discrepancy between the market's discount rate and the firm's perceived cost of capital:

$$\text{Adjusted Tobin's Q} = \text{Tobin's Q} \times \frac{1}{1 + \Delta\text{WACC} \times \text{Cashflow Duration}} \tag{16}$$

where ΔWACC is the wedge between actual and counterfactual WACC in panel (a) of Figure 11. The impact of this adjustment depends on both the size of the WACC wedge and the duration of cash flows. We set the duration to 32.5 years, the average of the stock market duration estimates of 28 years from Van Binsbergen (2025) and 36 years from Greenwald et al. (2021).

Panel (b) of Figure 11 shows that the WACC wedge can account for a large part of the missing investment puzzle. Without adjustment, the aggregate investment shortfall implied by Tobin's Q reaches 25% of the capital stock by 2019. Adjusting for the WACC wedge reduces the shortfall to 10.6%. The remaining gap likely reflects other developments, such as rising market power (Barkai, 2020, Crouzet & Eberly, 2023) and mismeasurement of intangibles (Peters & Taylor, 2017).

9 Conclusion

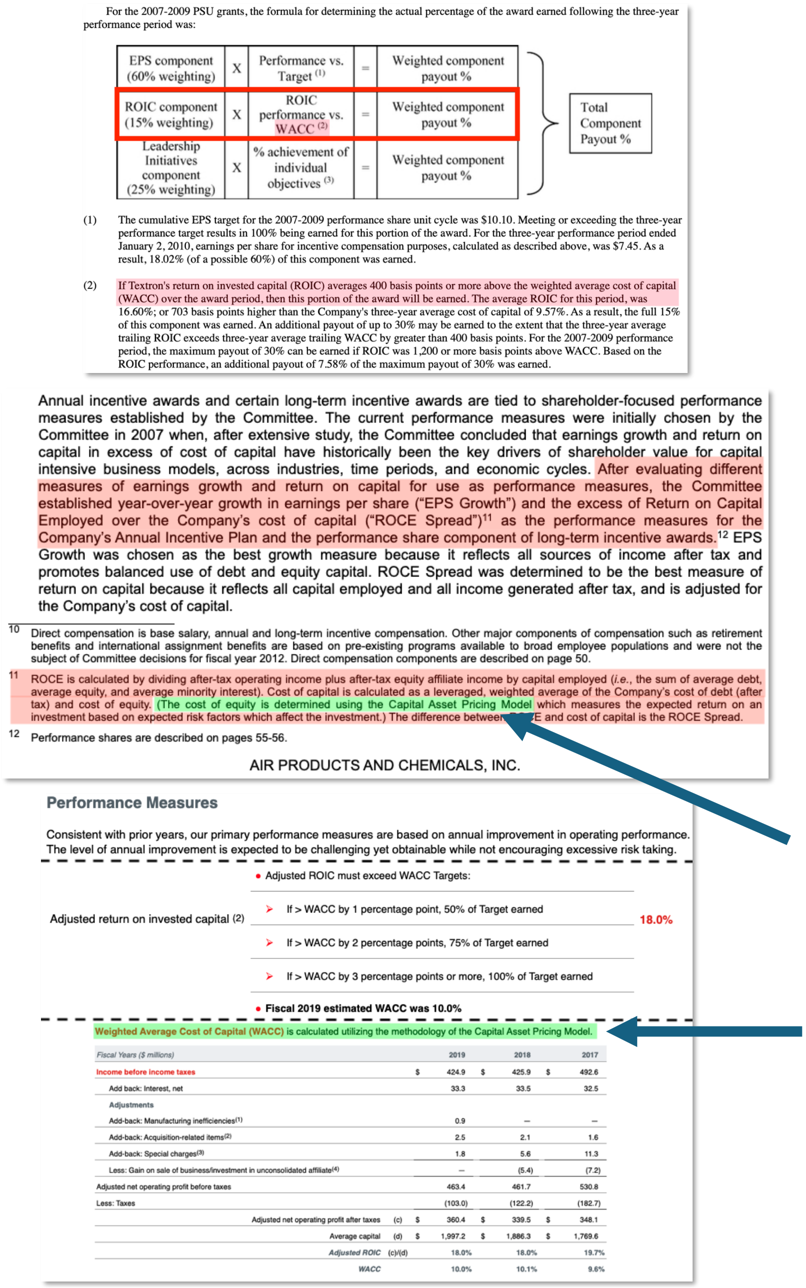
This paper investigates the consequences of mutual fund benchmarking and index investing for firm investment. Our findings challenge the prevailing view that benchmark-linked ownership benefits the real economy by lowering firms' cost of equity. We establish that greater benchmarking intensity raises CAPM $\hat{\beta}$ for the majority of firms. Over the past 25 years, this effect has increased the equal-weighted average $\hat{\beta}$ by around 0.36, raising the average firm's CAPM-implied cost of equity by over 200 basis points and largely offsetting the decline in the risk-free rate.

Firms respond to these benchmarking-induced increases in $\hat{\beta}$ by reducing investment. We attribute this response to managers' reliance on the CAPM in capital budgeting, without adjusting for the impact of benchmarking on asset prices. Evidence from managers, analysts, and regulators consistently shows a higher *perceived* cost of equity following an exogenous increase in benchmarking intensity.

Our findings offer a novel explanation for the shortfall of investment relative to valuations over the past two decades. They imply that the growth of benchmark-linked asset management has had unintended but quantitatively important consequences for firms' capital allocation and the real economy.

A Appendix

A.1 Appendix Figures



For the 2007-2009 PSU grants, the formula for determining the actual percentage of the award earned following the three-year performance period was:

EPS component (60% weighting)	X	Performance vs. Target (1)	=	Weighted component payout %
ROIC component (15% weighting)	X	ROIC performance vs. WACC (2)	=	Weighted component payout %
Leadership Initiatives component (25% weighting)	X	% achievement of individual objectives (3)	=	Weighted component payout %

Total Component Payout %

(1) The cumulative EPS target for the 2007-2009 performance share unit cycle was $10.10. Meeting or exceeding the three-year performance target results in 100% being earned for this portion of the award. For the three-year performance period ended January 2, 2010, earnings per share for incentive compensation purposes, calculated as described above, was $7.45. As a result, 18.02% (of a possible 60%) of this component was earned.

(2) If Textron's return on invested capital (ROIC) averages 400 basis points or more above the weighted average cost of capital (WACC) over the award period, then this portion of the award will be earned. The average ROIC for this period, was 16.60%; or 703 basis points higher than the Company's three-year average cost of capital of 9.57%. As a result, the full 15% of this component was earned. An additional payout of up to 30% may be earned to the extent that the three-year average trailing ROIC exceeds three-year average trailing WACC by greater than 400 basis points. For the 2007-2009 performance period, the maximum payout of 30% can be earned if ROIC was 1,200 or more basis points above WACC. Based on the ROIC performance, an additional payout of 7.58% of the maximum payout of 30% was earned.

Annual incentive awards and certain long-term incentive awards are tied to shareholder-focused performance measures established by the Committee. The current performance measures were initially chosen by the Committee in 2007 when, after extensive study, the Committee concluded that earnings growth and return on capital in excess of cost of capital have historically been the key drivers of shareholder value for capital intensive business models, across industries, time periods, and economic cycles. After evaluating different measures of earnings growth and return on capital for use as performance measures, the Committee established year-over-year growth in earnings per share ("EPS Growth") and the excess of Return on Capital Employed over the Company's cost of capital ("ROCE Spread")[11] as the performance measures for the Company's Annual Incentive Plan and the performance share component of long-term incentive awards.[12] EPS Growth was chosen as the best growth measure because it reflects all sources of income after tax and promotes balanced use of debt and equity capital. ROCE Spread was determined to be the best measure of return on capital because it reflects all capital employed and all income generated after tax, and is adjusted for the Company's cost of capital.

10 Direct compensation is base salary, annual and long-term incentive compensation. Other major components of compensation such as retirement benefits and international assignment benefits are based on pre-existing programs available to broad employee populations and were not the subject of Committee decisions for fiscal year 2012. Direct compensation components are described on page 50.

11 ROCE is calculated by dividing after-tax operating income plus after-tax equity affiliate income by capital employed (*i.e.*, the sum of average debt, average equity, and average minority interest). Cost of capital is calculated as a leveraged, weighted average of the Company's cost of debt (after tax) and cost of equity. (The cost of equity is determined using the Capital Asset Pricing Model which measures the expected return on an investment based on expected risk factors which affect the investment.) The difference between ROCE and cost of capital is the ROCE Spread.

12 Performance shares are described on pages 55-56.

AIR PRODUCTS AND CHEMICALS, INC.

Performance Measures

Consistent with prior years, our primary performance measures are based on annual improvement in operating performance. The level of annual improvement is expected to be challenging yet obtainable while not encouraging excessive risk taking.

Adjusted return on invested capital (2)

- Adjusted ROIC must exceed WACC Targets:
  - If > WACC by 1 percentage point, 50% of Target earned
  - If > WACC by 2 percentage points, 75% of Target earned
  - If > WACC by 3 percentage points or more, 100% of Target earned
- **Fiscal 2019 estimated WACC was 10.0%**

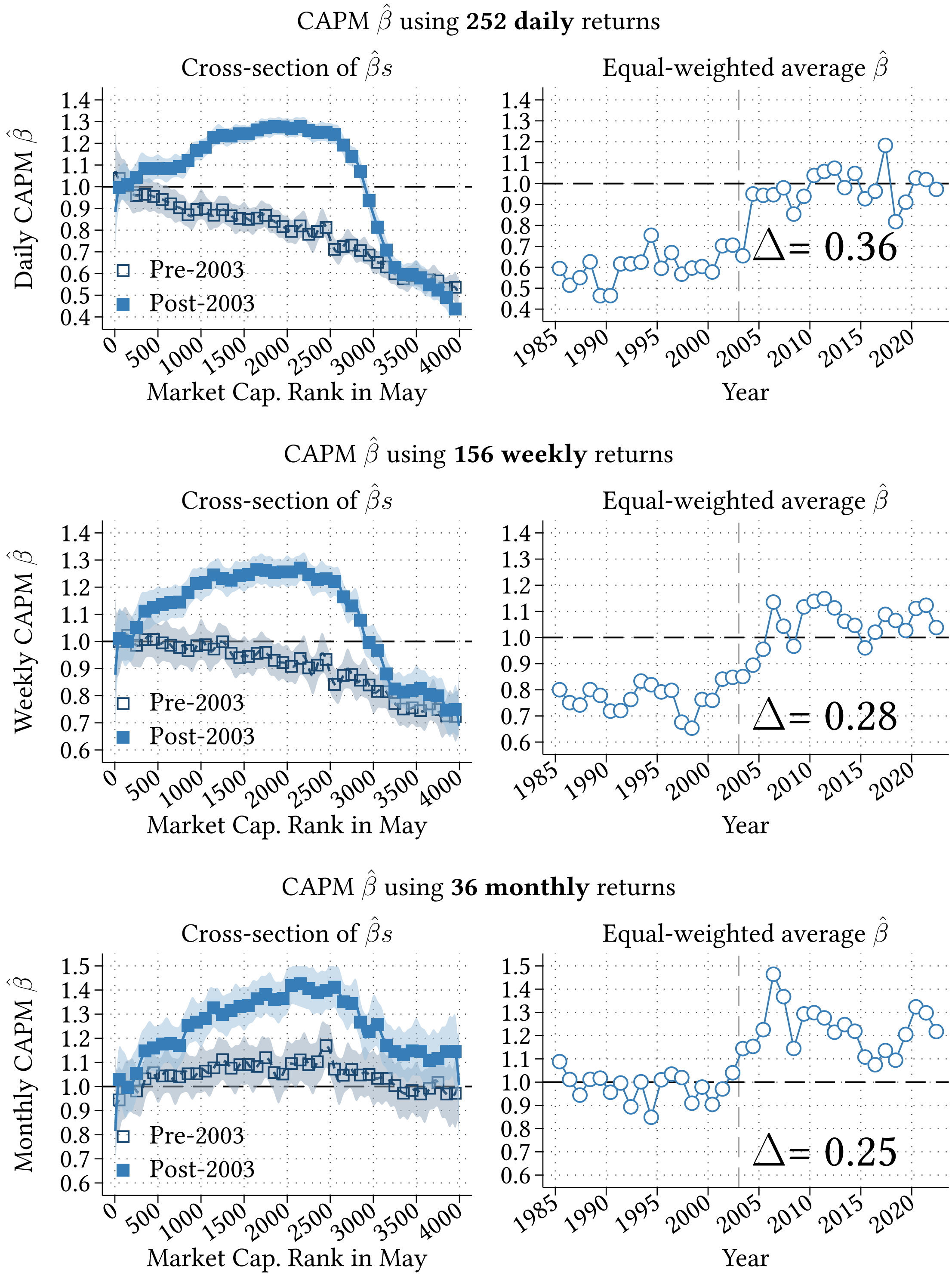
18.0%

Weighted Average Cost of Capital (WACC) is calculated utilizing the methodology of the Capital Asset Pricing Model.

Fiscal Years ($ millions)			2019		2018		2017
Income before income taxes		$	424.9	$	425.9	$	492.6
Add back: Interest, net			33.3		33.5		32.5
Adjustments							
Add-back: Manufacturing inefficiencies(1)			0.9		—		—
Add-back: Acquisition-related items(2)			2.5		2.1		1.6
Add-back: Special charges(3)			1.8		5.6		11.3
Less: Gain on sale of business/investment in unconsolidated affiliate(4)			—		(5.4)		(7.2)
Adjusted net operating profit before taxes			463.4		461.7		530.8
Less: Taxes			(103.0)		(122.2)		(182.7)
Adjusted net operating profit after taxes	(c)	$	360.4	$	339.5	$	348.1
Average capital	(d)	$	1,997.2	$	1,886.3	$	1,769.6
Adjusted ROIC	(c)/(d)		18.0%		18.0%		19.7%
WACC			10.0%		10.1%		9.6%

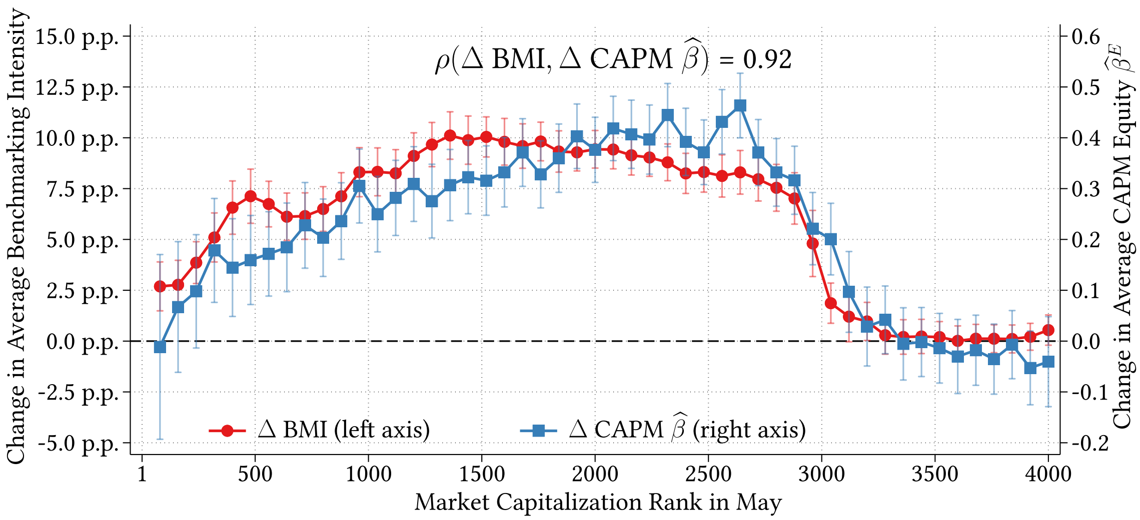
Figure A1: Clippings from the proxy statements (SEC Form DEF 14A) of Textron Inc., Air Products and Chemicals Inc., and Acuity Brands Inc., illustrating their use of ROIC/ROCE targets in executive compensation, with hurdle rates tied to the CAPM-implied WACC.

Figure A2: Rolling-Window CAPM $\hat{\beta}$s at Different Frequencies



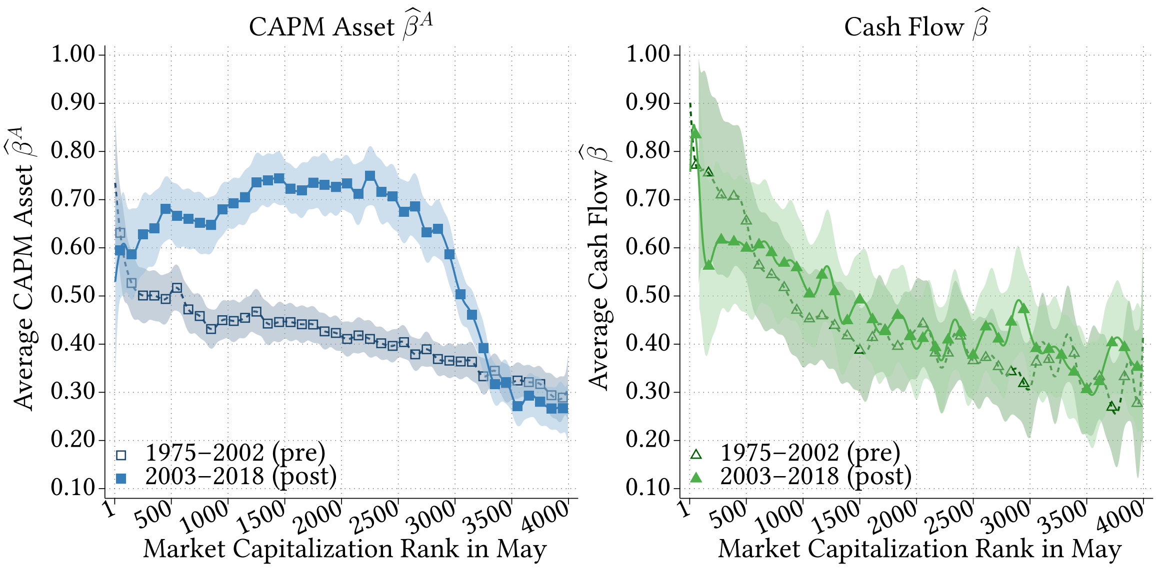
Notes: This figure plots binned scatters of rolling-window CAPM $\hat{\beta}$s against May market-cap ranks (left panels) and equal-weighted average CAPM $\hat{\beta}$ (right panels) using 252 daily, 156 weekly, and 36 monthly returns. Shaded areas show 90% confidence bands with errors clustered by stock and year-month.

Figure A3: Differences in Benchmarking Intensity and CAPM Equity $\hat{\beta}^E$ Between Pre and Post



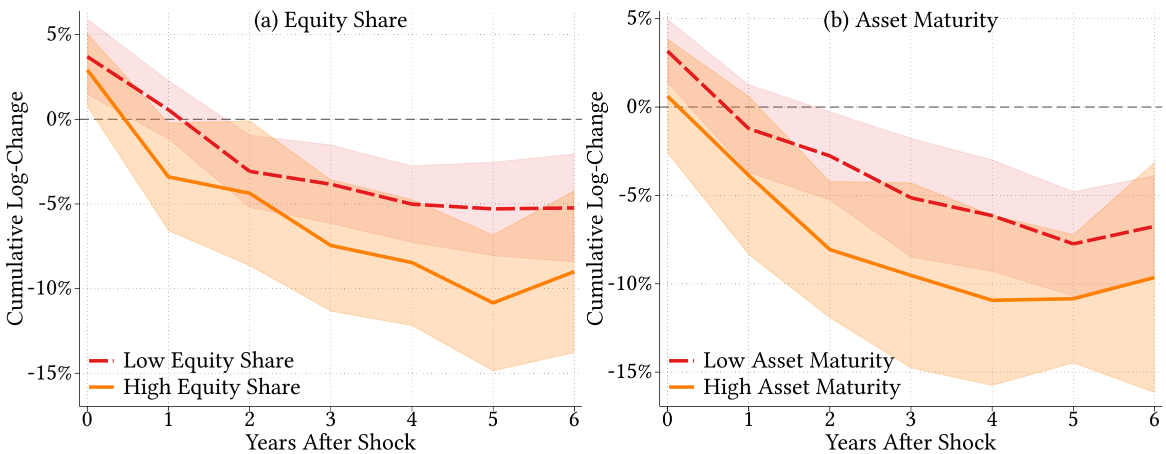
Notes: This figure plots changes in average BMI (left axis) and CAPM equity $\hat{\beta}^E$ (right axis) between the pre- and post-periods against May market capitalization ranks (based on Ben-David et al. 2019). Each bin shows the difference in conditional means from Figure 1. $\rho(\Delta\text{BMI}, \Delta\text{CAPM } \beta)$ reports the correlation between changes in BMI and CAPM $\hat{\beta}$s. Error bars indicate pointwise 95% confidence intervals with standard errors clustered by stock and year-month.

Figure A4: CAPM Asset $\hat{\beta}^A$ and Cash Flow β vs. Market Capitalization Rank in May



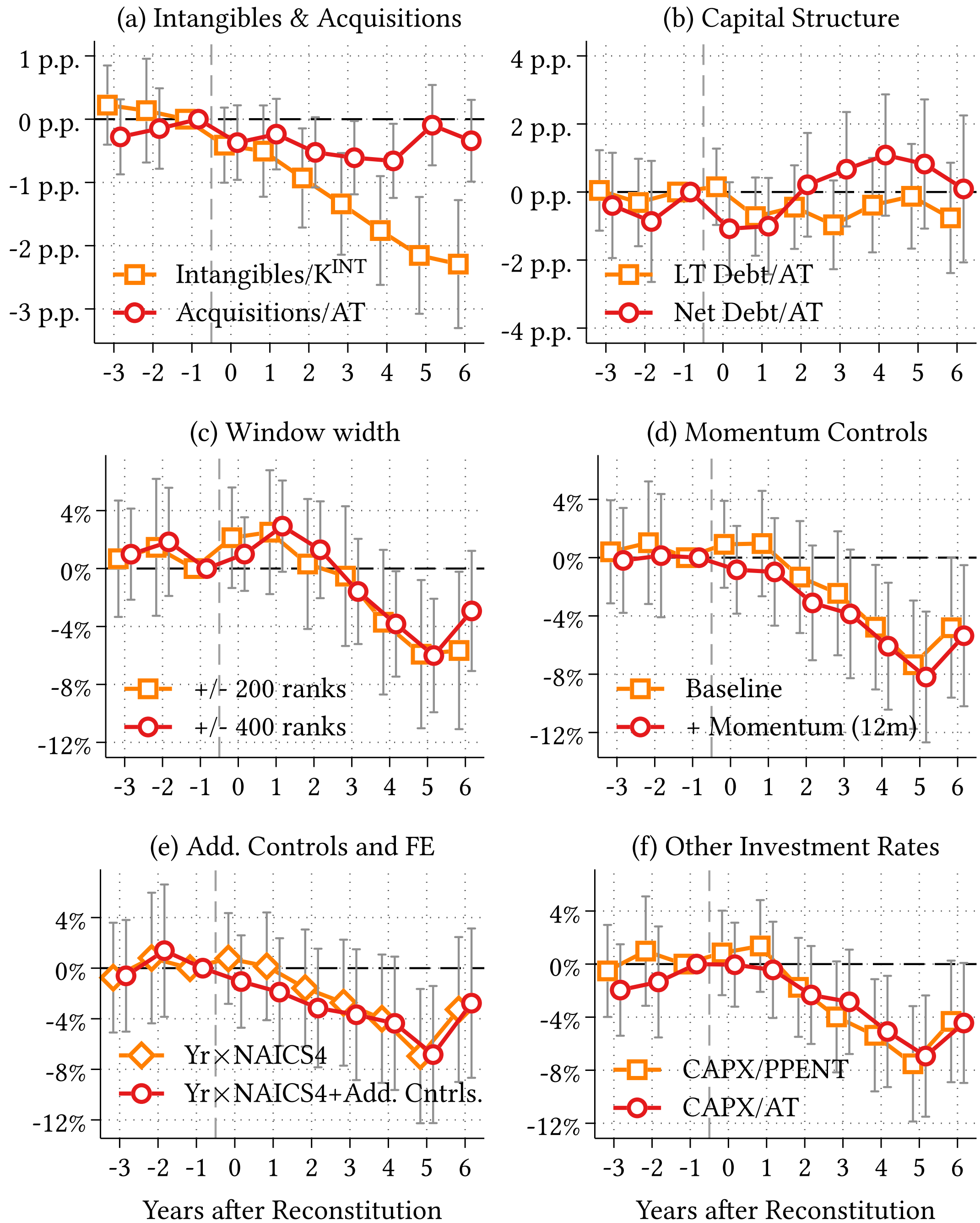
Notes: This figure plots binned scatters of quarterly cash flow $\hat{\beta}$s and CAPM asset $\hat{\beta}$s against May market capitalization ranks. Equity βs are unlevered following Krüger et al. (2015): $\hat{\beta}^A = \frac{E}{E+D} \times \hat{\beta}^E$, where E is the market value of equity and D is book debt Each bin is the equal-weighted average of 100 ranks, with conditional means identified from cross-sectional variation by absorbing year-quarter fixed effects. Outlined bins use 1975–2002 data; filled bins use 2003 to 2018. Shaded areas show 95% confidence bands with standard errors clustered by stock and year-quarter.

Figure A5: Cross-Sectional Heterogeneity in Cumulative Impulse Response of Investment to a 10 p.p. year-on-year Increase in Benchmarking Intensity



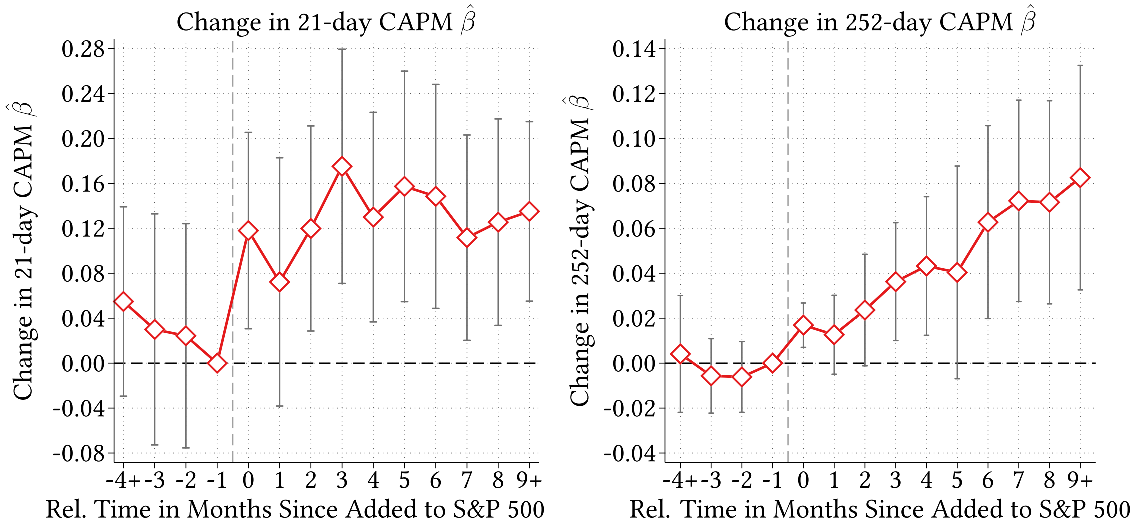
Notes: This figure shows coefficient estimates of γ_1^h (Low) and γ_1^h+γ_2^h (High) from local projection panel regressions of the form: $\log\left(Inv_{i,t+h}\right) - \log\left(Inv_{i,t-1}\right) = \alpha_{t,j}^h + \gamma_1^h\left(\mathrm{BMI}_{i,t} - \mathrm{BMI}_{i,t-1}\right) + \gamma_2^h \mathbb{1}\{\mathrm{High}\}_{i,t} \times \left(\mathrm{BMI}_{i,t} - \mathrm{BMI}_{i,t-1}\right) + \mathbb{1}\{\mathrm{High}\}_{i,t} + X_{i,t}'\xi^h + \varepsilon_{i,t+h}$, where $\mathbb{1}\{\mathrm{High}\}_{i,t}$ is an indicator for firms in the top tercile of (a) equity share of capital and (b) asset maturity (inverse of depreciation rate). $X_{i,t}$ includes log of market equity, Tobin's q, leverage, cash flow, current ratio, and firm age. Pointwise confidence intervals (95%) are based on double-clustered standard errors.

Figure A6: LP-RF: Robustness and Additional IRFs to a 6.7 p.p. increase in BMI



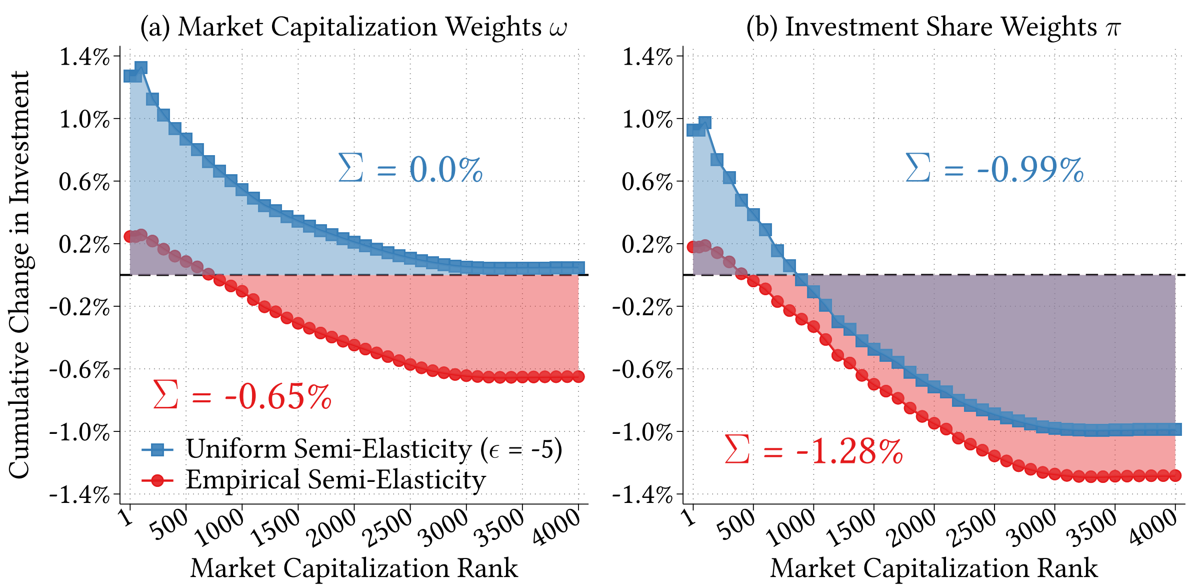
Notes: This figure shows local projection coefficient estimates for 100× cumulative (log-)changes of outcome variables from regression of the form $\log(Y_{i,t+h}) - \log(Y_{i,t-1}) = \alpha^h_{j,t} + \gamma^h \Delta \text{BMI}_{i,t} + \phi^h \log(\text{Market Cap.})_{i,t} + \text{Banding Vars.}_{i,t} + \xi^h X_{i,t} + \varepsilon_{i,t+h}$, where the shock is scaled to a 6.7 p.p. increase in BMI. We restrict the estimation sample to stocks within 300 ranks around Russell index cutoffs, except in Panel (c) where we vary it.

Figure A7: Effects of S&P 500 Benchmark Inclusion on CAPM $\hat{\beta}$ (avg. Δ BMI $\approx$ 8.6 p.p.)



Notes: This figure reports monthly difference-in-differences event-study estimates of changes in CAPM $\hat{\beta}$ for stocks added to the S&P 500, using rolling windows of 21 or 252 daily returns. Effects are identified from within-industry-month variation. Controls include log market cap, log Amihud illiquidity, log bid-ask spread, and momentum. Point-wise confidence intervals (95%) are based on double-clustered standard errors.

Figure A8: Cumulative Sum of Changes in Investment Across Market Capitalization Ranks



Notes: This figure shows the cumulative sum of the change in aggregate investment implied by Eq. (14) across market capitalization ranks i: $\Delta I_t / I_{t-1} \approx q_t \lambda_t \sum_i \pi_{i,t-1}\, \epsilon^C_{i,t}\, \mu_{i,t}\, \Delta\beta_{i,t}$ where weights $\pi_{i,t-1}$, semi-elasticity $\epsilon^C_{i,t}$, equity share $\mu_{i,t}$, and $\Delta\beta_{i,t}$ are given by the empirical distributions in Appendix Figure B10. We set $\lambda_t = 0.06\ \forall\, t$ and $q_t = 1\ \forall\, t$. Panel (a) uses market capitalization weights $\omega_{i,t-1}$ and panel (b) uses investment share weights $\pi_{i,t-1}$ to aggregate. Blue squares use a uniform investment semi-elasticity of $\epsilon^C = -5$ across all ranks, while red circles use rank-specific investment semi-elasticities estimated from Compustat data (see Appendix I).

A.2 Appendix Tables

Table A1: Time-Series Regression of CAPM $\hat{\beta}$ by Size Group on Average Benchmarking Intensity

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Avg. Top-50 $\widehat{\beta}$		Avg. Mega-Cap $\widehat{\beta}$		Avg. Large-Cap $\widehat{\beta}$		Avg. Small-Cap $\widehat{\beta}$		Avg. Micro-Cap $\widehat{\beta}$	
$\mathbb{1}\{\text{Year} > 2002\}$	-0.13***		0.04**		0.19***		0.43***		0.40***	
	(0.03)		(0.02)		(0.03)		(0.05)		(0.05)	
$\overline{\text{BMI}}_t$		-0.02***		0.01***		0.03***		0.06***		0.06***
		(0.01)		(0.01)		(0.01)		(0.01)		(0.01)
Constant	1.07***	1.18***	1.00***	0.89***	0.92***	0.66***	0.81***	0.45***	0.56***	0.18*
	(0.03)	(0.09)	(0.02)	(0.04)	(0.03)	(0.04)	(0.04)	(0.12)	(0.03)	(0.10)
Avg. Mkt. Cap. Share	0.42		0.34		0.16		0.06		0.02	
Avg. Cap. Exp. Share	0.27		0.40		0.20		0.09		0.04	
Avg. # Stocks	50		269		589		950		1768	
Observations	360	249	360	249	360	249	360	249	360	249
Adjusted R^2	0.38	0.28	0.13	0.27	0.55	0.62	0.69	0.49	0.65	0.55

Notes: This table reports estimates from regressions of the form: CAPM $\hat{\beta}_{j,t} = \alpha_j + \gamma\overline{\text{BMI}}_t + \varepsilon_{j,t}$, where $\hat{\beta}_{j,t}$ is the equal-weighted average of stocks in the jth size group in month t. $\overline{\text{BMI}}_t$ is the equal-weighted average BMI of all stocks in month t. Size groups are non-overlapping, based on NYSE breakpoints, at each month-end. Top-50 are the 50 largest firms. Mega-caps are the remainder above the 80th percentile, large-caps above the 50th, small-caps above the 20th, and micro-caps above the 1st. The $\hat{\beta}$ sample runs from 1989 to 2018. BMI is available only from 1998 to 2018. Average capital expenditure is measured in Compustat from 1998 to 2018. Newey–West standard errors in parentheses with $\lfloor 1.3\sqrt{T} \rfloor$ lags. * p<0.10, ** p<0.05, *** p<0.01.

Table A2: Summary Statistics of Monthly CAPM $\hat{\beta}$ Panel from 1998m1 to 2018m9

	count	mean	sd	min	p25	p50	p75	max
Benchmarking Intensity (BMI, %)	929,105	13.27	9.25	0.00	3.67	14.20	21.14	99.07
Institutional Ownership Ratio (IOR, quarterly %)	311,355	53.99	31.29	0.00	27.06	57.02	80.65	130.50
Avg. Implied Cost of Capital (ICC, %)	696,830	9.37	2.98	2.16	7.57	9.06	10.85	20.42
CAPM $\hat{\beta}$ (Welch)	886,432	0.95	0.47	-0.07	0.60	0.94	1.27	2.65
Unlevered CAPM $\hat{\beta}$ (Welch)	886,432	0.58	0.43	-1.95	0.22	0.52	0.86	3.30
CAPM $\hat{\beta}$ (21-day)	925,786	0.98	1.04	-4.93	0.36	0.91	1.50	13.63
CAPM $\hat{\beta}$ (252-day)	910,903	0.97	0.59	-0.60	0.54	0.94	1.33	3.69
CAPM $\hat{\beta}$ (156-week)	882,232	1.04	0.61	-0.37	0.60	0.98	1.39	4.07
CAPM $\hat{\beta}$ (36-month)	830,936	1.19	0.91	-1.47	0.57	1.05	1.64	5.92
Cash-Flow Beta (ROE, quarterly)	248,879	0.46	1.42	-8.25	-0.15	0.30	0.92	9.16
Consumption Beta (KKL, annual)	46,930	1.10	0.94	-2.62	0.51	1.01	1.66	5.46
Log Volume	929,038	17.64	2.59	10.67	15.74	17.75	19.57	23.65
Equity Ratio (%)	929,105	59.32	28.28	1.42	37.22	64.00	84.13	99.41
Amihud Illiquidity	920,947	1.44	9.30	0.00	0.00	0.01	0.12	216.27
Bid-Ask Spread	899,882	0.01	0.01	0.00	0.01	0.01	0.02	0.13
Log Market Equity	929,073	6.28	1.86	1.53	4.92	6.12	7.49	11.93
Momentum Return (12-month, %)	889,951	14.04	64.31	-96.90	-19.17	6.22	32.69	1478.13

Notes: This table reports summary statistics for the monthly CAPM β panel from 1998m1 to 2018m9.

Table A3: Effects of Exogenous BMI Change on CAPM $\hat{\beta}$s

Estimator:	Rolling Window with 21 Daily Returns				Welch (2022) Estimator			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Δ BMI $\times$ Post	0.027***	0.027***	0.026***	0.026***	0.022***	0.021***	0.019***	0.018***
	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Log(Mkt. Cap.) and Log(Bid-Ask Spread)	✓	✓	✓	✓	✓	✓	✓	✓
Fixed Effects & Additional Controls								
Firm	✓	✓	✓	✓	✓	✓	✓	✓
Year-Month	✓	✓	✓	✓	✓	✓	✓	✓
Banding Controls		✓				✓		
Momentum, Banding			✓				✓	
Liquidity, Momentum, Banding				✓				✓
Observations	250,713	250,713	250,214	244,894	157,955	157,955	157,950	155,705

Notes: This table reports $\hat{\gamma}$ from: CAPM $\hat{\beta}_{i,t} = \gamma\ \Delta\ \mathrm{BMI}_i \times \mathrm{Post}_t + \alpha_{i,c} + \alpha_{t,c} + q'_{i,t,c}\psi + \varepsilon_{i,t}$. All specifications control for log market capitalization (Ben-David et al., 2019) and log bid-ask spread. Controls and fixed effects are interacted with cohort fixed effects (Baker et al., 2022). The sample includes stocks within 300 ranks of the Russell 1000 and 3000 cutoffs, pooling additions and deletions. In columns (5)–(8), Δ BMI$_i$ $\times$ Post$_t$ is the average post-treatment effect after 12 months to account for expanding window estimation of $\hat{\beta}$, reducing the observation count. Standard errors (in parentheses) are double-clustered by stock and year-month. * p<0.10, ** p<0.05, *** p<0.01.

Table A4: Panel Regressions of CAPM $\hat{\beta}$ on Benchmarking Intensity

	(1)	(2)	(3)	(4)	(5)	(6)
	CAPM $\hat{\beta}$ in May of Year t					
Avg. BMI (in %) over past year	0.027***	0.026***	0.026***	0.025***	0.022***	0.023***
	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)	(0.001)
Avg. IOR (in %) over past year		0.000				
		(0.000)				
Constant	0.593***	0.588***				
	(0.022)	(0.021)				
Adj. R^2	0.26	0.26	0.29	0.49	0.55	0.74
Within R^2			0.24	0.29	0.18	0.17
Year FE			✓			
FF49 $\times$ Year FE				✓		
FF49 $\times$ Size $\times$ Year FE					✓	✓
Stock FE						✓
Observations	77,445	77,443	77,445	76,823	76,277	74,922

Notes: This table reports coefficient estimates of specifications of the form: CAPM $\hat{\beta}_{i,t} = \alpha_i + \alpha_t + \gamma \times$ Avg. BMI over past 12 months$_{i,t} + \varepsilon_{i,t}$ in May of year t for stock i. Standard errors in parentheses are double-clustered at firm and year level. * p<0.10, ** p<0.05, *** p<0.01.

Table A5: Summary Statistics of Annual Compustat Investment Panel

	count	mean	sd	min	p25	p50	p75	max
CAPX/PPEGT (%)	37,787	14.90	15.09	0.58	5.92	9.98	17.71	82.54
Benchmarking Intensity (BMI, %)	38,628	15.04	9.42	0.00	7.58	17.02	22.63	65.98
Institutional Ownership Ratio (IOR, %)	38,511	64.92	27.58	0.01	45.94	70.34	86.67	118.00
Tobin's q^{tot}	38,616	1.37	1.74	-0.55	0.43	0.84	1.59	14.91
Leverage (%)	37,947	54.78	29.77	5.82	33.10	51.92	70.37	169.38
Current Ratio (%)	38,619	284.73	231.02	52.10	145.69	212.50	330.50	1622.90
Log(Market Cap.)	38,581	6.80	1.71	2.54	5.54	6.64	7.91	11.23
Cash Flow (%)	37,904	-1.48	257.30	-7146.02	6.68	18.77	42.01	295.32
Firm Age (years)	38,628	23.67	18.50	1.42	10.42	17.42	32.42	92.42

Notes: This table reports summary statistics for the annual Compustat investment panel used in the investment analysis from 1998 to 2018.

Table A6: Capital Efficiency Targets

	(1)	(2)	(3)	(4)	(5)	(6)
	ROIC (in %)		ROCE (in %)		ROE (in %)	
1(Capital Efficiency Target)	5.400***		8.263***		11.016***	
	(0.667)		(1.222)		(1.746)	
ROIC Target (in %)		0.886***		0.653***		0.680***
		(0.126)		(0.104)		(0.108)
Year FE	✓	✓	✓	✓	✓	✓
Adj. R^2	0.07	0.21	0.06	0.19	0.05	0.12
Observations	21,685	1,282	22,384	1,448	21,328	1,378

Notes: This table reports coefficient estimates from regressions $\text{Outcome}_{i,t} = \alpha_t + 1(\text{Capital Efficiency Target}) + \varepsilon_{i,t}$ where Outcome is either Return on Invested Capital (ROIC), Return on Capital Employed (ROCE), or Return on Equity (ROE), derived from annual Compustat data. We trim ROIC, ROCE, and ROE at the 2% and 98% levels to remove outliers. Standard errors in parentheses clustered at year- and firm-level. * p<0.10, ** p<0.05, *** p<0.01.

Table A7: Panel Regressions of Firm Investment on BMI and Proxies for Firm Risk Exposure

	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent variable: CAPX_{t+1} / PPE_t (in %)					
	Measures of Hassan et al. (2019)		Measures of Alfaro et al. (2024)			
Risk Exposure Measure:	Risk	Sentiment	EPU	Oil	Euro	Yen
BMI (in %)	-0.087***	-0.108***	-0.077***	-0.070***	-0.067***	-0.079***
	(0.026)	(0.025)	(0.021)	(0.022)	(0.020)	(0.020)
$\mathbb{1}\{\text{High}\}$	0.281	-0.434	-0.497	0.145	0.536	-0.548
	(0.553)	(0.700)	(0.394)	(0.536)	(0.427)	(0.391)
$\mathbb{1}\{\text{High}\} \times$ BMI (in %)	-0.027	0.036	0.010	-0.016	-0.022	0.016
	(0.029)	(0.028)	(0.019)	(0.021)	(0.023)	(0.020)
Other Controls	✓	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓	✓
Industry × Year × Rank-Bin FE	✓	✓	✓	✓	✓	✓
Adj. R^2	0.65	0.65	0.64	0.64	0.64	0.64
Observations	20,636	20,636	27,701	27,701	27,701	27,701

Notes: This table reports estimates for panel regressions of the form: $\frac{\text{CAPX}_{i,t+1}}{\text{PPE}_{i,t}} = \alpha_{t,bin} + \alpha_i + \gamma\ \text{BMI}_{i,t} + \mathbb{1}\{\text{High Risk Exposure}\} \times \text{BMI}_{i,t} + \mathbb{1}\{\text{High Risk Exposure}\} + X'_{i,t}\xi + \varepsilon_{i,t}$, where $\mathbb{1}\{\text{High Risk Exposure}\}$ is proxied by being in the third tercile of the annual distribution of either (i) firm-level risk (Hassan et al., 2019), (ii) firm-level sentiment (Hassan et al., 2019), (iii) firm-level exposure to economic policy uncertainty (Alfaro et al., 2024), (iv) firm-level exposure to oil price uncertainty (Alfaro et al., 2024), (v) firm-level exposure to euro-dollar exchange rate uncertainty (Alfaro et al., 2024), and (vi) firm-level exposure to yen-dollar exchange rate uncertainty (Alfaro et al., 2024). Controls include leverage, cash flow to PPE, current ratio, Tobin's q, log of market capitalization, and firm age. Standard errors in parentheses are clustered at the year- and firm-level. * p<0.10, ** p<0.05, *** p<0.01.

Table A8: Panel Regressions of Firm Investment on BMI and Proxies for Common Ownership

	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent variable: CAPX_{t+1} / PPE_t (in %)					
Common Ownership/Competition Measure:	Density	MHHI Δ	MHHI	C	Mark-Up	PCM
BMI (in %)	-0.100***	-0.098***	-0.098***	-0.107***	-0.075***	-0.089***
	(0.030)	(0.028)	(0.028)	(0.029)	(0.021)	(0.023)
$\mathbb{1}\{\text{High}\}$=1	-0.312	0.555	0.483	-0.281	1.596*	0.625
	(0.727)	(0.459)	(0.464)	(0.350)	(0.778)	(0.726)
$\mathbb{1}\{\text{High}\}$=1 × BMI (in %)	-0.007	-0.014	-0.012	0.018	-0.055	-0.029
	(0.035)	(0.024)	(0.024)	(0.021)	(0.039)	(0.024)
Other Controls	✓	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓	✓
Industry × Year × Rank-Bin FE	✓	✓	✓	✓	✓	✓
Adj. R^2	0.54	0.54	0.54	0.54	0.54	0.54
Observations	22,744	22,744	22,744	22,744	25,628	35,757

Notes: This table reports estimates for panel regressions of the form: $\frac{\text{CAPX}_{i,t+1}}{\text{PPE}_{i,t}} = \alpha_{t,bin} + \alpha_i + \gamma\,\text{BMI}_{i,t} + \mathbb{1}\{\text{High CO in Industry}\} \times \text{BMI}_{i,t} + \mathbb{1}\{\text{High CO in Industry}\} + X'_{i,t}\xi + \varepsilon_{i,t}$, where $\mathbb{1}\{\text{High}\}$ is an indicator for industries with high common-ownership exposure, defined as NAICS-4 industries in the top tercile of one of the following measures: (1) CO density (Azar, 2012), (2) MHHI Δ, (3) MHHI (Bresnahan & Salop, 1986), or (4) the CO incentive term (Kennedy et al., 2017), as provided by Koch et al. (2021). In Columns (5) and (6), $\mathbb{1}\{\text{High}\}$ is instead defined using measures of market power at the NAICS-4 level: (5) the sales-weighted markup estimated via a production function approach following De Ridder et al. (2025), and (6) the sales-weighted price–cost margin. Controls include leverage, cash flow to PPE, Tobin's q, current ratio, log of market capitalization, and firm age. Standard errors in parentheses are double clustered at the year and firm level. * p<0.10, ** p<0.05, *** p<0.01.

Table A9: Panel Regressions of Firm Investment on BMI and Proxies for Private Information

	(1)	(2)	(3)	(4)	(5)
Dependent variable:	CAPX_{t+1} / PPE_t (in %)			Price Nonsync. (in %)	Bid-Ask (in %)
BMI (in %)	-0.110***	-0.116***	-0.107***	-0.150***	-0.002*
	(0.025)	(0.026)	(0.025)	(0.025)	(0.001)
Tobin's q^{tot}	2.828***	2.686***	2.605***		
	(0.180)	(0.186)	(0.176)		
$\mathbb{1}\{$High Price Nonsync.$\}$		-0.360			
		(0.253)			
$\mathbb{1}\{$High Price Nonsync.$\} \times$ Tobin's q^{tot}		0.544***			
		(0.181)			
$\mathbb{1}\{$High Bid-Ask Spread$\}$			-0.026		
			(0.150)		
$\mathbb{1}\{$High Bid-Ask Spread$\} \times$ Tobin's q^{tot}			0.500***		
			(0.148)		
Other Controls	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓
Year × Industry × Rank-Bin FE	✓	✓	✓		
Year FE				✓	✓
Adj. R^2	0.59	0.59	0.59	0.75	0.52
Observations	34,627	34,627	34,184	35,781	35,087

Notes: This table reports estimates for panel regressions of the form: $\frac{\text{CAPX}_{i,t+1}}{\text{PPE}_{i,t}} = \alpha_{t,bin} + \alpha_i + \gamma\,\text{BMI}_{i,t} + \mathbb{1}\{\text{High Private Info.}\} \times q^{tot} + \mathbb{1}\{\text{High Private Info.}\} + \theta q^{tot} + X'_{i,t}\xi + \varepsilon_{i,t}$, where $\mathbb{1}\{\text{High Private Info.}\}$ is proxied by either (i) price nonsynchronicity (Chen et al., 2007) or (ii) bid-ask spreads (Glosten & Milgrom, 1985). Controls include leverage, cash flow to PPE, current ratio, log of market capitalization, and firm age. Columns (4) and (5) regress the private information proxies on BMI. Standard errors in parentheses are clustered at the year- and firm-level. * p<0.10, ** p<0.05, *** p<0.01.

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