The Real Cost of Benchmarking*

Christian Kontz — Stanford GSB

Sebastian Hanson — Stanford GSB

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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.

JEL classification: G12, G23, G31, D24, G14

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

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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 index funds 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.

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 the growing trend of benchmark-linked investing 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 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.

[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).

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, benchmarking has an unambiguously negative effect on firm investment.

Executives 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.[3] 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 equals the fraction of a stock's market capitalization owned by funds benchmarked to a given index. 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 the BMI measure with CAPM $\hat{\beta}$s, market data from CRSP, accounting data from Compustat, and data on managers' perceived cost of capital from Gormsen & Huber (2025) 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 a set of novel stylized facts about U.S. stocks included in benchmark indices. Over the past 25 years, CAPM $\hat{\beta}$s and BMI increased in lockstep. The average stock's BMI increased from 8.3% in 1998 to 18.3% in 2018, while the (equal-weighted) average $\hat{\beta}$ rose by around 0.36. The large increase in the equal-weighted $\hat{\beta}$ is offset by a decrease in the $\hat{\beta}$ of the 50 largest stocks, on average. Assuming a 6% equity risk premium, the increase in the equal-weighted $\hat{\beta}$ translates into an increase of more than 200 basis points (bps) in the CAPM-implied cost of equity. Importantly, changes in fundamental risk or leverage do not drive this increase. Instead, BMI and $\hat{\beta}$ vary systematically across the market capitalization ranks used in the construction of benchmark indices. For example, the average levels of BMI and $\hat{\beta}$ change

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

[3]Gormsen & Huber (2024) show that managers' perceived cost of capital comoves closely with their firm's ROIC, and that the CAPM explains approx. 50% of the variation in managers' perceived cost of capital.

around the assignment thresholds for the Russell 1000 and 3000. This phenomenon has tangible consequences for corporate policy: we find that firms accounting for over 70% of annual capital expenditures in Compustat experienced an increase in $\hat{\beta}$. In the cross-section, firms with higher BMI invest less and issue less equity, suggesting that the growth of benchmark-linked investing and the institutional design of benchmark indices impact real and financial decisions.

Next, we link exogenous changes in BMI to changes in CAPM $\hat{\beta}$ using a continuous 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). The difference-in-differences approach does not require that benchmark inclusion is random or common support in covariate levels across stocks. It only requires that treated and control stocks' $\hat{\beta}$s would have evolved similarly absent changes in BMI. We use a similar strategy around S&P 500 and MSCI ACWI benchmark inclusion as a robustness check.

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, total 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 databases which allow us to accurately predict benchmark assignment and mitigate mismeasurement concerns (Glossner, 2024).[4] 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).[5] 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 risk exposure (either through peer-firm $\hat{\beta}$s or the firm-level risk measures of Hassan et al. 2019), in access to debt markets (via financial friction measures or CDS spreads), in governance scores, or in 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 benchmark reconstitution, consistent with a change in comovement rather than fundamentals. When using longer-horizon

[4] Appendix Table F18 replicates the main result in Pavlova & Sikorskaya (2023) in our sample, showing nearly identical estimates despite slight differences in sample, variable construction, and use of the Ben-David et al. (2019) proxy.

[5] In 2007, Russell introduced "bands" around the index cutoffs to ignore minor ranking shifts and reduce turnover during reconstitution. For details on the Russell's reconstitution methodology see Appendix F.1.

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. We find stronger effects for stocks that were previously not in a benchmark when they join the Russell 3000. In those cases, $\hat{\beta}$s increase by 0.32, on average. In contrast, larger stocks transitioning from the Russell 1000 to the Russell 2000 or joining the S&P 500 exhibit a smaller average increase in $\hat{\beta}$ of around 0.15 for a 10 p.p. shock to BMI. 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 benchmarking intensity 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 greater 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 mechanism: 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). The institutional design of benchmark indices segments the market (e.g., Russell 1000 vs. Russell 2000, value vs. growth), creating unequal ownership by benchmark-linked investors and, in turn, unequal exposure to correlated flows (Buffa & Hodor, 2023, Pavlova & Sikorskaya, 2023). Cross-sectional differences in exposure to passive flows raise covariances and measured $\hat{\beta}$ for high BMI stocks relative to others. If all passive funds indexed to a single comprehensive market benchmark such as the CRSP value-weighted market index, BMI would be uniform across stocks, index trading would shift prices proportionally, 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 7 years, we find that the cost of equity is still up to 100 bps higher than before the exogenous BMI increase. The long-run persistence reflects both sticky benchmark membership[6] 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, 2025).

In contrast, the effects of an exogenous BMI increase on the implied cost of capital (ICC) de-

[6]Russell 2000 membership and BMI exhibit annual autocorrelation of 0.86 and 0.84, respectively.

rived from stock prices are small and short-lived.[7] 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 perceive 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 for lowering the cost of equity or altering 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.

An exogenous increase in BMI results in higher perceived costs of capital and hurdle rates by managers in the Gormsen & Huber (2025) data, consistent with managers using the CAPM. 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 that support 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 benchmarking intensity 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 a decline in investment.

In OLS panel regressions, higher benchmarking intensity predicts lower investment rates. A 10 p.p. higher BMI is associated with a 12.5% reduction in the investment rate relative to the sample mean. This negative association holds after including time-by-industry and firm fixed

[7] The Implied Cost of Capital (ICC) is the internal rate of return that equates a firm's stock price to the present value of expected cash flows. We estimate 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).

effects, as well as controls for size, leverage, cash flow, and firm age. When we include Peters & Taylor's (2017) proxy for Tobin's q, the BMI coefficient shrinks by 50% but remains statistically and economically significant. The attenuation of the BMI coefficient, combined with q's positive effect on investment, implies that BMI is negatively correlated with Tobin's q. The correlation suggests that the market partially prices the higher $\hat{\beta}$ due to higher BMI into q. At the same time, BMI remains an economically significant predictor, suggesting that managers perceive and act on a steeper slope in the security market line than observed in the data. This is consistent with Gormsen & Huber (2024), who document wedges between managers' perceived cost of capital and market-implied cost of capital.

The dynamic response of investment to an 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 (lower depreciation rates). We perform a placebo test using changes in the institutional ownership ratio (IOR) as a regressor and find a small positive effect on investment. Since $\hat{\beta}$s are not affected by IOR, the placebo test provides evidence that the negative effect of BMI on investment is not driven by institutional ownership per se, but is specific to increased ownership by benchmarked mutual funds and ETFs. The placebo test also provides ancillary evidence that the negative effect of BMI on investment is not driven by omitted variables related to increased institutional ownership (e.g., changes in corporate governance, McCahery et al., 2016). However, year-on-year changes in BMI are subject to endogeneity concerns. We therefore turn to exogenous variation in BMI created by benchmark reconstitution events next.

Using exogenous variation in BMI from Russell reconstitution and S&P 500 additions, we find that higher BMI results in lower investment and increased payouts to shareholders. Our first natural experiment leverages the exogenous variation in BMI from Russell benchmark reconstitution to instrument for the endogenous relationship between β and investment in local projections.[8] A benchmarking-induced increase in a firm's CAPM $\hat{\beta}$ leads to a large and persistent reduction in investment. Specifically, a 100 bps increase in the CAPM-implied cost of capital results in a cumulative decrease in capital expenditures by 10.2% over a six-year period.

[8]The annual reconstitution of Russell benchmarks causes overlapping yearly treatments and makes it difficult to use a difference-in-difference event study design, we therefore use local projections with instrumental variables.

Rather than investing, firms initially accumulate cash and later increase shareholder payouts. The estimated treatment effects are consistent with managers gradually updating discount rates (Gormsen & Huber, 2025): the effects are negligible at short horizons, grow steadily over time, and become statistically significant after three years.

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. Our findings indicate that from 1998 to 2016, higher benchmarking-induced $\hat{\beta}$s significantly reduced capital accumulation by 9.9%, or about 0.5% annually. A key feature of this approach is that it nets out intra-industry reallocations, such as business stealing. The fact that we still observe a significant net effect suggests the presence of industry-wide spillovers. For instance, managers may learn from the asset prices of other firms in the industry (Foucault & Fresard, 2014, Dessaint et al., 2019, Goldstein et al., 2021, Kim et al., 2024), or the effects may propagate to private firms that estimate their cost of equity using publicly traded peers (Badertscher et al., 2019, Yan, 2024). The results are robust to controlling for industry pre-trends, exposure to the China shock (Autor et al., 2013), and the inclusion of sector fixed effects that restrict identification to 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 any aggregate effects of changes in the cross-section of βs cancel rests on two assumptions that the data reject: First, it assumes that market capitalization weights and investment share weights coincide. Empirically, the weights differ substantially. For instance, the financial sector averages 17.3% of U.S. market capitalization yet only 3.5% of capital expenditures.

Second, it assumes a uniform elasticity of investment with respect to the cost of capital across firms. However, a large body of literature shows that the investment of large firms is relatively inelastic to changes in financing costs, while the investment of smaller firms is highly elastic.[9] We show that the covariance between firms' investment elasticities and the distribution of $\hat{\beta}$ shocks determines the aggregate effect. A few large firms receive a subsidy through lower $\hat{\beta}$, while most face higher $\hat{\beta}$. Because large firms adjust little, their subsidy cannot offset the contraction of smaller firms, so aggregate investment falls even though the value-weighted market β equals one. We embed this mechanism in a general equilibrium model with heterogeneous firms facing capital adjustment costs and calibrate the model to match micro-level investment moments and the perceived cost of equity wedge in the cross-section. This allows us to show that the mechanism remains robust to changes in aggregate prices.

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 investing 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 capital flows tied to benchmark indices have unequal consequences for the cross-section of stocks: they increase the CAPM $\hat{\beta}$s of most firms, raising their perceived cost of equity, while a few large firms experience a decrease. Second, we show that increasing $\hat{\beta}$s pass through to corporate policy, as managers rely on the CAPM and thus invest less. Third, we provide evidence that this mechanism has aggregate consequences, resulting in lower aggregate investment and highlighting a significant friction introduced by the shift toward benchmark-linked investing.

First, we show that benchmark-linked investing 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 contribution 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 higher comovement around benchmark events (Vijh, 1994, Barberis

[9]For evidence that investment elasticity declines with size, see Gertler & Gilchrist (1994), Chaney et al. (2012), Zwick & Mahon (2017), Begenau & Salomao (2019), Crouzet & Mehrotra (2020), Cloyne et al. (2023), Best et al. (2024).

et al., 2005, Greenwood, 2008).[10] Our contribution differs from the existing 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 $\hat{\beta}$ rose in lockstep with benchmarking intensity over the past 25 years. We show that this increase affects stocks unevenly: most experience a rise in their CAPM $\hat{\beta}$, while only a small number of the largest firms exhibit a decline. Finally, we find that net flows into passive mutual funds and ETFs drive these changes in $\hat{\beta}$s.[11] We thus provide evidence for our and other recent theories that posit increased asset price comovement due to the structural shift to benchmark-linked, passive investing (Basak & Pavlova, 2013, Chabakauri & Rytchkov, 2021, Baruch & Zhang, 2022, Bond & Garcia, 2022, Davies, 2024).[12]

Second, we show that these benchmark-linked $\hat{\beta}$ increases affect the real economy because practitioners set discount rates using the CAPM.[13] We provide evidence that higher benchmarking intensity raises the perceived cost of equity and lowers investment. Relative to Kashyap et al. (2021), who predict more investment due to the price effect associated with the 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. We argue this behavior reflects managers' bounded rationality.[14] This bounded rationality may arise because managers believe that markets are efficient and therefore 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), face limited information-processing capacity (Sims, 2003), or rely on the

[10] On comovement, see also Shiller (1989), Pindyck & Rotemberg (1993), Campbell & Mei (1993), Peng & Xiong (2006), Veldkamp (2006), Kumar & Lee (2006), Green & Hwang (2009), Boyer (2011), Tang & Xiong (2012), Basak & Pavlova (2013), Wahal & Yavuz (2013), Claessens & Yafeh (2013), Antón & Polk (2014), Koch et al. (2016), Raffestin (2017), Da & Shive (2018), Jylhä et al. (2018), Cathcart et al. (2019), Buffa & Hodor (2023), Fang et al. (2024), Kim (2025).

[11] On the importance of institutional flows for asset prices, see Gabaix et al. (2006), Coval & Stafford (2007), Basak et al. (2007, 2008), Van Binsbergen et al. (2008), Chen & Pennacchi (2009), Chen et al. (2010), Greenwood & Thesmar (2011), Lou (2012), Chien et al. (2012), Singleton (2014), Goldstein et al. (2017), Gabaix & Koijen (2021), Ben-David et al. (2021), Dou et al. (2022), Koijen et al. (2024).

[12] For other theories of passive investing, see Stambaugh (2014), Bhattacharya & O'Hara (2018), Brown et al. (2021), Gârleanu & Pedersen (2022), Schmalz & Zame (2024), Cong et al. (2024), Haddad et al. (2025), Jiang et al. (2025).

[13] 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).

[14] However, we note that this behavior may partially also be a rational response to incentives, as changes in the CAPM-implied cost of equity affect capital efficiency metrics (e.g., ROIC) used in performance goals of executives. Reda & Tonello (2015) report that in 2010, 41% of Russell 3000 firms use capital efficiency metrics in long-term incentive plans and 28% use them in short-term incentive plans. The hurdle rates for these metrics are typically set using the WACC implied by the CAPM. The optimality of such compensation contracts is analyzed in Reichelstein (1997) and Rogerson (1997). Appendix Figure A1 provides illustrative examples from DEF 14A proxy statements.

CAPM heuristically to simplify complex decision-making (Tversky & Kahneman, 1974).[15]

Managers infer from the higher $\hat{\beta}$ that their cost of equity has increased and reduce investment. By linking the effect of passive flows to how practitioners use the CAPM in investment decisions, we shift the passive investing debate from questions of statistical price efficiency to revelatory efficiency (Bond et al., 2012). We show that benchmarking degrades the informativeness of covariance signals that guide real allocation, complementing recent evidence on information production and arbitrage frictions associated with benchmark-linked investing (Brogaard et al., 2019, Coles et al., 2022, Sammon, 2024, Sikorskaya, 2024).

Third, we establish aggregate implications and show that changes in investment in the cross-section do not cancel out, even though cross-sectional changes in CAPM βs sum to zero. We show that the covariance between firms' investment elasticities and the distribution of $\hat{\beta}$ shocks determines the aggregate effect. A few large firms receive a subsidy through lower $\hat{\beta}$, while most face higher $\hat{\beta}$. However, we document that larger firms' investment is relatively more inelastic with respect to the CAPM-implied cost of capital and thus adjusts little. Because large firms adjust little, their subsidy cannot offset the contraction of smaller firms, so aggregate investment falls even though the value-weighted market β equals one. We embed this mechanism into a general equilibrium model with heterogeneous firms (Khan & Thomas, 2008, Winberry, 2021) and calibrate the model to match micro-level investment moments and the perceived cost of equity wedge in the cross-section. Our results confirm that the aggregate implications of benchmarking survive price adjustments in general equilibrium. While Farhi & Gourio (2018) also attribute weak aggregate investment to a rise in perceived risk, our paper provides a novel, micro-founded channel for this increase: increasing CAPM $\hat{\beta}$s generated by benchmark-linked investing.

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 period covers 1998 to 2018, the period for which the

[15]For evidence that managerial behavioral biases influence investment policies, see, e.g., research on managerial overconfidence (Malmendier & Tate, 2005, Landier & Thesmar, 2008, Hirshleifer et al., 2012, Malmendier & Tate, 2015), managerial overprecision and miscalibration (Ben-David et al., 2013, Barrero, 2022, Boutros et al., 2025), managerial overreaction (Dessaint & Matray, 2017), lifetime experiences of managers (Malmendier et al., 2011, Benmelech & Frydman, 2015, Dittmar & Duchin, 2016, Schoar & Zuo, 2017), and managerial education (Bertrand & Schoar, 2003, Malmendier & Tate, 2005, Custódio & Metzger, 2014, Dessaint et al., 2020).

BMI measure is available. In some cases, we extend the sample back to earlier years when data availability allows. We provide variable definitions and corresponding data sources in Appendix J.

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 amount of capital that is invested in a firm's 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

$$\text{BMI}_{i,t} = \sum_{j=1}^{J} \frac{\text{AUM benchmarked to index } j_t \times \text{weight of stock } i \text{ in index } j_t}{\text{Market capitalization of stock } i_t} \quad (1)$$

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

Following the literature, we exploit plausibly exogenous variation in BMI generated by the mechanical rules of the annual Russell reconstitution (Pavlova & Sikorskaya, 2023, Sikorskaya, 2024, Chaudhry, 2025). Changes in BMI around the reconstitution date satisfy the relevance condition because they predict portfolio rebalancing of benchmarked investors. The exclusion restriction requires that index membership be conditionally exogenous. The literature finds this assumption valid after one controls for the market-cap rank used to determine index assignment.[16] Limburg (2024) directly tests whether firms try to self-select into Russell index membership and finds no evidence of such behavior.

To approximate Russell's proprietary market capitalization ranking, we follow Ben-David et al. (2019) and use publicly available databases that allow us to accurately predict index assignments and mitigate mismeasurement concerns (Glossner, 2024). Appendix Table F17 shows that our constructed ranking variable predicts assignment into Russell 1000 and 2000 with high accuracy. Furthermore, Appendix Table F18 shows that our proxy for the ranking variable allows us to replicate the main result in Pavlova & Sikorskaya (2023) almost perfectly.

Following Appel et al. (2019), we account for the specifics of the Russell's banding policy introduced in 2007. The banding policy only affects the Russell 1000/2000 cutoff; the Russell 3000 cutoff has no banding policy (see Appendix F.1 for details on the Russell indices).

[16] Pavlova & Sikorskaya (2023) show that for value-weighted indices, $\text{BMI}_{i,t} = \sum_j \frac{\text{AUM}_{j,t} \times \mathbb{1}\{\text{Index Membership}\}_{i,j,t}}{\text{Market Capitalization of Index}_{j,t}}$, which depends on i only through index membership, thus requiring conditional exogeneity of membership.

A key advantage of the BMI measure over an index inclusion indicator variable is its granularity. Changes in BMI capture the total, heterogeneous change in benchmarked capital when a stock switches not only between broad market indices (e.g., Russell 1000 and 2000) but also between style indices (e.g., Value and Growth). Pavlova & Sikorskaya (2023) note that this is important since a stock moving from the Russell 1000 Value to the Russell 2000 Value index experiences different capital 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). We primarily use CAPM β estimates from Welch (2022). The estimates are based on exponentially weighted least squares regressions on an expanding-window of a firm's winsorized daily excess return on the market excess return (using the CRSP value-weighted index). 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 A1 reports summary statistics for the monthly BMI-CAPM $\hat{\beta}$ panel covering 1998m1 to 2018m8.

Firm-level Data We use annual data for publicly listed companies incorporated and located in the U.S. from Compustat 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.[17] We winsorize the data at the 2.5% and 97.5% level. 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 Gormsen & Huber (2025).[18] 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 Appendix E).

[17]We verify that these sample restriction do not materially affect our results, cf. Table 6 and Appendix Table A7.
[18]For details on the data see Gormsen & Huber's project website at https://www.costofcapital.org/.

3 Novel Stylized Facts About Benchmark Stocks

We establish three novel stylized facts for the time-series and cross-section of U.S. stocks included in benchmark stock indices. Over the past 25 years, CAPM $\hat{\beta}$s and benchmarking intensity have increased in lockstep. The average stock's benchmarking intensity increased from 8.3% in 1998 to 18.3% in 2018, while the equal-weighted average CAPM $\hat{\beta}$ rose by around 0.36. Firms representing over 70% of annual capital expenditures in Compustat experienced a weighted average increase in $\hat{\beta}$ of around 0.1, corresponding to a CAPM-implied expected return increase of 60 bps under a 6% equity risk premium.

Importantly, changes in fundamental risk or leverage do not explain this increase. Instead, we find systematic differences in CAPM $\hat{\beta}$s across market capitalization ranks used in the construction of benchmark indices like the Russell indices. For example, Russell 2000 stocks have, on average, 0.12 higher $\hat{\beta}$s than Russell 1000 stocks. Moreover, the average level of $\hat{\beta}$ changes close to the mechanical cutoffs which determine index membership.

This phenomenon has tangible consequences for corporate policies: we find that, in the cross-section, firms with higher benchmarking intensity invest less and issue less equity, on average. These novel facts suggest that the growth of benchmark-linked investing and the institutional design of benchmark indices impact real and financial decisions.

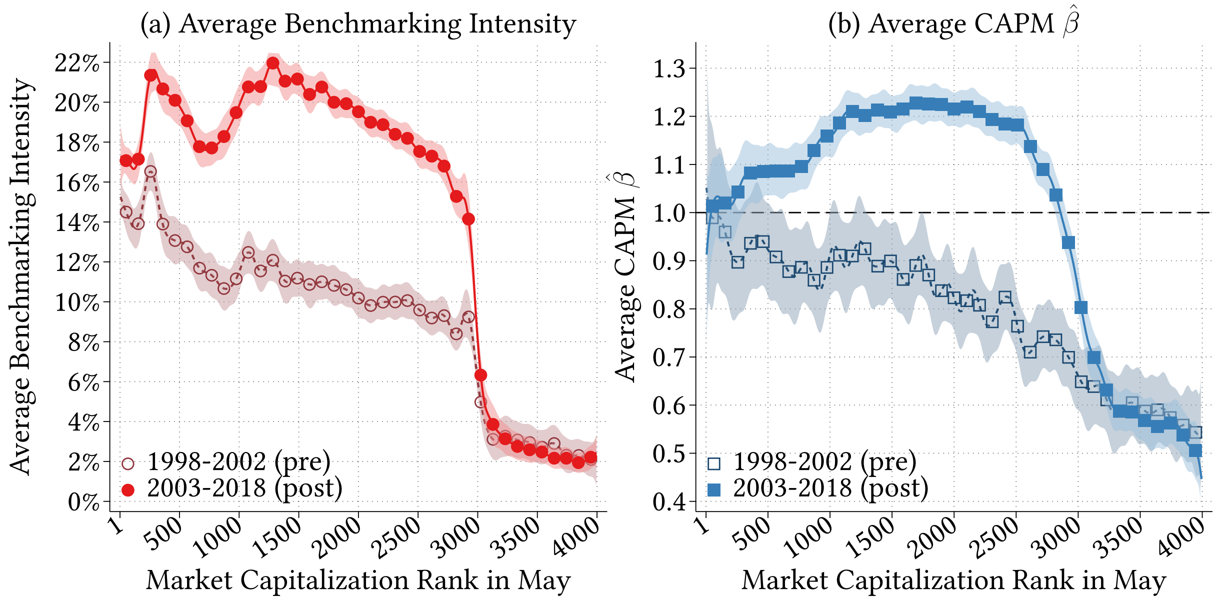
To visualize these facts across market capitalization ranks, we design our empirical strategy to mirror the construction of the Russell benchmark indices. We fix each stock's market capitalization rank at the end of May and plot the variables of interest over the subsequent year. This timing allows us to visualize the effects of Russell benchmark membership, as end-of-May market capitalization ranks hold no other inherent economic meaning. We group stocks into bins of approximately 100 consecutive ranks and compute equal-weighted means for BMI, CAPM $\hat{\beta}$, investment rate, and net equity issuance. By absorbing time fixed effects we isolate the cross-sectional relationship between these variables and a firm's rank within each period. We plot the conditional means for pre- and post-2003 periods using the nonparametric binscatter methods of Cattaneo et al. (2024).

To visualize the cross-sectional relationship between BMI and CAPM $\hat{\beta}$, investment, and equity issuance, we additionally plot the binned scatters of the following regressions in Figure 2,

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

in which $\alpha_{t,\text{Rank Bucket}}$ are time fixed effects interacted with rank buckets (defined every 250 market

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



Notes: This figure plots binned scatters of benchmarking intensity 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.

capitalization ranks). This specification allows us to flexibly control for time-varying differences across the market capitalization spectrum and ensures that the cross-sectional relationship between BMI and the outcome variable is not driven by firm size.

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. The figure reveals two patterns. First, both benchmarking intensity and $\hat{\beta}$s increased after 2002.[19] This rise occurred almost across the entire market capitalization spectrum. For stocks in the Russell 2000 (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 highly correlate (ρ=0.92) across market capitalization ranks (see Appendix Figure A4). Second, the figure displays changes in both series that align with Russell benchmark construction rules. Average BMI and $\hat{\beta}$s increase around the 1000th rank, the threshold between the Russell 1000 and 2000.[20] Both series

[19]The sample is split after 2002 because BMI increases substantially from that point onward. This increase is likely linked to the 2001 Economic Growth and Tax Relief Reconciliation Act, which increased contribution limits on defined contribution plans, and the 2003 Jobs and Growth Tax Relief Reconciliation Act, which reduced dividend and capital gain tax rates. Mainardi (2025) documents that both reforms led to substantial net capital flows into mutual funds beginning in 2002.

[20]Figure 3 shows jumps at the threshold: Russell 2000 stocks have 6 p.p. higher BMI and 0.12 higher $\hat{\beta}$s, on average.

Table 1: 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 $\hat{\beta}$		Avg. Mega-Cap $\hat{\beta}$		Avg. Large-Cap $\hat{\beta}$		Avg. Small-Cap $\hat{\beta}$		Avg. Micro-Cap $\hat{\beta}$	
$\mathbb{1}\{\text{Year} > 2002\}$	-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. $\hat{\beta}$ sample from 1989 to 2018. BMI is available only from 1998 to 2018. Avg. capital expenditure 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.

then decline near the Russell 3000 cutoff. These patterns suggest that the institutional design of benchmark indices affects a stock's estimated market risk.

The widespread increase in individual stock $\hat{\beta}$s shown in Figure 1 does not imply that the value-weighted market β changes, which equals 1 by construction. We apply an Olley-Pakes-style decomposition to the value-weighted market β to formalize these compositional dynamics:

$$\text{Value-weighted CAPM } \beta_t \equiv \sum_{i=1}^{N} \omega_{i,t}\, \hat{\beta}_{i,t} = \bar{\beta}_t + \text{cov}\left(\omega_{i,t}, \hat{\beta}_{i,t}\right) = 1 \tag{2}$$

in which $\bar{\beta}_t$ is the equal-weighted, cross-sectional average and $\omega_{i,t}$ is the market-cap weight of stock i. Since Figure 1 shows that the equal-weighted average increased to above 1, the identity in (2) can only hold if the covariance term changed from positive to negative.[21] This increase implies a structural shift in the cross-section of market risk: whereas larger stocks historically had higher CAPM $\hat{\beta}$s, this relationship has inverted, and smaller stocks now exhibit higher $\hat{\beta}$s.

Table 1 provides evidence for this inversion. We split stocks into five non-overlapping size groups based on NYSE market-cap breakpoints at each month-end. The odd-numbered columns report regressions of the average CAPM $\hat{\beta}$s of each group on an indicator for the post-2002 period.

[21] Appendix Figure A3 shows equal-weighted average $\hat{\beta}$s from 1985 to 2022, which increase to above 1 around 2003.

The average $\hat{\beta}$ of the 50 largest firms declined from 1.07 to 0.94 after 2002, while the $\hat{\beta}$s for almost all smaller size groups increased to above 1. Note that the market weight of the 50 largest firms is sufficient to offset the increase in $\hat{\beta}$s across the thousands of smaller stocks. However, the table also reports the average share of annual capital expenditure of each group. Firms which experienced $\hat{\beta}$ increases account for over 70% of capital expenditures in Compustat. The even-numbered columns show that a higher market-wide BMI predicts a lower average $\hat{\beta}$ for the 50 largest firms but a higher $\hat{\beta}$ for all other groups, with the effect strengthening for smaller firms.[22]

Greater benchmarking intensity is associated with an increase of up to 300 bps in the CAPM-implied cost of equity. Panel (a) of Figure 2 translates the CAPM $\hat{\beta}$s into excess return space by multiplying them by a constant equity risk premium of 6%, allowing for an intuitive interpretation of the economic significance. The figure shows a significant increase in the CAPM-implied cost of equity, especially for small- and mid-cap firms. Panel (b) confirms that CAPM $\hat{\beta}$s correlate with BMI in the cross-section. The estimation includes year-month-by-rank-bucket fixed effects to ensure that the positive correlation is not due to differences in firm size. A 10 p.p. higher BMI predicts a $\hat{\beta}$ increase of 0.25, corresponding to a 150 bps higher cost of equity.

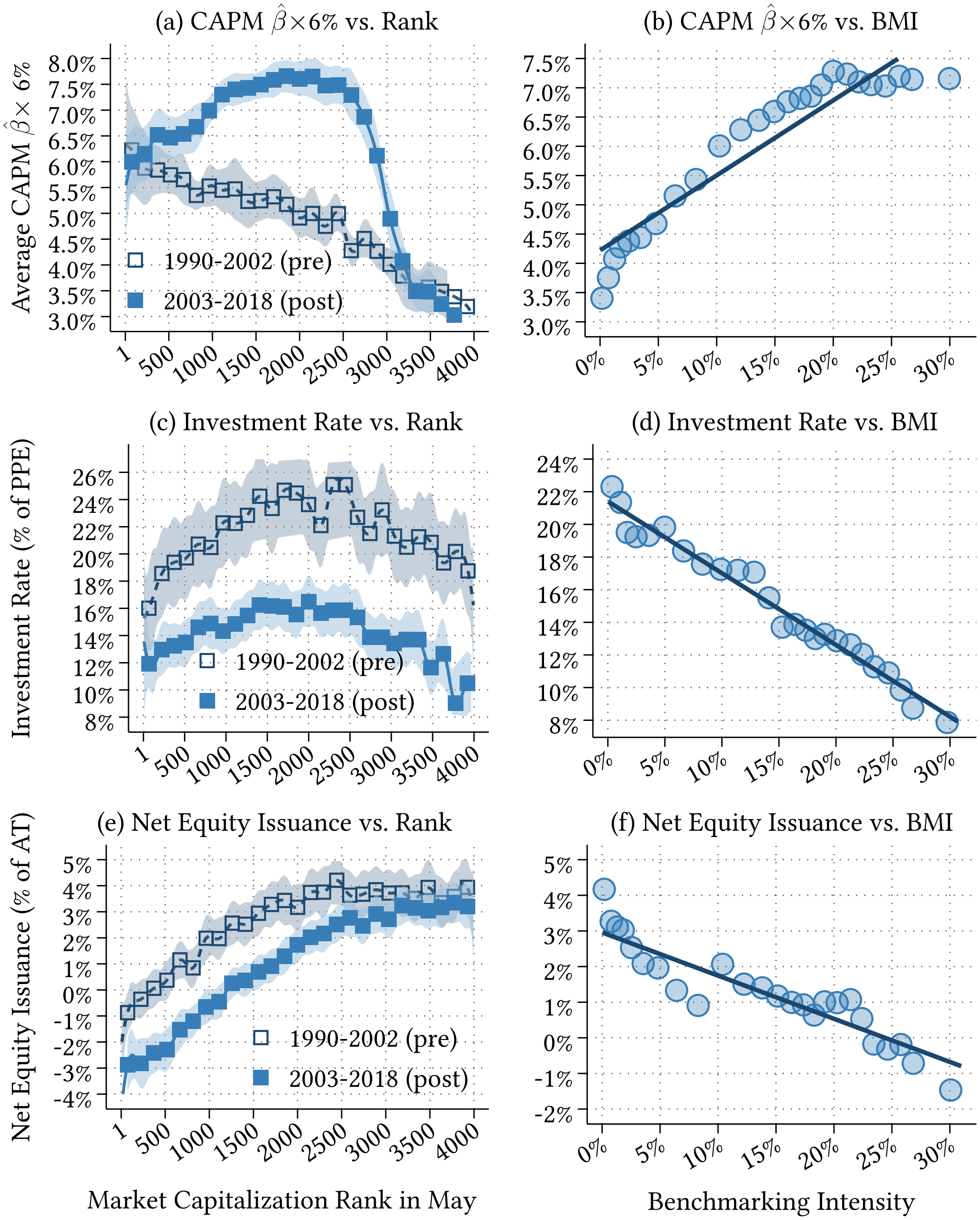
Changes in capital structure do not explain the rise in CAPM $\hat{\beta}$s. If leverage were the driver, unlevered asset $\hat{\beta}$s would remain stable. Instead, Appendix Figure A5 shows that asset $\hat{\beta}$s mirror equity $\hat{\beta}$s; for Russell 2000 stocks, the average asset $\hat{\beta}$ rose by 0.29. Appendix Figure A5 also extends the sample to 1975 and confirms these patterns are not a Dot-Com artifact. Appendix Figure A2 shows that the increase is robust to estimating β at daily, weekly, or monthly frequency.

The increase in CAPM $\hat{\beta}$s also does not reflect greater cash flow risk. Comparing market-based asset $\hat{\beta}$s to cash flow βs estimated from accounting data (Cohen et al., 2009), Appendix Figure A5 shows that cash flow βs did not change, while asset $\hat{\beta}$s rise sharply after 2003. This divergence indicates that higher CAPM $\hat{\beta}$s reflect a market-based shift rather than changes in firms' fundamentals. Appendix Figure A7 shows that this finding is robust to using consumption growth βs (Kim et al., 2024) as an alternative measure of fundamental risk exposure.

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 rates 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 relative to earlier decades. The decline is most pronounced for Russell 2000 firms, whose average investment rate fell by

[22] We do not analyze in detail why the largest firms' CAPM $\hat{\beta}$s declined. We conjecture, building on Jiang et al. (2025), that passive fund inflows disproportionately elevate their prices, thus amplifying their *idiosyncratic* returns.

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, 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 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.

8.5 p.p. (from 24.1% to 15.6%), compared to only 3.6 p.p. for the 100 largest firms. Panel (d) displays a strong negative correlation between investment rates and BMI. The estimation includes year-by-rank-bucket fixed effects to ensure that the negative correlation is not due to differences in firm size. This negative correlation suggests that the growth of benchmarking contributes to the aggregate decline in investment rates (Gutiérrez & Philippon, 2017).[23]

Fact 3: Benchmarking Intensity negatively correlates with net equity issuance. Panel (e) and (f) of Figure 2 show that firms more exposed to benchmarking issue less equity. We measure net equity issuance as the difference between equity issued and 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) of Figure 2 show that net equity issuance and BMI negatively correlate. 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 that the negative correlation is not due to differences in firm size. This finding adds a new cross-sectional dimension to the decrease in net equity issuance associated with the shift towards buybacks and away from dividend distributions (see, e.g., Grullon & Michaely, 2002). Taken together, these patterns suggest that the rise of benchmark-linked investing helps to explain cross-sectional variation in corporate payout and financing policies.

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, affect firm investment. We model the effects here in a stylized fashion as wedges in firm's discount rates. We formally derive these wedges in a three-period setting with (boundedly rational) firm managers in Appendix B.

Textbook Investment Policy Corporate finance textbooks instruct managers to adopt investment policies that maximize net present value (NPV). Calculating NPV requires expected cash flows and a discount rate. Most textbooks recommend the weighted average cost of capital (WACC) as discount rate, with the cost of equity derived from the CAPM. Formally, $V = \mathbb{E}[CF/R]$ equals the NPV of expected cash flows CF discounted at the firm-specific discount rate R. The discount rate R equals the firm's WACC, determined by the exposure of cash flows

[23] Appendix Figure A8 confirms robustness to alternative investment rate definitions.

generated by the firm's assets to the equity risk premium (ERP), β^A, and the risk-free rate R^f

$$R = R^f + \beta^A ERP. \tag{3}$$

Assuming that firm leverage is sufficiently low to not create default risk, the aggregate risk exposure of the firm's cash flows is proportional to exposure of the firm's equity to ERP:

$$\beta^A = \frac{\beta^E}{1 + (1-\tau)\frac{D}{E}}. \tag{4}$$

As such, it can be directly inferred from the empirical CAPM β of the firm's equity $\hat{\beta}^E = \frac{\widehat{\text{Cov}}(r, r_m)}{\widehat{\text{Var}}(r_m)}$. A manager considering a firm-typical project with cost C and future cash flows Y should invest in the project if it has positive NPV and thus increases firm value, that is if

$$\mathbb{E}\left[Y/\hat{R}\right] = \mathbb{E}\left[\frac{Y}{R_f + \hat{\beta}^E \left(1 + (1-\tau)\frac{D}{E}\right)^{-1} ERP}\right] > C \tag{5}$$

in which $\widehat{R}$ results from substituting the empirical counterpart of (4) into (3).

The Presence of Benchmarked Funds Affects Asset Prices Benchmarked funds' inelastic demand for benchmark constituents increases their price and thereby lowers their implied discount rate. 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 the discount rate proportional to ERP.

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 $\Delta_I(BMI)$. At the same time, β^E increases to $\hat{\beta}^E = \beta^E + \Delta_\beta(BMI)$. Both $\Delta_I(BMI)$ and $\Delta_\beta(BMI)$ monotonically increase in BMI and satisfy $\Delta_I(0) = \Delta_\beta(0) = 0$. The discount rate, adjusted for benchmarking, is

$$\widetilde{R} = R^f + \frac{\beta^E + \Delta_\beta(BMI)}{1 + (1-\tau)\frac{D}{E}} ERP - \Delta_I(BMI). \tag{6}$$

CAPM Investment Policy with Benchmarking Whether the benchmarking-induced changes to the discount rate in (6) incentivize managers to invest more or less is ambiguous: the price effect, $\Delta_I(BMI)$, encourages investment, whereas the $\hat{\beta}$ increase, $\Delta_\beta(BMI)$, discourages it.

What if managers are boundedly rational and do not internalize the effects of benchmarked funds on asset prices but instead follow textbook guidance and use the cost of capital implied by the CAPM to evaluate investment opportunities as in Eq. (5)?

In this case, the presence of benchmarked funds has an unambiguously negative effect on investment for benchmark constituents. A boundedly rational manager, with subjective expectations $\mathbb{E}^{\star}[\cdot]$, observes an increase in their stock's CAPM β from β^E to $\hat{\beta}^E = \beta^E + \Delta_\beta(BMI)$ and infers an increase in the firm's cost of equity. The manager now invests only in projects that satisfy

$$\mathbb{E}^{\star}\left[Y/\widetilde{R}^{\star}\right] = \mathbb{E}^{\star}\left[\frac{Y}{R^f + (\beta^E + \Delta_\beta(BMI))\left(1 + (1-\tau)\frac{D}{E}\right)^{-1} ERP}\right] > C. \tag{7}$$

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

Testable Hypothesis Our proposed mechanism rests on the behavioral assumption that managers do not internalize the total effect of benchmarking-induced discount rate changes. Instead, managers follow textbook guidance to form a weighted average cost of capital using their firm's empirical CAPM $\hat{\beta}$s. Benchmarking-induced comovement biases the CAPM $\hat{\beta}$s upward and leads benchmark constituents to under-invest. We empirically validate our mechanism by presenting evidence that supports three testable hypotheses directly derived from it. All else equal,

(i) there is a monotonic positive relationship between changes in firm BMI and changes in $\hat{\beta}^E$,

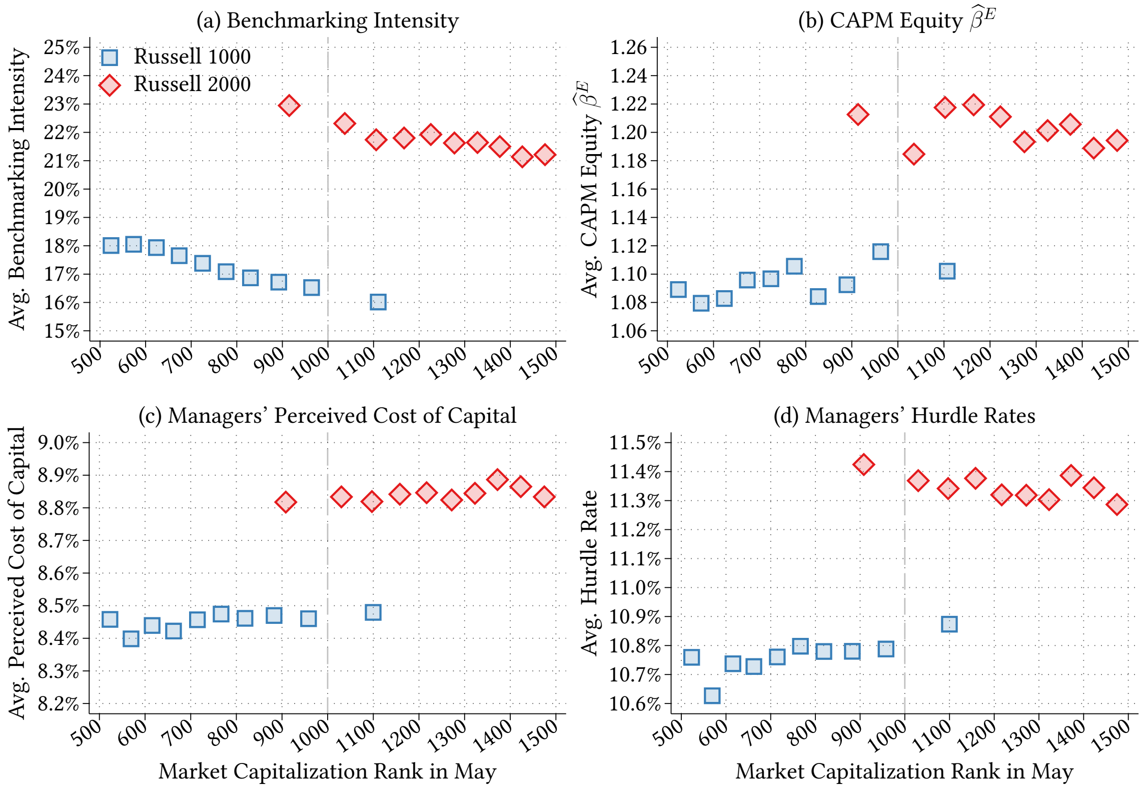
(ii) an increase in firm BMI increases the firm's perceived cost of equity, and

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

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

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, we observe a clear jump at the rank-1000 threshold. Panel (a) shows that as firms move from just inside the Russell 1000 to just inside the Russell 2000, their average benchmarking intensity (BMI) jumps from approximately 17% to 23%. Panel (b) shows this increase in BMI coincides with an increase in average CAPM $\hat{\beta}$ from 1.09 to 1.21. Crucially, managers' own assessments mirror these patterns: Panel (c) and (d) show that average perceived cost of capital and hurdle rates also jump at the cutoff. While

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.

consistent with our hypothesis, these discontinuities are suggestive rather than conclusive; other factors might influence the $\hat{\beta}$ and the perceived cost of capital at the index cutoff, such as liquidity effects or unobserved differences between the largest small-cap and smallest mid-cap firms. Note that the banding policy introduced by Russell in 2007 precludes using regression discontinuity designs at the cutoff (see Appel et al., 2024, for details).

To establish that these discontinuities stem from changes in benchmarking intensity, we exploit quasi-exogenous variation in BMI induced by Russell reconstitution. We estimate the effect of changes in a firm's BMI on its CAPM $\hat{\beta}$ using a difference-in-differences design. We compare the evolution of $\hat{\beta}$s of (treated) stocks that experience BMI changes around Russell reconstitution dates to (control) stocks that do not. We find that CAPM $\hat{\beta}$ increase by between 0.015 and 0.027 for every 1 p.p. increase in BMI.

The effect on estimated market risk exposure directly influences managers' perceived cost of capital. Using the BMI change as an instrument for the change in $\hat{\beta}$, our IV estimates show that a 0.2 increase raises managers' perceived cost of capital by 70 bps. We corroborate the pass-through in five alternative datasets. We find that stock analysts as well as state and federal regulators of monopolies (e.g., utilities) also incorporate benchmarking-induced $\hat{\beta}$ increases into their perceived cost of equity, 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 effect 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:

$$\text{CAPM } \hat{\beta}_{i,t} = \theta_{i,c} + \theta_{t,c} + \sum_{k=-4}^{9} \gamma_k \left(\Delta \text{ BMI} \times \mathbb{1}\{t - T_i = k\}\right) + X'_{i,t}\psi + \varepsilon_{i,t} \tag{8}$$

where $X_{i,t}$ is a vector of controls. The parameters $\{\gamma_{-k}\}_{k=-4}^{9}$ measure the dynamic effects of changes in BMI around Russell benchmark reconstitution on CAPM $\hat{\beta}$. 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 $\{\gamma_{-k}\}_{k=-4}^{9}$ is never estimated by comparing later-treated units with earlier-treated units.

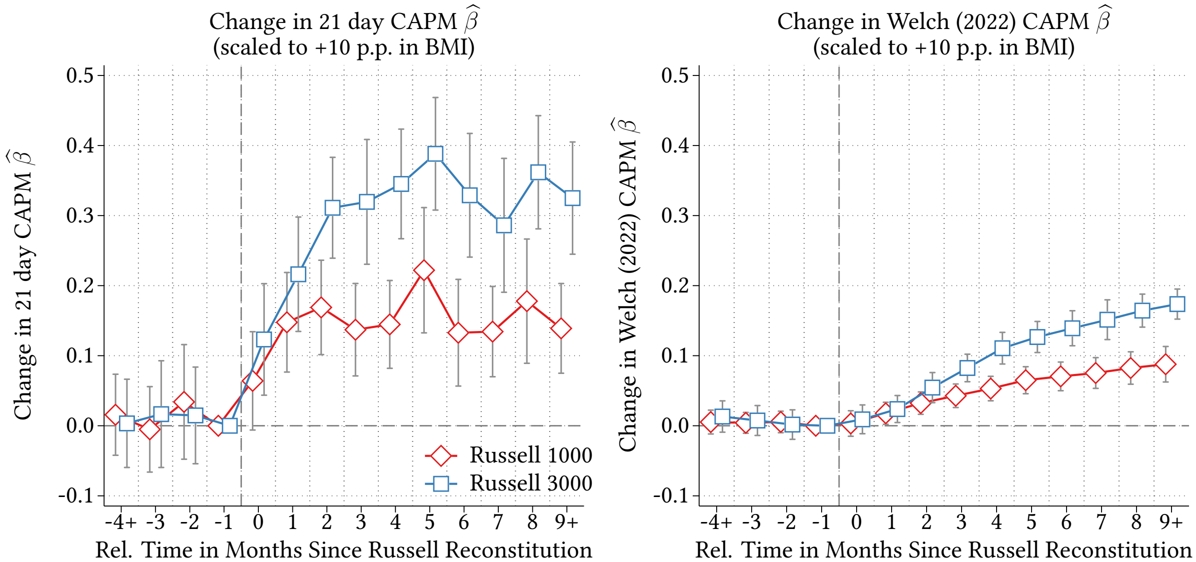
Identification Strategy Our identification strategy exploits quasi-exogenous variation in BMI resulting from the annual Russell benchmark reconstitution. The key identifying assumption is parallel trends: conditional on our fixed effects and controls, the CAPM $\hat{\beta}$s of firms experiencing BMI changes would have evolved similarly in the absence of the treatment. Figure 4 presents visual evidence supporting the validity of the parallel trends assumption.

The main identification concern in using changes in BMI is that benchmark membership is potentially endogenous to firm characteristics that also affect CAPM $\hat{\beta}$.

We address this concern in several ways. First, following Pavlova & Sikorskaya (2023), Sikorskaya (2024), and Chaudhry (2025), we include a comprehensive set of control variables in $X_{i,t}$ to ensure the conditional exogeneity of ΔBMI. It includes the log market capitalization, the May ranking variable used by Russell to construct the indices. Specifically, we follow Ben-David et al. (2019) in constructing the May ranking variable.[24] We further add indicator variables for the banding policy introduced by Russell in 2007 (i.e., indicators for being in the band, for membership in

[24]See Appendix Table F17 for a validation test of our proxy ranking variable against actual Russell membership.

Figure 4: Difference-in-differences Event Study of Changes in BMI on Changes in CAPM $\hat{\beta}^E$



Notes: This figure shows the dynamic effects of a 10 p.p. increase in BMI on CAPM $\hat{\beta}$s around Russell reconstitution. The left panel uses a 21-day rolling β; the right panel uses the Welch (2022) estimator. We plot results for reconstitution at the Russell 1000 (red diamonds) and Russell 3000 (blue squares) cutoffs, restricting the sample to stocks within 300 ranks of each cutoff. Controls include market capitalization, bid-ask spread, Amihud illiquidity, momentum, and banding variables. Pointwise confidence intervals (95%) based on double-clustered standard errors.

the Russell 2000 in May, and their interaction) as suggested by Appel et al. (2019). Conditional on these baseline controls, the change in BMI due to Russell reconstitution is exogenous. Second, we address the potential endogeneity of ΔBMI to stock liquidity by including the logarithms of bid–ask spreads and Amihud illiquidity as controls. Third, we control for momentum using the cumulative 12-month return. We interact all controls with cohort fixed effects.

We restrict the sample to firms within a 300 rank window of the Russell cutoffs to isolate variation from reconstitution. 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).

Results Figure 4 presents the results from our continuous difference-in-differences event study, showing how CAPM $\hat{\beta}$s change around a Russell benchmark reconstitution. We estimate changes at 1000th and 3000th rank cutoffs separately and scale the results so that the coefficients represent the effect of a 10 p.p. increase in BMI.[25] We normalize the dynamic treatment effects relative to

[25] Appendix Figures A9a and A9b show robustness results using an indicator variable for BMI changes larger than +5 p.p. and smaller than -5 p.p., respectively.

May and estimate dynamic treatment effects for the period from 4 months before to 9 months after benchmark inclusion. We plot the results using two different CAPM $\hat{\beta}$ estimators: The left panel uses a rolling-window estimator based on 21 daily returns, while the right panel uses Welch's (2022) exponentially weighted expanding window estimator.

Several results are worth noting. First, the plots support our identification strategy. In the months leading up to the reconstitution in June (time 0), the coefficients for both groups are statistically indistinguishable from zero. The lack of a differential pre-trend supports the parallel trends assumption underlying our design.

The left panel, using a short-term 21-day estimator, shows a large and immediate jump in $\hat{\beta}$ in the months after reconstitution. For a 10 p.p. increase in BMI, $\hat{\beta}$ rises by approximately 0.3 for stocks near the Russell 3000 cutoff and by 0.15 for stocks near the Russell 1000 cutoff. This immediate jump shows the economic effect is instantaneous. In contrast, the right panel uses the longer-horizon estimator from Welch (2022), which shows a much more gradual increase.

The contrast between the two panels highlights a crucial measurement issue. Using long-horizon estimators, BMI changes increase CAPM $\hat{\beta}$ gradually and are detectable only 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.

The estimated treatment effect is larger at the Russell 3000 cutoff than at the Russell 1000 cutoff. This difference is due to the underlying characteristics of the firms; stocks near rank 3000 are smaller, less liquid, and have lower initial BMI and $\hat{\beta}$s compared to firms at the 1000th rank.

Our continuous difference-in-differences specification pools variation from both increases and decreases in BMI, thereby assuming a symmetric effect. We validate this assumption in Appendix Figure A9, which estimates the effect separately for firms experiencing BMI increases versus decreases. The results confirm this symmetry: the size of the effect is statistically similar for both positive and negative BMI changes, differing only in the expected sign.

Table 2 reports the average post-treatment effect on CAPM $\hat{\beta}$, pooling reconstitution from the Russell 1000 and 3000 cutoffs. We report the results for the 21-day rolling-window $\hat{\beta}$ (Columns 1-4) and the exponentially weighted $\hat{\beta}$ from Welch (2022) (Columns 5-8). To account for the latter's long-horizon estimation, we report the treatment effect after 12 months. The magnitudes are economically significant and consistent with the correlational evidence in Figures 1, 2, and 3.

We find similar effect sizes in panel regressions where we regress CAPM $\hat{\beta}$s on benchmarking

Table 2: Effects of Changes in Benchmarking Intensity 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 $\hat{\gamma}$ for specifications of the form: CAPM $\hat{\beta}_{i,t} = \gamma \, \Delta \, \text{BMI}_i \times \text{Post}_t + \alpha_{i,c} + \alpha_{t,c} + q'_{i,t,c}\psi + \varepsilon_{i,t}$. All specifications control for log of market capitalization (Ben-David et al., 2019) and log bid-ask spread. We interact all controls and fixed effects with cohort fixed effects (Baker et al., 2022). The estimation sample includes stocks within 300 ranks of the Russell 1000 and 3000 cutoffs, pooling both benchmark additions and deletions. Δ $\text{BMI}_i \times \text{Post}_t$ in column (5) to (8) is average post-treatment effect after 12 months (which reduces the observation count) to account for the expanding-window estimation of $\hat{\beta}$. Standard errors in parentheses are double-clustered at stock and year-month level. * p<0.10, ** p<0.05, *** p<0.01.

intensity in levels (see Appendix Table A2). Across six specifications with increasingly stringent fixed effects, the coefficient on BMI remains stable at around 0.025 and highly significant. The level of BMI explains between 17% and 29% of residual variation in $\hat{\beta}$ after absorbing fixed effects. After accounting for all time-invariant firm traits by absorbing firm fixed effects and various time-varying shocks at the industry-size level, BMI explains 17% of the residual variation in $\hat{\beta}$. Notably, institutional ownership (IOR) has no discernible effect on $\hat{\beta}$ when included alongside BMI, suggesting the observed relationship is specific to benchmark-sensitive investors.

The increase in CAPM $\hat{\beta}$s also translates into an increase in the R^2 of the CAPM. Appendix Figure A10, panel (i), shows that after Russell reconstitution, stocks experiencing a 10 p.p. BMI increase see a significant 5 p.p. increase in the R^2 of the CAPM, on average. Relative to the pre-period R^2 of the treated firms of around 20%, this increase is economically significant. Panel (ii) further shows that, in the cross-section, firms with higher BMI have higher CAPM R^2.

Note that the increase in CAPM $\hat{\beta}$s and R^2 of the CAPM does not imply that investors receive compensation for the increased market risk exposure. Pavlova & Sikorskaya (2023) find *lower* realized returns after an exogenous increases in BMI. This finding is consistent with the negatively sloped security market line reported by Baker et al. (2011) and with their argument that benchmarking introduces limits to arbitrage, preventing 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.

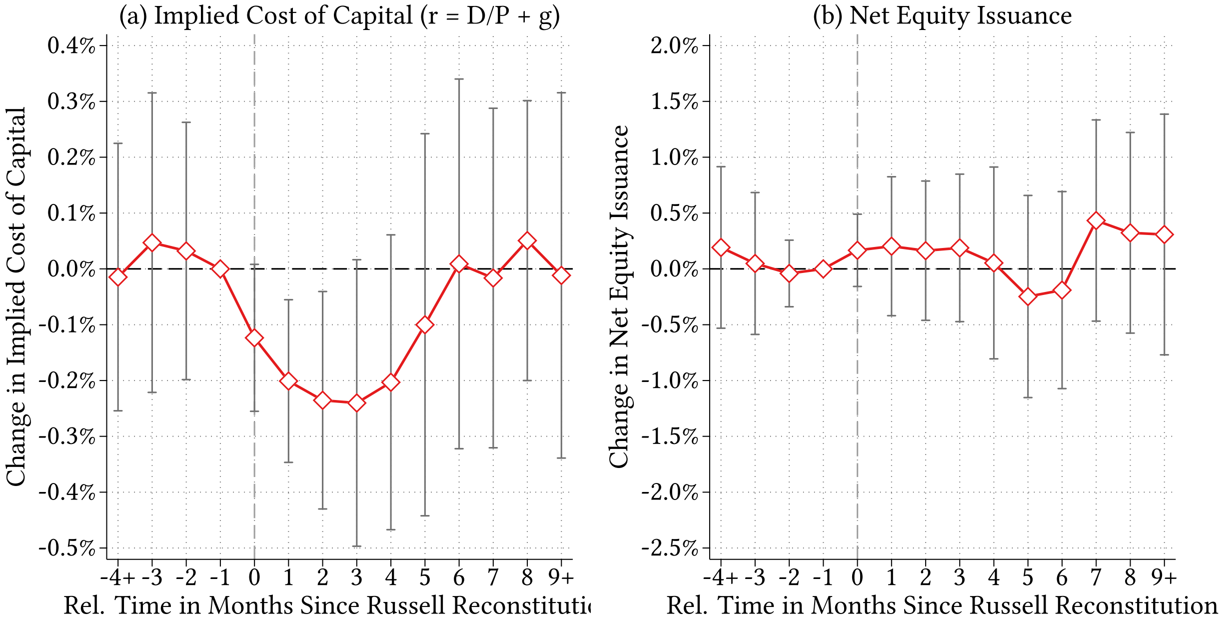
We note that while our evidence establishes a direct link between BMI changes and CAPM $\hat{\beta}$, the coefficient estimates are not structural parameters. Since the value-weighted market β must equal one, a change in one firm's $\hat{\beta}$ necessarily affects others, violating SUTVA. Second, because the formula for β is a non-linear function of the market's covariance matrix, the effect of BMI on β is also inherently non-linear. For this reason, we interpret the estimates as reduced-form evidence of a causal effect rather than as structural parameters.

Additional Evidence From S&P 500 Additions We examine stocks added to the S&P 500 to provide additional evidence on benchmarking's effect on CAPM $\hat{\beta}$s, following Vijh (1994) and Barberis et al. (2005). Figure 11 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 the $\hat{\beta}$ increase by approximately 0.016 per 1 p.p. increase in BMI, somewhat smaller but similar to the estimate from Russell reconstitution in Table 2. 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. Appendix Table A3 shows that BMI remains a statistically significant predictor of $\hat{\beta}$ across all estimators, including those proposed by Blume (1975), Dimson (1979), and Welch (2022). Furthermore, we decompose the increase and find that its increase is due to a rise in market correlation, 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 benchmarking intensity on $\hat{\beta}$s, we test for cointegration between the aggregate time series of average BMI and average CAPM $\hat{\beta}$. As shown in Appendix Table A4, we strongly reject the null hypothesis of no cointegration. This test validates our use of Dynamic OLS (DOLS) (Stock & Watson, 1993) 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.

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%) based on double-clustered standard errors.

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 can infer the discount rate from stock prices and expected cash flows, as in Kashyap et al. (2021). 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.[26]

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. We perform a back-of-the-envelope calculation to estimate the implied stock return using Gordon's growth model. We assume the expected dividend, D, and expected dividend growth rate, g, remain constant when BMI changes. We set r to the pre-period

[26]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).

average of the ICC of 8.9% and g to the long-run average of U.S. stocks' real dividend growth of 1.6% (from Robert Shiller's website). The 21 bps decrease in ICC, at event-time coefficient 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).[27] The 95% confidence interval (which we obtain using the delta method) similarly covers the 5% average price effect which Chang et al. (2015) find.

However, our difference-in-differences event study also shows that this price effect is temporary and reverts within six months. The small and short-lived impact on the price make it unlikely that increased benchmarking affects investment through a price-level channel. Our results are consistent with evidence from Harris & Gurel (1986), Petajisto (2011), Patel & Welch (2017), and Chaudhry (2025) who similarly show that price effects of benchmark inclusion revert over time.

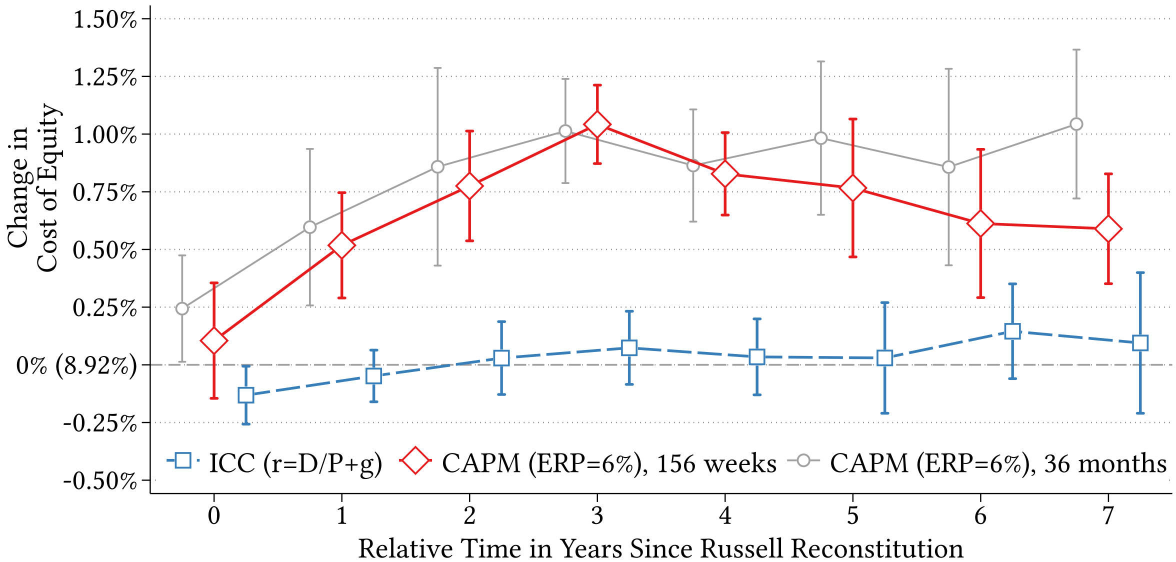
We find no significant change in net equity issuance, implying firms do not opportunistically exploit the temporary price dislocation. Firms likely refrain because the costs of issuing equity exceed the potential benefits. First, investors may perceive issuing equity as a negative signal about firm quality (Myers & Majluf, 1984). This concern is particularly salient for the Russell 1000 firms moving into the less-prestigious Russell 2000. Second, even absent signaling concerns, the direct transaction and underwriting costs of an equity offering may render it unprofitable given the modest price increases. Third, any buyer of the newly issued shares would take on considerable market risk, as the shares would be subject to the benchmarking-induced $\hat{\beta}$ increase, without receiving a commensurate increase in expected return.[28]

Qualitative evidence from earnings call transcripts indicates that managers do not view Russell benchmark inclusion as a financing event. In Appendix D.1, we analyze 163 earnings call transcripts of firms added to the Russell benchmark indices from 2008 to 2024. Among 163 transcripts that mention benchmark inclusion, only five link it to equity offerings, two of which are from Real Estate Investment Trusts (REITs) that issue equity frequently as part of their busi-

[27] Appendix Table F18 replicates the return results of Pavlova & Sikorskaya (2023) using our sample and identification strategy. Our return results overlap almost perfectly with Pavlova & Sikorskaya (2023), despite minor differences in sample, construction of variables, and the use of the proxy ranking variable proposed by Ben-David et al. (2019).

[28] We note that earlier work suggests that opportunistic firms exploit sentiment-driven stock price overvaluation (e.g., Morck et al., 1990, Stein, 1996, Baker & Wurgler, 2000, Shleifer & Vishny, 2003, Bergman & Jenter, 2007). However, Warusawitharana & Whited (2016) document that while misvaluation can affect firm behavior, the effects on financial decisions are much stronger than those on real investment decision.

Figure 6: Persistence of BMI Shocks on the Cost of Equity Over Long Horizons



Notes: This figure shows the persistence of a 10 p.p. benchmarking intensity shock on Implied Cost of Capital (ICC) and CAPM β estimates using: CAPM $\hat{\beta}_{i,t+h} \times 6\%$ ERP $= \gamma^h_{t,s} + \gamma^h_1 \Delta \text{BMI}_{i,t} + X'_{i,t}\xi^h + \varepsilon_{i,t+h}$. Controls include market capitalization, bid-ask spread, Amihud illiquidity, momentum, lagged BMI, lagged outcome, banding variables, and year-by-industry fixed effects (the ICC regression is analogous; see Eq. (9)). We restrict the estimation sample to stocks within 300 ranks around Russell index cutoffs. Value in parentheses on the Y-axis is the median ICC over the sample. Pointwise confidence intervals (95%) based on double-clustered standard errors.

ness model.[29] In over 60% of transcripts, executives announce their stock's benchmark inclusion without further context. The rest briefly discuss expected gains in visibility (21%) or in trading liquidity and volume (16%). The qualitative evidence indicates that 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 Persistence of Effects on CAPM $\hat{\beta}$ and Implied Cost of Capital

We investigate whether benchmarking creates persistent changes in the cost of equity. Our difference-in-differences analysis shows that BMI-induced increases in CAPM $\hat{\beta}$s persist for at least 12 months. If these increases in the cost of equity fade after a year, long-term effects on investment are unlikely. We thus extend our analysis to test for effects on the ICC and CAPM $\hat{\beta}$s

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

over a seven-year horizon using the following specifications:

$$\text{Avg. ICC}_{i,t+h} = \theta^h_{t,s} + \theta^h_1 \Delta\text{BMI}_{i,t} + X'_{i,t}\xi^h + \varepsilon_{i,t+h}, \quad h = 0, \ldots, 7, \tag{9}$$

$$\text{CAPM } \hat{\beta}_{i,t+h} \times 6\% = \gamma^h_{t,s} + \gamma^h_1 \Delta\text{BMI}_{i,t} + X'_{i,t}\zeta^h + \epsilon_{i,t+h}, \quad h = 0, \ldots, 7. \tag{10}$$

for firm i in industry s in year t+h. The coefficients of interest, γ^h_1 and θ^h_1, summarize the long-term effects of an BMI increase on a firm's CAPM $\hat{\beta}$ or ICC after h years, respectively. The vector of controls $X_{i,t}$ contains the log market capitalization, bid-ask spread, Amihud illiquidity, momentum, lagged BMI, lagged outcome, banding variables. We account for unobserved time-varying industry shocks by absorbing year-by-industry fixed effects. We restrict the sample to stocks within 300 ranks around the Russell index cutoffs and estimate CAPM $\hat{\beta}$s using weekly and monthly returns, consistent with common managerial practice.

Results Figure 6 shows estimates for θ^h_1 and γ^h_1 of Eq. (9) and (10), respectively. We scale the estimates to a 10 p.p. increase in BMI for ease of interpretation and adjust the CAPM estimates to match the units of the ICC estimates by multiplying them by a 6% ERP.

BMI-induced increases in CAPM $\hat{\beta}$s persist for at least seven years. At all horizons, the effects are positive and statistically significant. For both weekly and monthly rolling-window estimators, the impact grows as old observations leave the sample and new observations reflecting higher BMI enter. Three years after the increase, the CAPM cost of equity is about 100 bps higher for both estimators. With the weekly estimator, effects taper over longer horizons but remain economically meaningful. This prolonged impact shows that benchmarking has a long-term effect on firms' perceived cost of equity, potentially leading to sustained changes in investment.

In contrast, changes in BMI have only a short-lived impact on the implied cost of equity derived from stock price levels. The ICC decreases upon benchmark inclusion, but this effect dissipates entirely by the following year, remaining statistically insignificant thereafter.

5.3 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 fundamental 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). To test this hypothesis directly, we analyze the effect of net flows into active and passive mutual funds using data from Morningstar. Panel regressions show that net inflows into passive funds have a significant association with $\hat{\beta}$s increases, particularly for smaller stocks where passive ownership is more concentrated. In contrast, net flows into active mutual funds have a modest effect which is limited to the early part of the sample and likely reflect the quasi-indexing behavior of active managers.

A simulation exercise in Appendix C provides further, more structural support for this mechanism. We construct a parsimonious two-factor model in which stock returns depend on a "fundamental" factor and a "flow" factor. When we calibrate the flow factor to the observed passive fund flows, with exposures proxied by BMI, the model successfully replicates the cross-sectional and time-series evolution of CAPM $\hat{\beta}$s from 1998 to 2018. However, a model calibration using active fund flows fails to match these empirical patterns.

The panel and simulation evidence indicates that the root cause of the increase in CAPM $\hat{\beta}$s is the structural shift toward passive index investing.[30] Our findings lend direct empirical support to our and other recent theories positing that the shift to passive, benchmark-linked investing increases asset price comovement (e.g., Bond & Garcia, 2022). Contemporaneous independent research by Fang et al. (2024) corroborates our results, finding that passive fund ownership increases comovement with the market.

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, distribution, or reinvested dividends (Morningstar Direct, 2024). Rather, the flows present the net amount that investors put into or withdraw from mutual funds and ETFs.

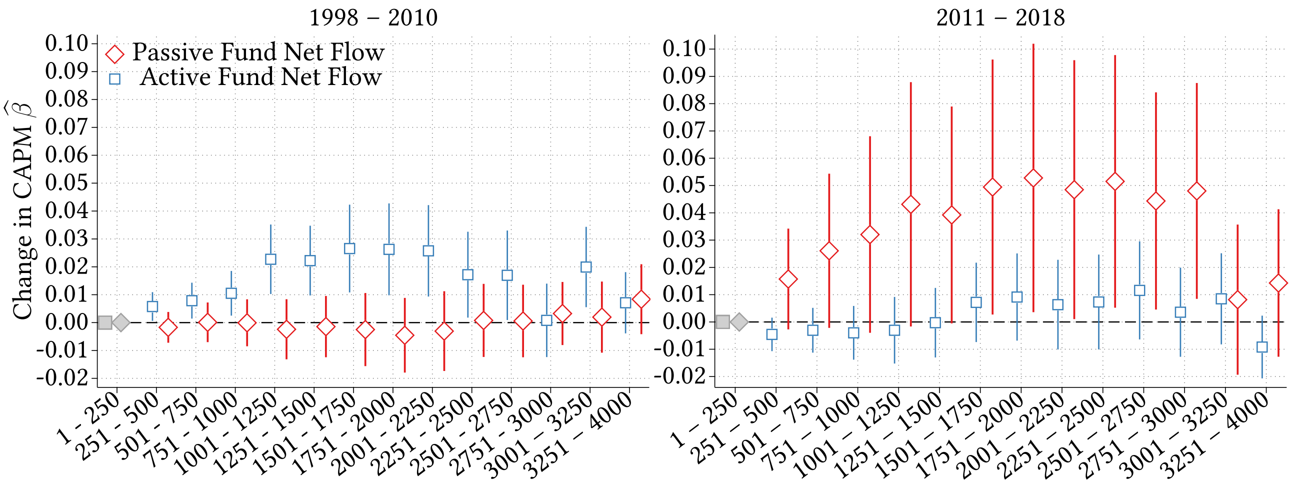
We estimate the following panel regression at the monthly frequency (using end of month $\hat{\beta}$s):

$$\begin{aligned}\text{CAPM } \hat{\beta}_{i,t} = &\sum_{j \notin \{250\}} \gamma_j^A \, \mathbb{1}\{i \in \text{Bin } j\} \times F_t^A / A_{t-1}^A + \sum_{j \notin \{250\}} \gamma_j^P \, \mathbb{1}\{i \in \text{Bin } j\} \times F_t^P / A_{t-1}^P \\ &+ \alpha_i + \alpha_t + \rho \, \text{CAPM } \hat{\beta}_{i,t-1} + X_{i,t}' \zeta + \varepsilon_{i,t} \end{aligned} \quad (11)$$

where F_t^A and F_t^P are net flows into active and passive funds, respectively. The model includes stock fixed effects (α_i) to absorb time-invariant firm heterogeneity and year-month fixed effects (α_t) to absorb aggregate shocks. Time fixed effects absorb the average market-wide effect of fund flows. We identify the coefficients of interest, γ_j^ι, from the differential impact of flows across

[30] This trend culminated in 2024, when assets in U.S. passive mutual funds and ETFs surpassed those in active funds (Morningstar Direct, 2025). Appendix Figure A11 shows that this milestone reflects a multi-decade trend, with cumulative net flows into passive funds surpassing those into active funds by more than $10 trillion since 1998.

Figure 7: 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 $\hat{\beta}_{i,t} = \alpha_i + \alpha_t + \sum_j \gamma_j^A \mathbb{1}\{i \in \text{Bin } j\} \times F_t^A / A_{t-1}^A + \sum_j \gamma_j^P \mathbb{1}\{i \in \text{Bin } j\} \times F_t^P / A_{t-1}^P + X'_{i,t}\xi + \varepsilon_{i,t}$. 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%) based on double-clustered standard errors.

market-capitalization-rank bins. We control for the lagged dependent variable, so the γ coefficients capture the effect of flows on changes in CAPM $\hat{\beta}$. The vector $X_{i,t}$ includes controls for size, bid-ask spread, Amihud illiquidity, and momentum. We identify the γ_j^P coefficients relative to the first bin (the largest 250 stocks). Each coefficient measures the change in $\hat{\beta}$ for stocks in bin j relative to top-250 stocks after net passive fund inflows.

Figure 7 plots the estimated γ_j^A and γ_j^P coefficients, scaled to reflect the effect of a two standard deviation (sd) net inflow into active and passive funds ($\approx 1\%$ of A_{t-1}). Panel (a) covers 1998–2010. In this period, a 2 sd inflow into active funds raises the CAPM $\hat{\beta}$ of small-cap stocks by about 0.02, while passive flows have no significant effect. Panel (b) covers 2010–2018. Here, passive flows dominate: a 2 sd inflow increases $\hat{\beta}$s of mid- and small-cap stocks by 0.02 to 0.05, with effects large and statistically significant. By contrast, active flows have no measurable impact after 2010.

The cross-sectional pattern aligns with differences in benchmarking intensity. 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-

Table 3: 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 $\hat{\beta}_{i,t} = \alpha_i + \alpha_t + \gamma\text{BMI}_{i,t-1} + \psi\text{BMI}_{i,t-1} \times F_t/A_{t-1} + X'_{i,t}\xi + \varepsilon_{i,t}$ in which 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 parenthesis. * p<0.10, ** p<0.05, *** p<0.01

free validation of our mechanism: stocks with higher implicit BMI exhibit larger $\hat{\beta}$ responses to flows. The results mirror our earlier BMI-based evidence and reinforce the interpretation that benchmark-driven flows increase CAPM $\hat{\beta}$s.

Figure 7 suggests that flows affected CAPM $\hat{\beta}$s through different channels over time, with active flows dominating before 2010 and passive flows afterward. We argue, however, 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 which were not recorded as passive.

BMI assumes active portfolios scale with benchmark weights (Pavlova & Sikorskaya, 2023), it thus provides a consistent proxy for benchmark-driven demand across periods. We interact flows with BMI to formally test this channel. We again split the sample into pre-2010 and post-2010 periods and estimate the panel regression:

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

Table 3 shows that before 2010, a positive and significant interaction between BMI and active flows drove variation in CAPM $\hat{\beta}$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 coefficient magnitudes are similarly instructive: 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 effect is not mechanical because we standardize both flows to mean zero and unit variance. Rather, it suggests that up to a third of active flows have been quasi-indexing before 2010, consistent with evidence from Cremers & Petajisto (2009). Column 6 shows the result remains robust to including a time trend and estimating across the full sample. Simulation evidence in Appendix C further corroborates this pattern: BMI–active flow interactions can explain the early in-sample distribution of $\hat{\beta}$s but fail from 2004 onward. One interpretation of these findings is that quasi-indexing among active managers declined as explicitly passive products became widely available. This interpretation is consistent with evidence from Cremers et al. (2016) who find that the expansion of low-cost passive products intensifies competition, lowers fees, and erodes the market share of high-fee quasi-indexers.

5.4 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. We use the perceived cost of capital and hurdle rate data from Gormsen & Huber (2025).

Managers frequently reference the CAPM when discussing their cost of equity and capital budgeting decisions. For example,[31]

> "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. [...] this is really how we view our weighted average 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, LKQ Corp. (Q1 2016)

or

> "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)

[31]See Appendix D.2 for more executive quotes referencing the CAPM in cost of equity discussions in earnings calls.

Empirical Strategy 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:

$$\text{CAPM } \hat{\beta}_{i,t+1} = \delta^{(1)}_{j,t} + \theta\, \Delta\, \text{BMI}_{i,t} + X'_{i,t}\xi^{(1)} + \varepsilon^{(1)}_{i,t} \tag{12}$$

$$\text{Perceived Cost of Capital}_{i,t+1} = \delta^{(2)}_{j,t} + \lambda^{(2)}\, \widehat{\text{CAPM } \beta_{i,t+1}} + X'_{i,t}\xi^{(2)} + \varepsilon^{(2)}_{i,t+1} \tag{13}$$

$$\text{Managers' Hurdle Rate}_{i,t+3} = \delta^{(3)}_{j,t} + \lambda^{(3)}\, \widehat{\text{CAPM } \beta_{i,t+1}} + X'_{i,t}\xi^{(3)} + \varepsilon^{(3)}_{i,t+3} \tag{14}$$

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 (2025) 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 4 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 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

Table 4: 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 $\times$ 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 Russel reconstitution. Perceived cost of capital is $t+1$ year 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.

of estimates is consistent with the interpretation that hurdle rates embed an additional buffer reflecting managerial risk aversion (Gormsen & Huber, 2025).

These findings provide a specific mechanism for how benchmarking through managers' perceptions of the cost of capital affect real economic activity. Recent work by Gormsen & Huber (2024) 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 (2025) 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.

5.4.1 Other Perceived Cost of Equity Measures

We corroborate our findings on the pass-through of benchmarking-induced changes in the CAPM $\hat{\beta}$ to perceived cost of equity using several alternative data sets. Specifically, we focus on two qualitative measures of perceived equity riskiness by stock analysts: (1) Morningstar's cost of equity, which reflects Morningstar's qualitative assessment of systematic risk, and (2) Value Line's safety rank, a subjective rating ranging from 1 (safest) to 5 (riskiest), capturing analysts' evaluations of price stability and firm financial strength. Following Eskildsen et al. (2024), we convert

Table 5: Benchmarking Intensity and Stock Analysts' Perceived Cost of Equity

	Δ Morningstar Cost of Equity (in p.p.)				Value Line Safety Rank × 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 regression in which 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.

Value Line's rank into a required return on equity by multiplying it by 1.5 p.p. Additionally, we examine whether benchmarking influences subjective return expectations derived from I/B/E/S consensus price targets and dividend forecasts. Appendix E provides further details.

We estimate whether exogenous increases in benchmarking intensity affect stock analysts' perceived cost of equity using specifications of the following form:

$$\Delta\text{ Perceived Cost of Equity}_{i,t} = \alpha_t + \lambda\, \widehat{\Delta\text{ CAPM }\beta}_{i,t} + X'_{i,t}\xi + \varepsilon_{i,t} \tag{15}$$

in which we instrument changes in CAPM $\hat{\beta}$ with changes in BMI due to the Russell index reconstitution between May and June within a narrow window around Russell index cutoffs. The vector $X_{i,t}$ contains our baseline controls: log market capitalization on the rank day in May and banding controls. We additional control for the log bid-ask spread, log Amihud illiquidity, and momentum. The year fixed effect α_t ensures that we identify λ from cross-sectional variation.

Table 5 shows that exogenous increases in a stock's BMI increase analysts' perceived risk and return expectations. The IV specifications of (15) imply perceived equity risk premia between 3.95% and 12.3% across the three datasets. Marketing material by Morningstar (2022, page 4f) indicates that their analysts use a perceived equity risk premium of 4.5%. Our point estimates are smaller but close to this number. Results in even columns confirm that the results continue to hold after accounting for liquidity and momentum.

While the perceived equity risk premium implied by I/B/E/S analyst forecasts is higher than our other estimates, its interpretation is ambiguous. The higher and imprecise estimate could reflect either a genuinely higher perceived risk of equities or, alternatively, be an artifact of BMI affecting analysts' growth expectations. Evidence from the literature supports the latter: analysts adjust their expectations in response to temporary index-inclusion price effects (Chaudhry, 2025) or in an attempt to reconcile a flat security market line (Jylha & Ungeheuer, 2021).

Additional Evidence from Regulated Monopolies Appendix E.2 provides further evidence that benchmarking affects the perceived cost of equity in regulatory rate-setting process of public utilities and railroads. Regulators in this context use the CAPM to determine an "authorized" cost of equity that monopolies then pass on to consumers (Kontz, 2025). For public utilities, a 10 p.p. increase in BMI translates to a 70 bps increase in the authorized cost of equity, implying a 6.1% perceived equity risk premium. Analysis of the railroad industry validates this result, as our IV-implied 6.4% premium is statistically indistinguishable from the 6.85% average premium regulators actually applied. The estimates are stable when including a powerful control for the DCF-implied risk premium. This stability mitigates concerns about unobserved confounders (Oster, 2017). Moreover, a falsification test showing a null effect of BMI on the authorized cost of debt supports the exclusion restriction. Together, these findings show that benchmarking-induced changes in CAPM $\hat{\beta}$s directly translate into a higher, government-sanctioned cost of equity.

6 Effects of Benchmarking on Investment at the Firm-level

Our second set of results explores how firms react to changes in their CAPM $\hat{\beta}$. For a manager who follows textbook guidance to set investment policies using the CAPM, an increase in $\hat{\beta}$ raises the user cost of capital and should lead to a decline in investment.

Our firm-level results show that managers react to BMI-induced changes in their CAPM $\hat{\beta}$ by reducing investment. We show this behavior in panel regressions, instrumental variable regressions around Russell benchmark reconstitutions, and in a difference-in-differences event study using additions to the S&P 500 benchmark index. The findings are robust to the inclusion of other known predictors of investment like cash flow, leverage, firm size, and Tobin's Q.

Table 6: 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)	
Leverage				0.024***	0.022***	0.022***	0.033***
				(0.006)	(0.006)	(0.006)	(0.007)
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 report estimates for panel regressions of the form: $\frac{CAPX_{i,t+1}}{PPE_{i,t}} = \alpha_{t,bin} + \alpha_i + \gamma\, BMI_{i,t} + X'_{i,t}\xi + \varepsilon_{i,t}$, 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 begin by documenting the reduced-form relationship between benchmarking intensity (BMI) and investment using panel regressions of the following form:

$$\frac{CAPX_{i,t+1}}{PPE_{i,t}} = \alpha_i + \alpha_{t,bin} + \gamma\, BMI_{i,t} + X'_{i,t}\xi + \varepsilon_{i,t+1}$$

for firm i in year $t+1$. The vector $X_{i,t}$ includes 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. The specification includes firm fixed effects, α_i, to absorb time-invariant firm heterogeneity. We include year-by-rank-bin fixed effects, $\alpha_{t,bin}$, to identify γ from variation among firms of similar size within the same year.

Table 6 shows that, across all specifications, the coefficient on BMI is negative and statistically significant. The economic magnitude is large. The estimate in Column (3) implies that a one standard deviation increase in BMI corresponds to a 2 p.p. decrease in the firm's investment rate, a 12.5% reduction relative to the sample mean. We progressively add controls and fixed effects to assess the robustness of this relationship. Column (1) includes firm fixed effects which absorb firm heterogeneity and a linear time trend. Column (2) exploits cross-sectional variation by using year-by-rank-bin fixed effects, ensuring comparisons among similarly sized firms within the same year. Column (3) introduces both firm and year fixed effects, absorbing both unobserved firm heterogeneity and macroeconomic shocks. Across these models, the BMI coefficient ranges between −0.22 and −0.30.

The inclusion of the Tobin's q proxy in Column (4) through (6) attenuates the BMI coefficient by approximately 50%, though it remains statistically significant at the 1% level. When we exclude Tobin's q in Column (7), the BMI coefficient reverts to a magnitude comparable to that in Column (3). This attenuation indicates a negative correlation between BMI and Tobin's q, such that Tobin's q is lower for firms with high benchmarking intensity. In other words, firms with high BMI tend to have lower Tobin's q values, consistent with a higher perceived cost of capital. In theory, marginal q is the present value of future marginal profits, discounted at the market's required rate of return. If benchmarking increases the firm's priced systematic risk, the market's discount rate rises, and marginal q falls.[32]

Our empirical finding that BMI remains a significant predictor of investment even after controlling for Tobin's q suggests two non-exclusive interpretations. First, our proxy for the unobservable marginal q is imperfect. The residual significance of BMI could capture the portion of its effect on the true marginal q that our proxy fails to measure. However, Appendix Table A6 shows that BMI remains an economically and statistically significant predictor of firm investment after adjusting for measurement error in Tobin's q (Erickson & Whited, 2012). Second, the residual effect may reflect a divergence between the discount rate used by managers for capital budgeting and the discount rate priced by investors into Tobin's q. For example, if managers perceive a steeper security market line than what markets price, their subjective discount rate for new projects is higher. This perception leads them to invest less than the level prescribed by Tobin's q. In this case, BMI captures the incremental effect of managerial risk perception on investment, beyond the channel priced into the firm's q.

To distinguish the effect of benchmarking from the influence of general institutional ownership, Columns (4) to (7) include the institutional ownership ratio (IOR) as a control. The coefficient

[32]Heuristically, marginal q is given by $q_0 = E_0 \int_0^\infty e^{-\int_0^t (r_s+\beta_s\lambda_s)ds} \left[\Pi_{K,t} - \Phi_{K,t}\right] dt$ where BMI amplifies β.

on IOR is not statistically different from zero, while the coefficient on BMI remains negative and significant. This result indicates that the estimated effect is specific to benchmarking activity, not a proxy for institutional ownership levels.

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

$$\log\left(Inv_{i,t+h}\right) - \log\left(Inv_{i,t-1}\right) = \alpha_{t,j}^{h} + \gamma^{h}\left(\text{BMI}_{i,t} - \text{BMI}_{i,t-1}\right) + X_{i,t}'\xi^{h} + \varepsilon_{i,t+h} \tag{16}$$

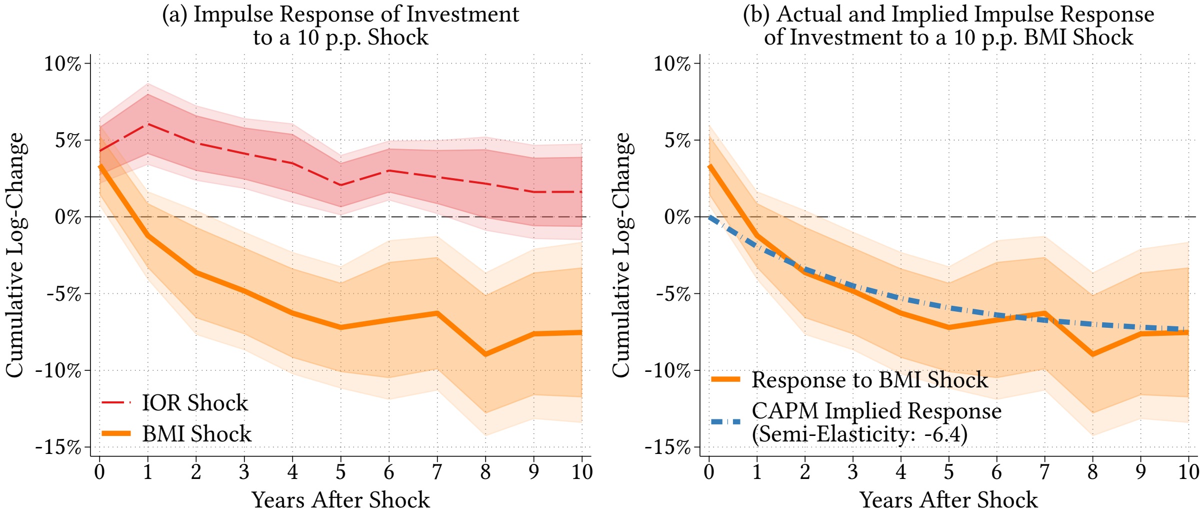
where $Inv_{i,t}$ is the investment rate and $(\text{BMI}_{i,t} - \text{BMI}_{i,t-1})$ is the year-on-year change in BMI for firm i in industry j in year t. We include industry-by-year fixed effects $\alpha_{j,t}$ to control for time-varying unobserved heterogeneity across industries, such as industry-level 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 interests, γ^h, provide cumulative effects in % after $h = 0, 1, \ldots, 10$ 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 benchmarking intensity.

Panel (a) of Figure 8 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 6).

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

Figure 8: 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: $\log(Inv_{i,t+h}) - \log(Inv_{i,t-1}) = \alpha^h_{t,j} + \gamma^h(\text{BMI}_{i,t} - \text{BMI}_{i,t-1}) + X'_{i,t}\xi^h + \varepsilon_{i,t+h}$, 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.

Graham (2022) and Gormsen & Huber (2025).

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 2 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

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

The response of the investment 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 (2025) 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.[33]

Panel (b) of Figure 8 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). Since the IOR does not affect CAPM $\hat{\beta}$s (see Table A2), it should not influence investment through a perceived cost of equity channel. To test this, we replace the year-on-year increase in BMI in equation (16) with a year-on-year increase in IOR and re-estimate the local projections.

Panel (a) of Figure 8 shows the estimated investment response to a 10 p.p. increase in IOR (red dashed line). The results indicate a positive investment response: at impact, the investment rate rises by approximately 5% and remains elevated before gradually converging towards zero over the subsequent 10 years. This pattern supports the interpretation that the negative investment response documented earlier is specific to benchmarking activity and not driven by institutional ownership more broadly. The placebo test also provides ancillary evidence that the negative effect of BMI on investment is not driven by omitted variables related to increased institutional ownership (e.g., changes in corporate governance).

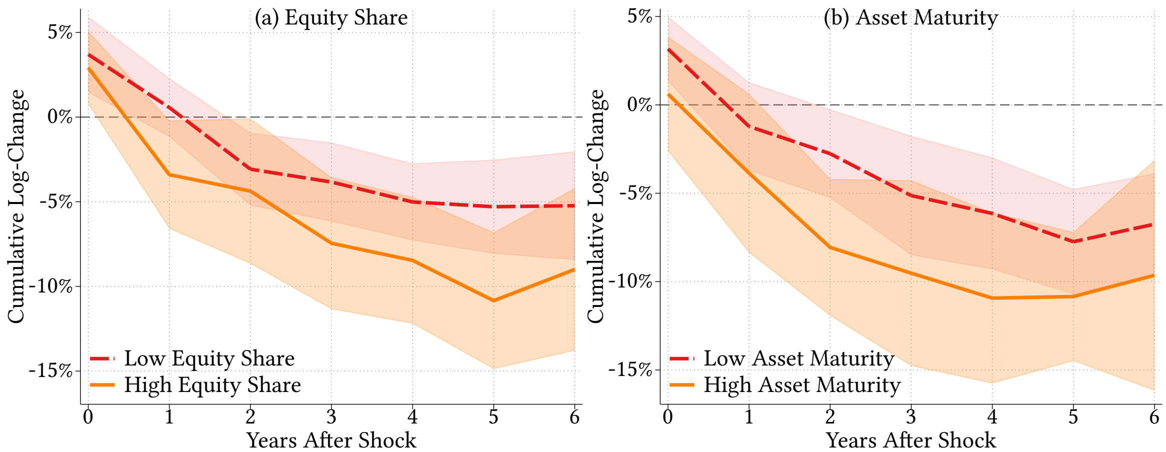
Cross-sectional Heterogeneity in Firms' Investment Response We next test a key implication of our mechanism: if benchmarking intensity shocks affect investment through the perceived cost of equity, their impact should be larger for firms more reliant on equity financing. We estimate the cumulative impulse responses using Eq. (16) but add interaction terms to compare firms in the top vs. bottom terciles of equity share of capital. We additionally test whether firms with high asset maturity (i.e., long duration capital) are more sensitive to changes in BMI. We measure the asset maturity as the inverse of the firm's capital depreciation rate (Hubert De Fraisse, 2024).[34] A stronger investment response among firms with these characteristics provides evidence for the perceived cost of equity channel.

Figure 9 shows that the investment response to a positive benchmarking intensity shock is significantly more negative for firms that rely more on equity financing or firms with high

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

[34] In a neo-classical investment 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 (see, e.g., House, 2014).

Figure 9: 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 $\gamma_1^h+\gamma_2^h$ (High) from local projection panel regressions of the form: $\log(Inv_{i,t+h})-\log(Inv_{i,t-1}) = \alpha_{t,j}^h+\gamma_1^h(\text{BMI}_{i,t}-\text{BMI}_{i,t-1})+\gamma_2^h\mathbb{1}\{\text{High}\}_{i,t}\times(\text{BMI}_{i,t}-\text{BMI}_{i,t-1})+\mathbb{1}\{\text{High}\}_{i,t}+X_{i,t}'\xi^h+\varepsilon_{i,t+h}$, where $\mathbb{1}\{\text{High}\}_{i,t}$ 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%) based on double-clustered standard errors.

asset maturity. While firms less reliant on equity or lower asset maturity also experience an investment decline, the magnitude of this response is consistently smaller. These cross-sectional findings support our hypothesis: results are stronger for firms which use more equity financing and have longer-lived assets, both of which heighten sensitivity to changes in the cost of equity.

Summary Overall, 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 increased perceived cost of equity. This suggests that managers adjust their investment decisions in response to changes in their CAPM $\hat{\beta}$ induced by benchmarking. However, we note that these results are correlational, as the level of BMI or year-on-year changes in BMI may be endogenous and correlated with omitted variables. We therefore next turn to natural experiments which provide plausibly exogenous variation in BMI and allow us to identify the effects of benchmarking on firm investment more cleanly.

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.[35]

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

$$\Delta\text{CAPM } \hat{\beta}_{i,t} = \delta_{j,t} + \theta \Delta \text{BMI}_{i,t} + \psi \log\left(\text{Market Cap.}\right)_{i,t} + \text{Banding Vars.}_{i,t} + \zeta X_{i,t} + \epsilon_{i,t} \tag{17}$$

$$\log\left(Y_{i,t+h}\right) - \log\left(Y_{i,t-1}\right) = \alpha^h_{j,t} + \gamma^h \widehat{\Delta\text{CAPM } \beta}_{i,t} + \phi^h \log\left(\text{Market Cap.}\right)_{i,t} + \text{Banding Vars.}_{i,t} + \xi^h X_{i,t} + \varepsilon_{i,t+h} \tag{18}$$

where $Y_{i,t}$ is the outcome variable of interest (e.g., capital expenditures) and $\Delta\text{BMI}_{i,t}$ is the change in BMI between May and June (due to Russell reconstitution) for firm i in calendar year t. The coefficients of interests, 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 $\alpha_{j,t}$ and $\delta_{j,t}$ to control for time-varying unobserved heterogeneity across industries.

Identifying Assumptions and Threats to Identification The instrumental variable exclusion restriction in a local projection setting differs from the usual one due to the dynamic structure of the problem. Identification requires a contemporaneous and a lead-lag exclusion restriction. The instrument must not correlate with past and future shocks, at least after including control variables. In our case, the exclusion restriction requires that changes in BMI only affect firm outcomes 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, total 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 databases 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). Second, we saturate our LP-IV estimator with industry-by-year fixed effects to remove as much time-varying unobserved heterogeneity as possible. Third, we include a set of known predictors of capital accumulation: Tobin's q and cash flow. We additionally control for the cumulative 12-month return (momentum), log bid-ask spreads, and log Amihud Illiquidity in $X_{i,t}$.

[35] Similarly, researchers often use LP-IVs to study the effects of monetary policy on investment or asset prices (e.g., in Jordà et al., 2020, Kroen et al., 2021, and Bauer & Swanson, 2023).

Table 7: 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

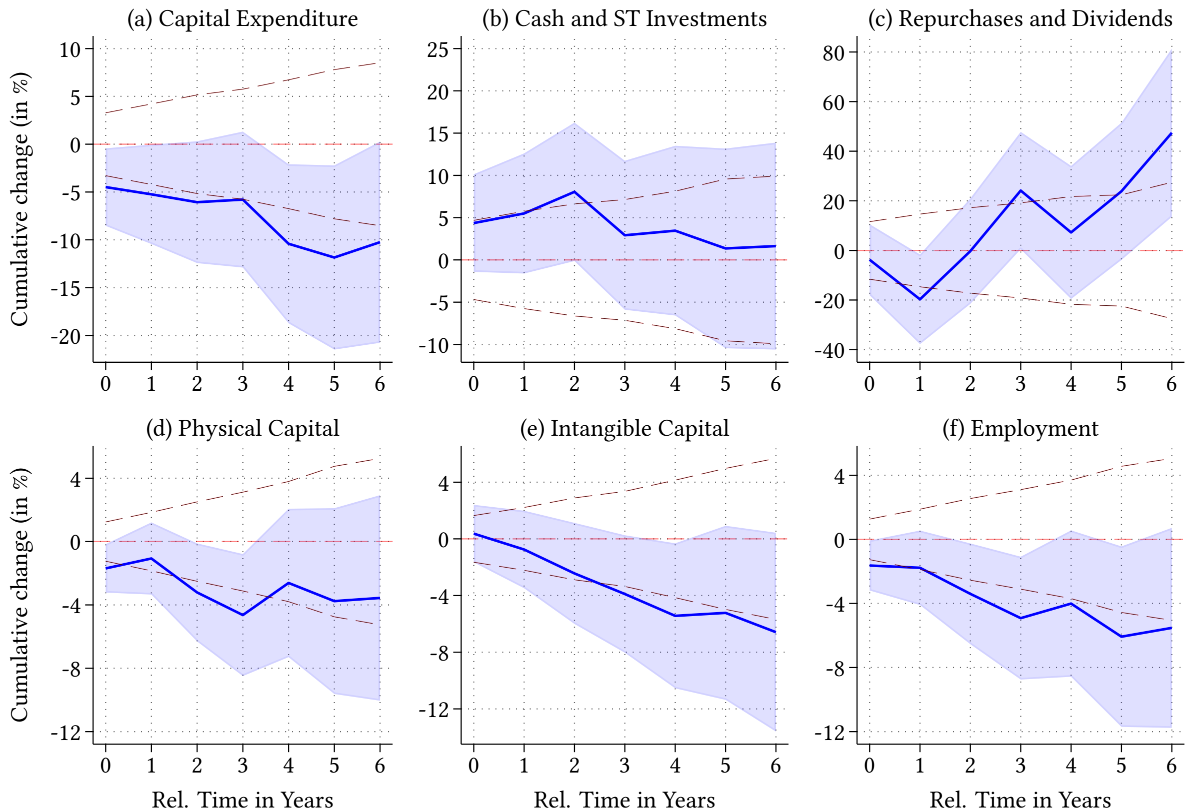
Notes: This table reports estimates for regressions of the form: $100 \times (\log(Inv_{i,t+h}) - \log(Inv_{i,t-1})) = \alpha_t^h + \gamma^h \Delta\, \text{BMI}_{i,t} + \rho^h \log(\text{Market Cap.})_{i,t} + \psi^h \log(\text{Bid-Ask-Spread})_{i,t} + \phi^h \text{Banding Variables}_{i,t} + \varepsilon_{i,t+h}$, 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 $\text{Net Payout Ratio}_{t+h} = \frac{\text{Dividends}_{i,t+h} + \text{Net Stock Repurchases}_{i,t+h}}{\text{Total Asset}_{i,t+h-1}}$ in Panel B. Market capitalization in May using Ben-David et al. (2019) methodology. 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.

However, concerns may arise that other factors, such as risk exposure, access to debt markets, or governance, could change alongside CAPM $\hat{\beta}$s when BMI changes, potentially violating the exclusion restriction. In Appendix F, we test whether changes in BMI correlate with changes in firm risk, financial frictions, or governance, but find no evidence that they do. Importantly, Column (1) of Appendix Table F21 shows that changes in BMI do not correlate with firm statements about delaying investments.

Reduced Form Results We start by presenting reduced-form evidence on the effect of exogenous changes in BMI on firm investment rate and net payout ratio.

Table 7 presents reduced-form results on the effect of exogenous changes in BMI due to Russell reconstitution on firm investment and net payouts. Panel A shows that Firms which

Figure 10: LP-IV: Impulse Response of Outcome to 100 bps CAPM-implied WACC shock



Notes: This figure shows local projection coefficients estimates for $100\times$ cumulative log-changes of outcome variables from regression of the form $\log(Y_{i,t+h}) - \log(Y_{i,t-1}) = \alpha^h_{j,t} + \gamma^h \widehat{\Delta\text{CAPM}\ \beta}_{i,t} + \phi^h \log(\text{Market Cap.})_{i,t} + \text{Banding Vars.}_{i,t} + \xi^h X_{i,t} + \varepsilon_{i,t+h}$, where the shock is scaled to a 0.25 increase in CAPM $\hat{\beta}$, which translate into a 100 bps rise in the CAPM-implied WACC ($0.25 \times 6\% \times \frac{2}{3}$) estimated with change in BMI as an instrumental variable. We restrict the estimation sample to stocks within 300 ranks around Russell index cutoffs. Dashed red lines represent 90% significance bands for the null of zero treatment effect, computed by inverting the F-statistic of joint significance around zero using Scheffé's method (see Jordà, 2023).

see an exogenous BMI increase of 10 p.p. have a 7.23% lower investment rate after 6 years. The effect strengthens over time: it is negligible during the first two years but becomes increasingly negative from year $t+2$ onward, with investment rates declining steadily in response to the BMI shock. Panel B of shows that firms respond to the BMI-induced increase in their perceived cost of equity by increasing net payouts (dividends plus net stock repurchases). Appendix Table A8 shows robustness of the results to different window widths around the Russell 1000/2000 cutoffs.

Second Stage Results Next, we present second stage results where we estimate the effects of BMI-induced changes in CAPM $\hat{\beta}$s on firm outcomes like 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 $= 0.25 \times 6\% \times 2/3$).

Figure 10 shows several key results. First, the impulse responses across all outcome variables have the expected signs: capital expenditure and physical and intangible capital stocks decrease in response to the perceived cost of equity. Cash holdings increase, suggesting that firms self-insure against the increased exposure of benchmark-linked capital flows. Eventually, firms increase dividends and stock repurchases.[36] Employment also decreases, suggesting that firms reduce labor input in response to an increase in their perceived cost of equity.[37]

Second, firms respond gradually to an increase in CAPM $\hat{\beta}$, 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 gradual adjustment likely reflects the gradual pass-through from managers' perceived cost of capital to hurdle rates documented by Gormsen & Huber (2024).

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

6.4 Natural Experiment 2: S&P 500 Benchmark Inclusion

We exploit additions to the S&P 500 as a natural experiment to provide additional evidence that changes in BMI affect capital accumulation. We analyze 325 benchmark inclusions between 2000 and 2018 using a difference-in-differences event-study design. We focus exclusively on additions, as most deletions stem from mergers or acquisitions, making it difficult to measure post-event real outcomes for the affected firms.[38]

Unlike the mechanical annual reconstitution of the Russell indices, S&P 500 additions are discretionary. A selection committee determines inclusion based on a set of criteria, e.g, market capitalization, liquidity, sector classification, profitability, and listing history. This discretion

[36]This pattern provides indirect evidence that treated firms are not financially constrained. In a broad class of macro-finance models, financially constrained firms do not distribute cash to shareholders (see, e.g., Albuquerque & Hopenhayn 2004, Khan & Thomas 2013, and Begenau & Salomao 2019).

[37]Borovička & Borovičková (2018) argue that fluctuations in discount rates and labor market frictions play an important role for employment. For empirical evidence that financing frictions affect employment see, e.g., Hombert & Matray (2017), Bai et al. (2018), Berton et al. (2018), Caggese et al. (2019), Benmelech et al. (2019), Fonseca & Van Doornik (2022), Baghai et al. (2021), Benmelech et al. (2021), Fonseca & Matray (2024).

[38]Our list of inclusions dates is drawn from Chinco & Sammon (2024).

introduces concerns about endogeneity. The committee may select firms based on unobserved characteristics that also affect investment, such as growth opportunities or managerial quality. Aghaee (2024) decomposes the price effect of S&P 500 inclusion into information signaling and demand-driven price pressure. The author documents that while positive information effects dominated the pre-2000 period, price pressure from passive funds primarily drives the index effect post-2000, with negligible informational effects. Since our sample begins in 2000, we interpret this evidence as supporting the exogenous nature of S&P 500 additions in our setting.

At the same time, S&P 500 inclusion represents a persistent shock: in our sample, additions remain in the index for an average of 9.5 years. We can therefore use a difference-in-differences design, comparing the investment response of 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 investment, rather than unobserved *level* differences.

Benchmarking intensity rises sharply upon S&P 500 inclusion, reflecting its widespread use as a reference index. On average, stocks experience an 8.6 p.p. increase in BMI in the month of addition, relative to a baseline level of 14.1%.

To estimate the effect on CAPM $\hat{\beta}$s, we use a similar difference-in-differences event study as in Eq. (8), controlling for log market cap, Amihud illiquidity, bid-ask spreads, momentum, and industry-by-month fixed effects. The key identifying assumption is that, absent S&P 500 inclusion, added firms' $\hat{\beta}$s would have evolved similarly to non-included firms within the same industry and year. We again caution that our estimates are reduced form rather than structural.

Panel (a) of Figure 11 shows that S&P 500 inclusion leads to a sharp increase in CAPM $\hat{\beta}$s. The 21-day $\hat{\beta}$ rises by approximately 0.14 immediately after addition, implying a change of 0.016 per p.p. increase in BMI. The 252-day $\hat{\beta}$ increases gradually, reaching 0.10 after nine months. Given that included firms are, on average, 80% equity-financed, these $\hat{\beta}$ increases imply a rise in the user cost of capital of 50–70 bps, assuming a 6% equity risk premium.[39]

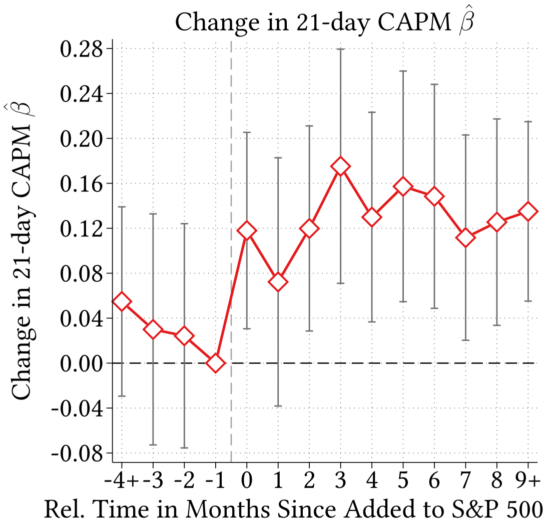
We next examine real effects of S&P 500 inclusion. Using the same event-study setup but switching to annual frequency, we estimate the impact on firms' investment rates and net payout ratios. We control for Tobin's q, cash flow, momentum, and absorb industry-by-year fixed effects to isolate within-industry variation in investment and payouts.

Panel (b) of Figure 11 shows that inclusion leads to a gradual but significant decline in investment, alongside a sharp and sustained increase in net payouts. Investment rates bottom out

[39] We find no significant effect on the Implied Cost of Capital following S&P 500 inclusion, consistent with Patel & Welch (2017) and Greenwood & Sammon (2024) documenting a disappearance of S&P 500 inclusion price effects.

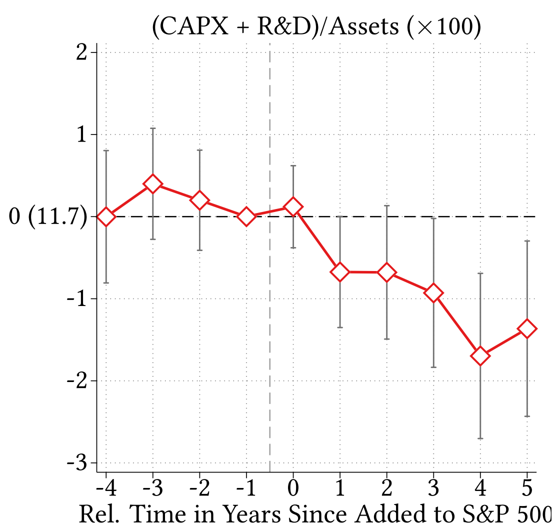
Figure 11: Difference-in-differences Event Study of S&P 500 Benchmark Inclusion

(a) Effects of S&P 500 Benchmark Inclusion on CAPM $\hat{\beta}$ (avg. Δ BMI ≈ 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 identified from within-industry-month variation. Controls include log market cap, log Amihud illiquidity, log bid-ask spread, and momentum. Pointwise confidence intervals (95%) based on double-clustered standard errors.

(b) 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 identified from within-industry-year variation. Controls include log market cap, Tobin's q, cash flow, and momentum. Pointwise confidence intervals (95%) based on double-clustered standard errors.

four years post-inclusion, consistent with managerial discount rates updating slowly in response to higher perceived cost of equity. Payouts, by contrast, 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. These results are consistent with 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.

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 and interpretation. We argue that the decline reflects a higher perceived cost of equity arising from increased benchmarking. Managers perceive to be acting in their shareholders' interests, reduce investment and increase payouts. Bennett et al. (2023) emphasize peer effects and categorical thinking, arguing that managers' incentives shift because compensation peer groups expand to include more S&P 500 firms, and boards begin to evaluate management relative to index peers. We note that these explanations are not mutually exclusive but leave disentangling them to future work.

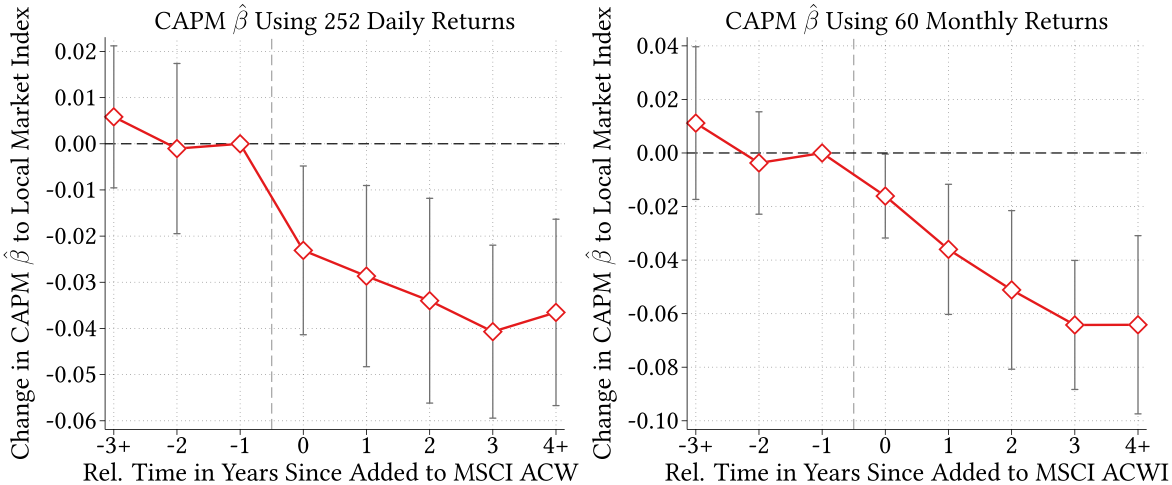
6.5 Natural Experiment 3: MSCI ACWI Benchmark Inclusion

Prior research finds that, in an international setting, a firm's inclusion in the MSCI All Country World Index (ACWI) is associated with a modest increase in firm investment. The proposed mechanisms through which inclusion in the ACWI affects investment are that increased foreign ownership disciplines entrenched managers (Bena et al., 2017) and enhances price efficiency (Kacperczyk et al., 2021).

We offer a complementary mechanism based on a reduction in the perceived cost of equity. We find that inclusion in the MSCI ACWI persistently decreases a stock's CAPM $\hat{\beta}$ to its local market index. Because ACWI flows increase covariance with global factors, and the local index is not perfectly correlated with those factors, the stock's covariance with the domestic index mechanically falls. This covariance reallocation explains the observed drop in local $\hat{\beta}$. A smaller $\hat{\beta}$ lowers managers' perceived cost of capital and can explain a modest increase in investment after inclusion. This interpretation assumes that managers use local market $\hat{\beta}$s to estimate their cost of equity. This assumption is consistent with evidence from stock analysts using indices from a firm's home country rather than international benchmarks (Décaire & Graham, 2024).

Figure 12 plots difference-in-differences event study coefficients of CAPM $\hat{\beta}$s, measured relative to local market indices. After ACWI inclusion, firms' local market $\hat{\beta}$ declines persistently with effects appearing in the year of inclusion and deepening over three years. Taken together,

Figure 12: Difference-in-difference Event Study of MSCI ACWI Inclusion on CAPM $\hat{\beta}$



Notes: This figure shows dynamic treatment effects of MSCI ACWI benchmark inclusion on CAPM $\hat{\beta}$s to the local market index. Sample from 1999 to 2018, covering 23 developed and 24 emerging markets. The left panel uses a 252-day rolling β; the right panel uses a 60-month rolling β estimator. Specifications include year-by-industry-by-country fixed effects and log market capitalization, bid-ask spread, momentum, and log trading volume. Data from Jensen et al. (2023). Pointwise confidence intervals (95%) based on double-clustered standard errors.

the results that $\hat{\beta}$ to the local index decreases and investment increases following addition to the ACWI are consistent with our perceived cost of equity channel. We thus view the positive effects of ACWI inclusion on investment as providing external validity to our findings in the U.S..

6.6 Alternative Mechanisms

We interpret our empirical findings as evidence that rising levels of benchmarking reduce corporate investment by increasing managers' perceived cost of equity. In this subsection, we examine three plausible alternative mechanisms that could explain our results: (i) firm-level risk exposure, (ii) corporate governance, and (iii) the private information content of stock prices.

Risk Exposure First, we investigate whether firm-level risk exposures can account for the documented investment effects of benchmarking intensity. Table A9 in the Appendix presents results from tests for differential effects of BMI for firms with high risk exposure. We proxy for high risk exposure by identifying firms in the top tercile of the annual distribution of one of the following measures: firm-level risk and sentiment of Hassan et al. (2019) and firm-level exposure to economic policy uncertainty, oil price uncertainty, euro-dollar exchange rate uncertainty, and yen-dollar exchange rate uncertainty of Alfaro et al. (2024). The interaction between these risk exposure proxies and BMI is statistically insignificant, suggesting that these firm-level risks do not mediate the effect of BMI on investment.

These findings are consistent with additional evidence on other risk measures. As shown in Appendix Figure A7, neither accounting-based βs (Cohen et al., 2009) nor consumption growth βs (Kim et al., 2024) exhibit significant changes in response to the changes in benchmarking intensity over the past 25 years. Furthermore, in Appendix F, we test whether changes in BMI around Russell index reconstitution are correlated with changes in the firm risk measures or the CAPM $\hat{\beta}$ of peer firms. We find no evidence of such a correlation.

Corporate Governance Next, we consider the role of corporate governance, focusing on the implications of common ownership. Theories of common ownership (e.g., Rotemberg, 1984, Azar, 2012) predict outcomes consistent with our findings: a decrease in investment and an increase in payouts (Gutiérrez & Philippon, 2017).[40] Alternative theories regarding the impact of benchmark-linked investing 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 Appendix F, 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 A10 presents results from investment rate regressions where we interact BMI with proxies for high common ownership and low competition. 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. The common ownership measures themselves have mixed and statistically insignificant effects on investment. We also test for differential effects in industries with high mark-ups, estimated using the production function approach of De Ridder et al. (2025), or high price-cost margins, and again find no significant difference. Therefore, common ownership does not appear to be a primary channel through which benchmarking intensity affects firm investment.

Private Information Finally, we test whether a reduction in the private information content of stock prices can explain our findings. If managers learn from stock prices (Dow & Gorton, 1997, Durnev et al., 2004) and prices of highly benchmarked stocks incorporate less private information (Chen et al., 2007, Bakke & Whited, 2010), managers may reduce investment due to increased uncertainty about project values. Consistent with this premise, Appendix Figure A10 shows that an exogenous increase in BMI leads to a higher CAPM R^2, and that BMI explains a large share of the cross-sectional variation in R^2. This suggests that less firm-specific private information

[40] See also Azar et al. (2018), Azar & Vives (2021), Koch et al. (2021), Antón et al. (2023, 2025).

is incorporated into the prices of highly benchmarked stocks. This finding is consistent with Sammon (2024), who shows that the rise in passive ownership has reduced the extent to which stock prices anticipate future earnings.

To test this channel, we examine whether the investment response to BMI varies with the degree of private information in a firm's stock price. We use two proxies for private information: price non-synchronicity (Chen et al., 2007) and the bid-ask spread, which captures market makers' compensation for adverse selection risk (Glosten & Milgrom, 1985). The results, presented in Appendix Table A11, show that while firms with more private information in their stock price (lower 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 In summary, our tests of alternative mechanisms do not support channels related to firm-level risk exposure or corporate governance. Our finding on governance is consistent with Koch et al. (2021), who document that "common ownership is not associated with significant reductions in net capacity investment, even in concentrated industries" (see also Lewellen & Lowry, 2021). Instead, our results indicate that benchmark-linked investing operates through a distinct channel: It affects investment directly by increasing managers' perceived cost of equity and may have an indirect effect by reducing the amount of private information in stock prices.

7 Effects of Benchmarking on Investment at the Industry-level

We complement our firm-level findings with evidence 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 the inclusion of industry pre-trends and sectoral fixed effects. Increases in CAPM $\hat{\beta}$ and BMI are strongly associated with lower capital accumulation, while changes in institutional ownership ratio have small, positive, and insignificant effects. This supports our interpretation that benchmarking-driven changes in the cost of equity reduce capital accumulation, rather than increases in institutional ownership per se. Furthermore, we show that benchmarking-induced dispersion in CAPM $\hat{\beta}$s increasingly explains within-industry dispersion in marginal products of capital. This indicates that benchmarking reduces allocative efficiency by creating non-fundamental dispersion in firms' perceived cost of equity (Gormsen & Huber, 2024).

Data We use the NBER CES Manufacturing Industry database to study the long-term effects of higher CAPM $\hat{\beta}$s on industry-wide capital accumulation. The analysis is at the NAICS-5 digit level. Because the CES data on real capital stocks end in 2016, we focus on 1998–2016.

Table 8: 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)
Real Capital Stock/Value-Added		-0.155***		-0.195***	-0.203***
(1998)		(0.049)		(0.058)	(0.057)
log (Employment)		-0.00165		0.0349	0.0537
(1998)		(0.033)		(0.043)	(0.036)
log (TFP)		0.321*		-0.110	-0.152
(1998)		(0.188)		(0.264)	(0.244)
Pre-trend Capital					-0.309***
(1980-1996)					(0.106)
Pre-trend Employment					0.256**
(1980-1996)					(0.107)
Pre-trend Wage					0.557
(1980-1996)					(0.426)
Constant	0.243***	0.420**			
	(0.074)	(0.183)			
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: $\Delta \log(\text{Real Capital Stock})_i = \alpha_j + \gamma \Delta \text{CAPM } \hat{\beta}_i + X_i' \xi + \varepsilon_i$ in which 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 at industry level of Compustat firms. We exclude industries with less 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% level to remove outliers. Robust standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

Specifications We estimate IV long-difference regressions for 1998–2016 of the form:

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

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

in which α_j are NAICS 3-digit subsector fixed effects. The control vector X_i includes 1998 industry characteristics, such as log employment and TFP, to account for initial differences affecting capital accumulation. We define the change in CAPM $\hat{\beta}$ for industry i as the difference between the weighted average CAPM $\hat{\beta}$ of firms in 2016 and 1998. We construct the industry's change in

BMI analogously, exclude industries with fewer than five firms, and weight observations by 1998 value-added shares to emphasize economically important sectors.[41]

A potential concern is that other secular changes or pre-existing growth paths may confound the effects of benchmarking on capital accumulation. We address this concern by controlling for pre-trends in capital accumulation, employment, and wages from 1980 to 1996. We also include NAICS 3-digit sub-sector fixed effects such that coefficients are identified from variation across industries within the same sub-sector.[42]

Results Table 8 reports coefficient estimates. Several things are worth noting. First, across all specifications, we find that increases in CAPM $\hat{\beta}$s have a statistically significant negative effect on long-term capital accumulation at the industry-level. Second, the size of the coefficients is economically meaningful. Column (5) implies that a 0.3 increase in average CAPM $\hat{\beta}$ results in a 9.9% ($\approx 0.3 \times 0.33 \times 100\%$) lower capital stock from 1998 to 2016, or about 0.53% lower annually. Third, the results are robust to the inclusion of industry-level controls and sub-sector fixed effects. Fourth, changes in BMI are strong instruments for changes in CAPM $\hat{\beta}$ even at the industry-level, with first-stage F-stats averaging 15.8 across columns.

A potential concern is that the secular rise in institutional ownership since the 1990s, rather than changes in $\hat{\beta}$ due to benchmarking, drives our results. Increased institutional ownership, e.g., by large activist or common ownership, could reduce investment through monitoring and governance changes. Appendix Table A12 reports OLS and reduced-form estimates of the effects of changes in CAPM $\hat{\beta}$, BMI, and the institutional ownership ratio (IOR) on capital accumulation. Increases in CAPM $\hat{\beta}$ and BMI are associated with lower capital accumulation, while changes in IOR have a small, positive, and statistically insignificant coefficient — the opposite sign to the prediction that rising institutional ownership reduces investment. These findings support the interpretation that benchmarking-driven changes in the perceived cost of equity, not secular changes in institutional ownership, drive our results.

To test the robustness of our industry findings, we replicate the analysis using data from the Bureau of Economic Analysis (BEA) Fixed Asset Table 3.1. This dataset offers broader sectoral coverage than the NBER-CES Manufacturing data by including all economic sectors at the 3-digit NAICS level. We trade off broader coverage for reduced granularity: the BEA covers 38 industries at the 3-digit level, compared to 103 industries at the 5-digit level in the NBER-CES data.

Table 9 presents results confirming the negative relationship between changes in benchmark-

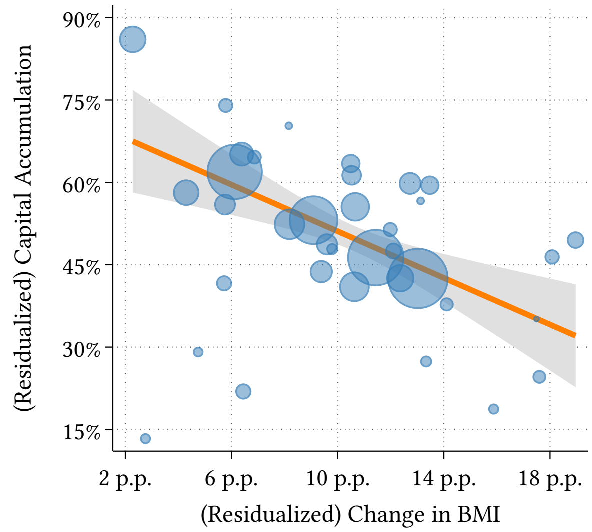
[41]We find similar results when using investment-shares as weights.
[42]For example, the NAICS sub-sector 311 “Food Manufacturing” contains 12 5-digit industries.

Table 9: BEA Capital Accumulation vs. Change in BMI

	(1)	(2)	(3)	(4)
	Dep. var.: Capital Accumulation (1998-2018)			
Change in BMI (1998-2018)	-1.683** (0.703)	-2.010*** (0.624)	-1.960** (0.757)	-1.660** (0.787)
Capital/Value-Added (1998)			-0.008 (0.007)	-0.004 (0.007)
Log(Value-Added) (1998)			0.006 (0.031)	0.023 (0.034)
Log(Labor) (1998)			0.048 (0.049)	0.028 (0.046)
Pre-trend Capital (1980-1996)				0.115 (0.087)
NAICS-2 Fixed Effect		✓	✓	✓
Weights		VA_{1998}	VA_{1998}	VA_{1998}
Adj. R^2	0.10	0.70	0.70	0.71
Observations	38	38	38	38

Notes: This table shows estimates of regression of the form $\log\left(\text{Real Capital}_i^{`18}/\text{Real Capital}_i^{`98}\right) = \alpha_j + \gamma \Delta_{98}^{18}\,\text{BMI}_i + X_i'\zeta + \varepsilon_i$ for industry i in sector j from 1998 to 2018 using the BEA Fixed Asset Table. We weight each industry by its value-added share in 1998. Robust standard errors in parentheses.

Figure 13: Capital Accumulation vs. Change in BMI



Notes: This figure plots residualized capital accumulation versus residualized changes in benchmarking intensity for 3-digit NAICS industries in long-differences from 1998 to 2018 using the BEA Fixed Asset Table. The specification is the same as in Column (3) of Table 9. Pointwise confidence interval (95%) based on robust standard errors.

ing intensity and capital accumulation from 1998 to 2018. The point estimate in Column (4) implies that a 10 p.p. increase in BMI, equal to a two standard deviation change, corresponds to a 16% lower in capital accumulation over the sample period, or about 0.9% lower annually. The regression specifications weigh each industry by its 1998 value-added share, include controls for capital accumulation pre-trends and baseline differences in employment and value-added, and absorb NAICS 2-digit sector fixed effects.

7.1 Misallocation due to Benchmarking

Appendix G examines whether benchmarking-induced changes in perceived equity costs create within-industry capital misallocation. We find that benchmarking is a growing source of within-industry dispersion in firms' CAPM $\hat{\beta}$: the share of within-industry $\hat{\beta}$ variation explained by benchmarking intensity rose from under 3% before 2000 to over 10% by 2018. We test whether this excess dispersion in $\hat{\beta}$ translates into greater dispersion of marginal revenue products of capital (MRPK). Our results show that benchmarking-induced $\hat{\beta}$ dispersion raises within-industry MRPK dispersion, suggesting that benchmarking impedes efficient marginal product equalization and contributes to rising productivity dispersion (Cunningham et al., 2023).

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. We argue that CAPM-implied increases in the perceived cost of equity do not cancel out in aggregate. An aggregate effect 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' capital expenditure weights mirror their market capitalization weights. Second, it assumes that all firms respond identically to cost of capital shocks.

The data reject both assumptions, creating a channel for aggregate effects. First, market capitalization weights and investment share weights 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, smaller firms' investment is more sensitive to financing costs than that of larger firms.[43] Benchmarking creates a net 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 suggest that the rise in benchmarking can reduce aggregate investment by approximately 1.28%, annually. We test the robustness of this result in a calibrated heterogeneous-firm general equilibrium model with capital adjustment costs (Winberry, 2021) where aggregate prices can adjust in response to the β shock. When we introduce a cross-sectional cost of equity shock consistent with our empirical findings, aggregate investment falls by around 1.8%.

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 both the Jorgensonian and q-theory versions of the neoclassical investment model, the 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

[43] See, e.g., Gertler & Gilchrist (1994), Chaney et al. (2012), Zwick & Mahon (2017), Begenau & Salomao (2019), Crouzet & Mehrotra (2020), Cloyne et al. (2023), Best et al. (2024).

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 investment with 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

$$\frac{\Delta I_t}{I_{t-1}} \approx q_t\lambda_t \sum_i \pi_{i,t-1}\, \epsilon^C_{i,t}\, \mu_{i,t}\, \Delta\beta_{i,t} \tag{19}$$

Equation (19) shows that aggregate investment responses to changes in CAPM βs depend 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.[44]

A covariance decomposition of (19) provides further economic insights,

$$\begin{aligned} \frac{\Delta I_t}{I_{t-1}} \approx q_t\lambda_t \Bigg[& \mathbb{E}_\pi[\epsilon^C_{i,t}]\; \mathbb{E}_\pi[\mu_{i,t}]\; \mathbb{E}_\pi[\Delta\beta_{i,t}] + \text{Cov}_\pi(\epsilon^C_{i,t}, \Delta\beta_{i,t})\; \mathbb{E}_\pi[\mu_{i,t}] \\ & + \text{Cov}_\pi(\mu_{i,t}, \Delta\beta_{i,t})\; \mathbb{E}_\pi[\epsilon^C_{i,t}] + \text{Cov}_\pi(\epsilon^C_{i,t}, \mu_{i,t})\; \mathbb{E}_\pi[\Delta\beta_{i,t}] \Bigg] \end{aligned} \tag{20}$$

in which all expectations and covariances are taken under π.[45]

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 1). Importantly, even if the average firm's investment does not respond, aggregate investment can still change due

[44]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.
[45]We suppress a third-order term in the decomposition.

Table 10: 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 (20). $\mathbb{E}_\pi[\cdot]$ 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. $^{*}p<0.10$, $^{**}p<0.05$, $^{***}p<0.01$.

to reallocation effects that the covariance terms in (20) 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.

To compute the covariance term, we need estimates of investment semi-elasticities across firms. We estimate these by regressing firm investment 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). Appendix H details this estimation. We map decile-level semi-elasticities to market capitalization ranks and use GMM to jointly estimate the moments in Equation (20), using the empirical distributions of ε, π, μ, and $\Delta\beta$ (plotted in Appendix Figure A12).

Table 10 shows that aggregate investment falls by 1.28%, all else equal. The average firm's response contributes about 31% to this decline. The dominant force, however, is the covariance between $\Delta\beta_i$ and ϵ^C_i. This strong negative relationship generates a reallocation effect that accounts for approximately 70% of the total. The other two covariance terms in (20), which link financing patterns to risk exposure and to investment flexibility, are negligible. Appendix Figure A13 shows the cumulative 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 Appendix I. 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.[46]

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. Firm heterogeneity drives this mechanism, which operates on the extensive margin. Specifically, the adverse shock to their cost of capital pushes small, high-growth firms to delay their investment. In contrast, large, inframarginal firms near their optimal scale show little response to the shock. While this richer framework captures our primary mechanism, it still abstracts from other margins like firm entry/exit and innovation, which represent promising avenues for future research (Pindyck, 2009, Gutiérrez et al., 2021, Bustamante & Zucchi, 2023).

8.2 Counterfactual WACC and the Missing Investment Puzzle

We estimate a counterfactual weighted average cost of capital (WACC) for the average firm by removing benchmarking-induced distortions from its CAPM $\hat{\beta}$ and test whether the resulting WACC is sufficiently lower to account for the missing investment puzzle.

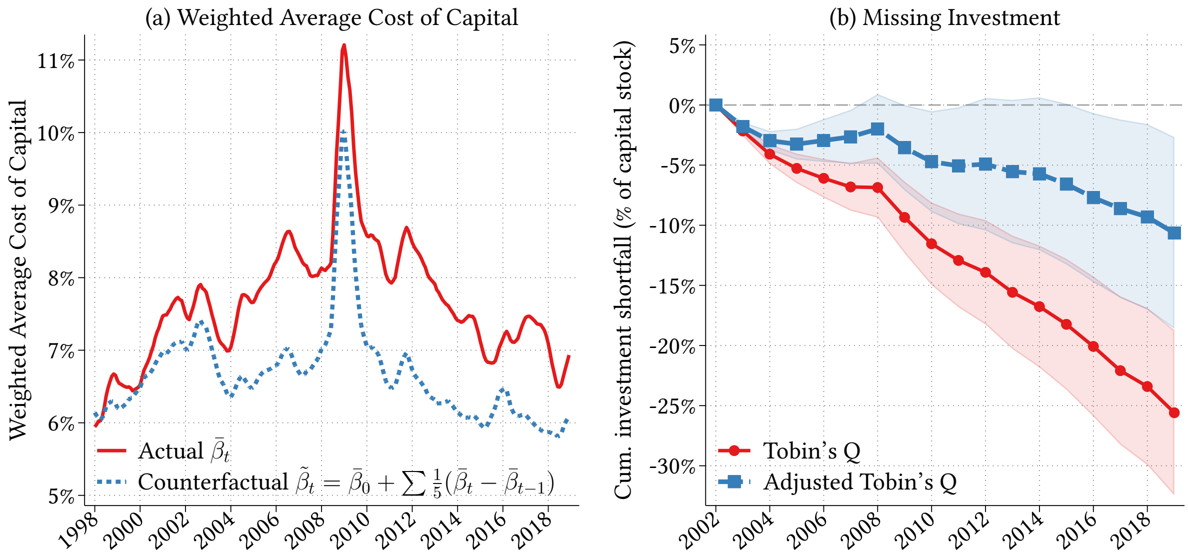
Panel (a) of Figure 14 plots the average firm's weighted average cost of capital (WACC) from 1998 to 2019.[47] We construct a counterfactual WACC where we assume that the average firm's CAPM $\hat{\beta}$ increases only by 20% of the actual increase since 1998, while allowing other components of the WACC to vary as observed.[48] The counterfactual shows that increased benchmarking has raised the average firm's WACC by over 120 bps after 2003, effectively offsetting much of the

[46]While price adjustments could in theory offset these distributional β shocks, Koby & Wolf (2020) show that empirical investment semi-elasticities are too low to produce meaningful general equilibrium smoothing.

[47]Constructed as $\text{WACC}_t = (1-\mu_t)(1-\tau_t)r_t^d + \mu_t\big(r_t^f + \beta_t\lambda_t\big)$, where μ_t is the equity share, r_t^d the cost of debt, r_t^f the risk-free rate, and λ_t the equity risk premium (ERP). The ERP is proxied by $\lambda_t = \mathbb{E}_t[r^{Mkt}] - r_t^f$ where $\mathbb{E}_t[r^{Mkt}] = 1/\text{CAPE}_t + 2\% + \mathbb{E}_t[\text{Inflation}]$, with expected inflation from the SPF, and the 10-year U.S. Treasury yield as r_t^f. Cost of debt r_t^d is proxied by the yield on the ICE–BofA HY Bond Index. The equity share is computed as $\mu_t = \frac{\text{Equity}_t}{\text{Equity}_t + \text{Debt}_t}$, and the effective tax rate as $\tau_t = \frac{\text{Tax Expense}_t}{\text{Pre-Tax Income}_t - \text{Extraordinary Items}_t}$, using Compustat data.

[48]This is a conservative calibration. The dynamic OLS estimates in Appendix Table A4 imply that the rise in the average stock's benchmarking intensity 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 are due to the increase in BMI.

Figure 14: Actual and Counterfactual Weighted Average Cost of Capital and Missing Investment



Notes: Panel (a) shows the average firm's actual and counterfactual WACC, calculated as $\text{WACC}_t = \mu_t r_t^e + (1 - \mu_t)(1 - \tau_t) r_t^d$ where $r_t^e = r_t^f + \beta \left(\mathbb{E}_t[r^{Mkt}] - r_t^f \right)$. We proxy the expected return on the market as $\mathbb{E}_t[r^{Mkt}] = 1/\text{CAPE}_t + 2\% + \mathbb{E}_t[\text{Inflation}]$ and proxy r_t^D with the yield on the ICE-BofA HY Bond Index. In the counterfactual, we assume that CAPM $\hat{\beta}$ increase only by 20% of the actual increase since 1998 while allowing other components of the WACC to vary as observed. Panel (b) shows the cumulative investment shortfall as a percentage of the capital stock, estimated separately using Tobin's Q and Adjusted Tobin's Q. Following Gormsen & Huber (2025), Tobin's Q is calculated using market value data from the Flow of Funds and tangible plus intangible capital data from the BEA. Adjusted Q accounts for the wedge between financial market discount rates and managers' perceived cost of capital (see Eq. (21)). The relationship between investment and Q is estimated using 1990–2002 data for each Q type. For post-2002 years, cumulative residuals are computed as the difference between observed investment and predictions based on 1990–2002 estimates. Pointwise confidence intervals (95%) are derived using Newey-West standard errors with 5 lags.

decline in risk-free rates over the past 25 years.

We adopt the methods of Gutiérrez & Philippon (2017) and Gormsen & Huber (2025) to test whether the wedge between actual and counterfactual WACC is large enough to account for the missing investment puzzle.[49] Using data from 1990 to 2002, we estimate the relationship between aggregate investment and Tobin's Q, then predict post-2002 investment under the assumption that this relationship remained unchanged. The "missing investment" is the cumulative shortfall since 2002, reflecting the divergence between Tobin's Q and observed investment. Gormsen & Huber (2025) show that when a firm's perceived discount rate exceeds the market's discount rate, it undervalues profits generated by capital relative to the market. Following their approach, we adjust Tobin's Q to account for the average discrepancy between the market's discount rate and the firm's perceived cost of capital, yielding an adjusted Tobin's Q:

$$\text{Adjusted Tobin's Q} = \text{Tobin's Q} \times \frac{1}{1 + \Delta\text{WACC} \times \text{Cashflow Duration}} \tag{21}$$

[49]On missing investment, see also Peters & Taylor (2017), Alexander & Eberly (2018), Andrei et al. (2019), Barkai (2020), Gutiérrez et al. (2021), Gala et al. (2022), Crouzet & Eberly (2023), Cho et al. (2025), Corhay et al. (2025)

in which ΔWACC is the wedge between actual and counterfactual WACC in panel (a) of Figure 14. The impact of this adjustment depends on both the size of the discount rate wedge and the duration of cash flows. A higher duration amplifies the effect of the discount rate on asset value. We set the duration to 32.5 years which is the midpoint 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 14 shows that the wedge between actual and counterfactual WACC could account for a large part of the missing investment puzzle. Without adjustment, the aggregate investment shortfall implied by Tobin's Q is approximately 25% of the capital stock by 2019. After adjustment for the WACC wedge, the shortfall is reduced to approximately 10.6% of the capital stock. The remaining gap is likely related to other macro developments, such as rising market power (Barkai, 2020, Crouzet & Eberly, 2023) and mismeasurement of intangibles (Peters & Taylor, 2017).

Alternative Estimation of Aggregate Investment Effects As an alternative way to quantify the aggregate impact of benchmarking on investment, we analyze the extent to which BMI explains the aggregate time-series variation in investment. We estimate two parallel panel regression models of the firm-level investment rate. Both specifications include a full set of control variables and firm fixed effects. The first specification excludes BMI, while the second includes it. In this framework, the year fixed effects from the first model capture all common time-series variation in investment. In the second model, the year fixed effects capture the residual time-series variation after accounting for the influence of BMI. The difference between the two sets of year fixed effects therefore isolates the portion of aggregate investment dynamics explained by the secular trend in BMI.

Appendix Figure A14 shows that accounting for BMI reduces the absolute size of year fixed effects by 43%, on average. In early years, the series track each other closely, indicating that BMI played little role in explaining aggregate time-series variation. After 2002, however, the two diverge: the specification excluding BMI attributes a larger negative time trend to investment, while including BMI shifts this trend upward by 1.2 p.p., on average. Including BMI reduces the absolute size of the year fixed effects by around 43%. Economically, this pattern implies that the increase in benchmarking intensity explains a growing share of the post-2002 investment slowdown. In other words, as benchmark-linked capital rises, the portion of the investment decline attributed to aggregate time trends shrinks once BMI is accounted for. This further implies that benchmarking is an increasingly important determinant of aggregate investment dynamics.

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 investing benefits the real economy by lowering firms' cost of equity. We establish that greater benchmarking intensity, for most firms, leads to a significant increase in their CAPM $\hat{\beta}$.

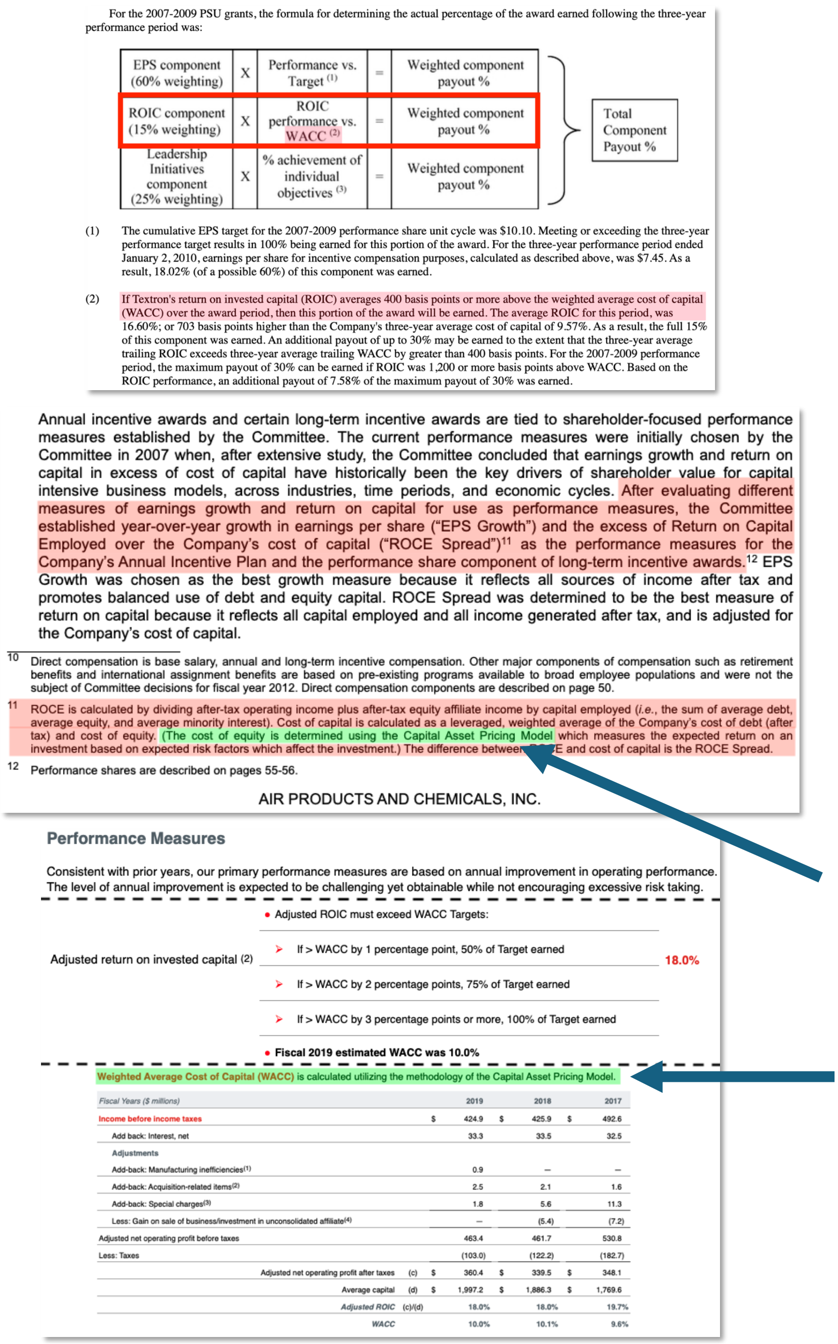
Firms respond to these benchmarking-induced increases in $\hat{\beta}$ by reducing investment. We attribute this response to managers' application of the CAPM for capital budgeting decisions, a practice that fails to adjust for the impact of benchmarking on asset prices. Evidence from managers, analysts, and regulators shows a higher perceived cost of equity following an exogenous increase in benchmarking intensity.

These findings offer a novel explanation for the shortfall of investment relative to valuations over the past two decades. Our analysis shows that the growth in benchmark-linked asset management has significant negative real effects on aggregate investment. Our results imply that executives, policymakers, and investors must account for the unintended consequences of benchmark-linked investing on firms' capital allocation and the real economy.

Appendix Table of Contents

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 %	}	Total Component Payout %
Leadership Initiatives component (25% weighting)	X	% achievement of individual objectives (3)	=	Weighted 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%**

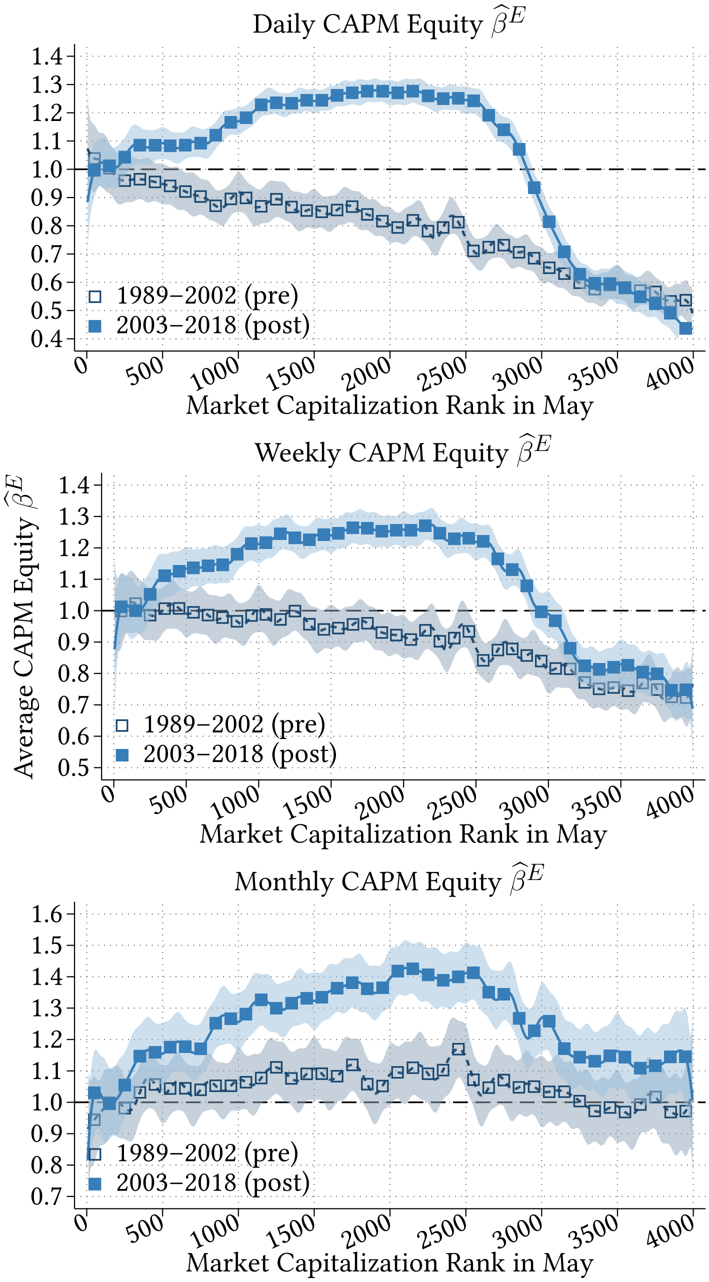
18.0%

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%

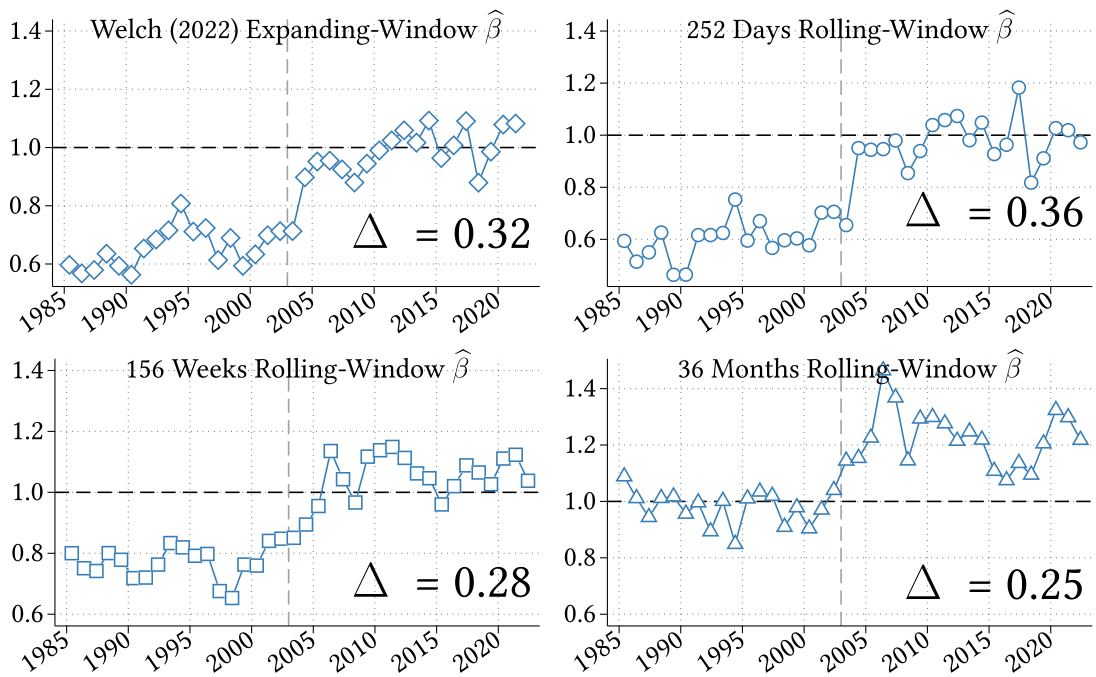
Figure A1: Clipping from the proxy statements (SEC Form DEF 14A) of Textron Inc., Air Products and Chemicals Inc., and Acuity Brands Inc., illustrating their use of ROIC/ROCE targets in executive compensation, with hurdle rates tied to the CAPM-implied WACC.

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



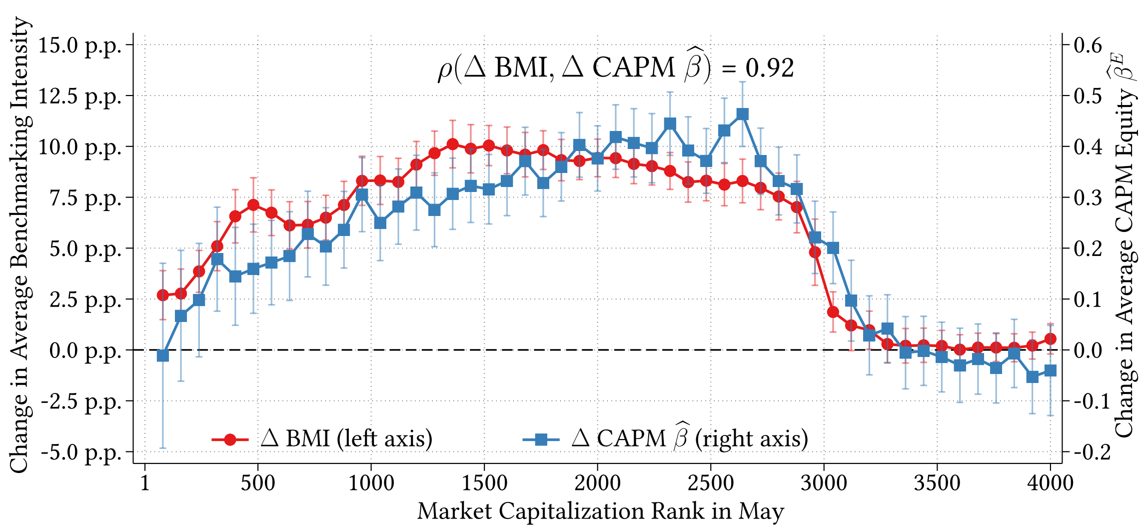
Notes: This figure plots binned scatters of rolling-window CAPM $\hat{\beta}$s against May market-cap ranks by estimation frequency: 252 trading days (daily), 156 weeks (weekly), and 36 months (monthly). Shaded areas show 90% confidence bands with errors clustered by stock and year-month.

Figure A3: Time Series of Equal-weighted Average CAPM $\hat{\beta}$ of all Common Stocks Since 1985



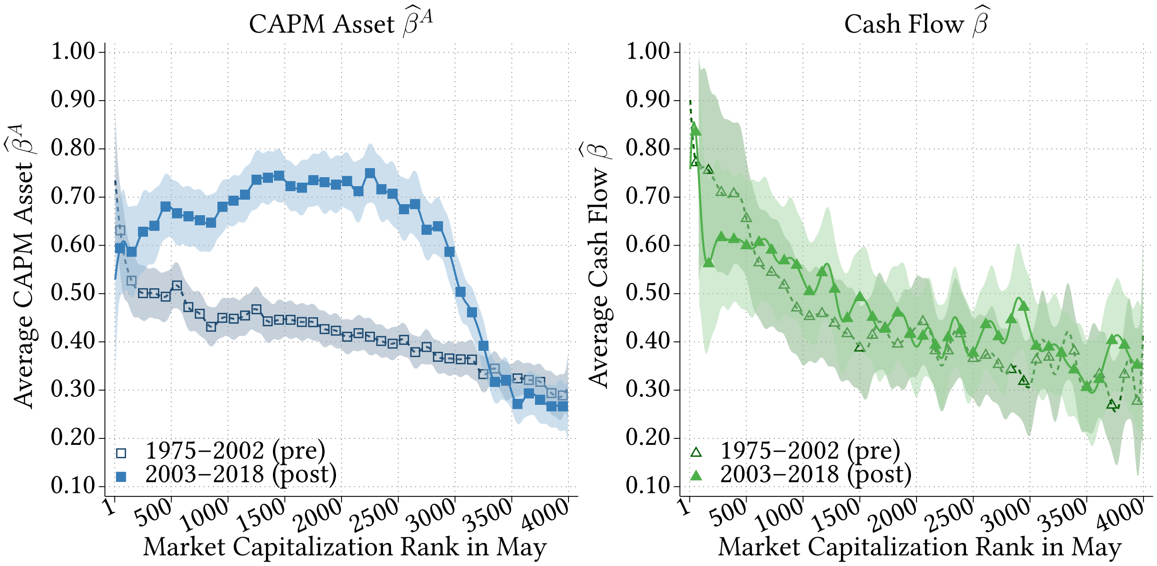
Notes: This figure shows cross-sectional equal-weighted average CAPM $\hat{\beta}$ since 1985 of all common stock listed on the NYSE, AMEX, and NASDAQ. Δ is the change in CAPM $\hat{\beta}$ post-2002 relative to pre-period.

Figure A4: Differences in Benchmarking Intensity and CAPM Equity $\hat{\beta}^E$ Between Pre and Post



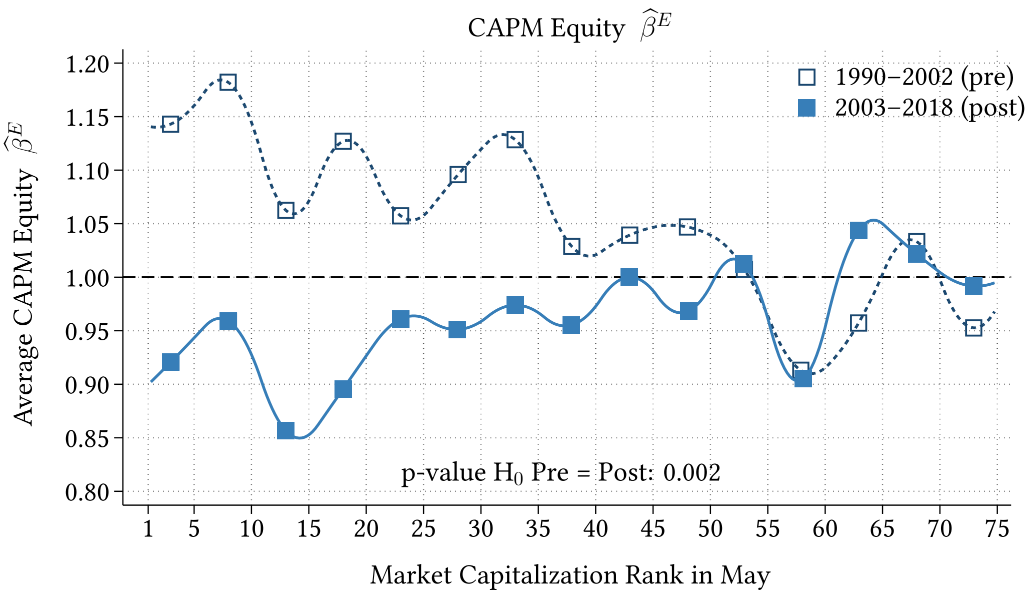
Notes: This figure plots changes in average BMI (left axis) and CAPM equity $\hat{\beta}^E$ (right axis) between the pre- and post-periods against May market capitalization ranks (based on Ben-David et al. 2019). Each bin shows the difference in conditional means from Figure 1. $\rho(\Delta\text{BMI}, \Delta\text{CAPM } \beta)$ 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 A5: CAPM Asset $\hat{\beta}^A$ and Cash Flow β vs. Market Capitalization Rank in May



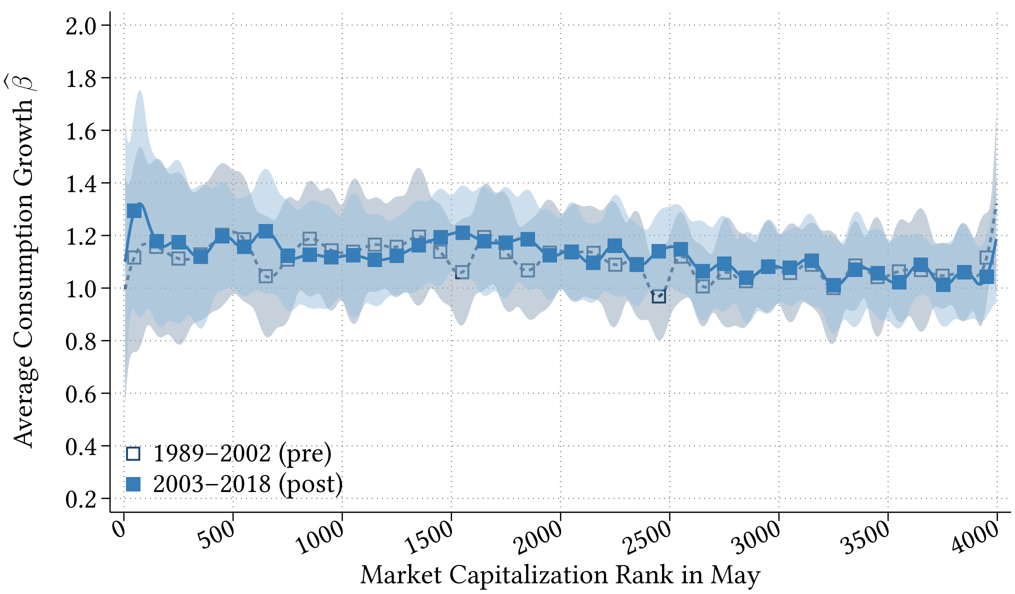
Notes: This figure plots binned scatters of quarterly cash flow $\hat{\beta}$s and CAPM asset $\hat{\beta}$s against May market capitalization ranks. Equity βs are unlevered following Krüger et al. (2015): $\hat{\beta}^A = \frac{E}{E+D} \times \hat{\beta}^E$, with E market value of equity and D book 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 A6: Largest Stocks' CAPM $\hat{\beta}^E$ vs. Market Capitalization Rank in May



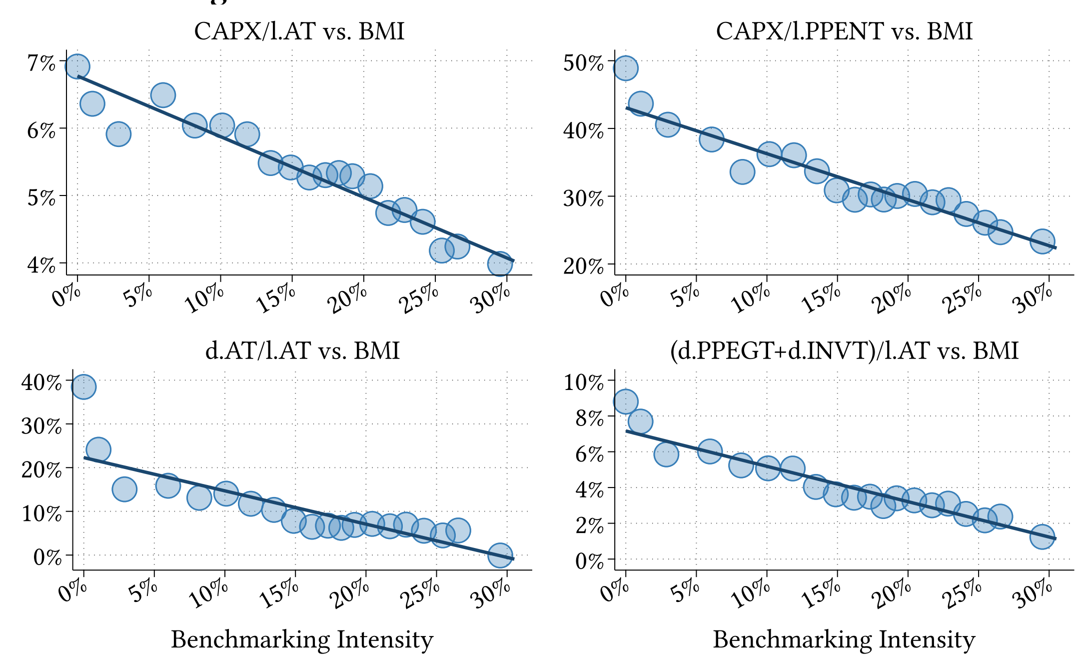
Notes: This figure shows binned scatter plots of CAPM equity $\hat{\beta}^E$ against May market capitalization ranks for the largest 100 stocks by market capitalization. Each bin reflects the equal-weighted average of 5 ranks. Conditional means are identified absorbing year-month and stock fixed effects. Outlined bins use data from 1990 to 2002; filled bins from 2003 to 2018. p-value is for the null hypothesis that $\hat{\beta}(\text{rank bin } j)_{t=Pre} = \hat{\beta}(\text{rank bin } j)_{t=Post}\ \forall\ j \in \mathcal{J}$ using the nonparametric pairwise group comparison test of Cattaneo et al. (2024).

Figure A7: Consumption Growth $\hat{\beta}$s vs. Market Capitalization Rank in May



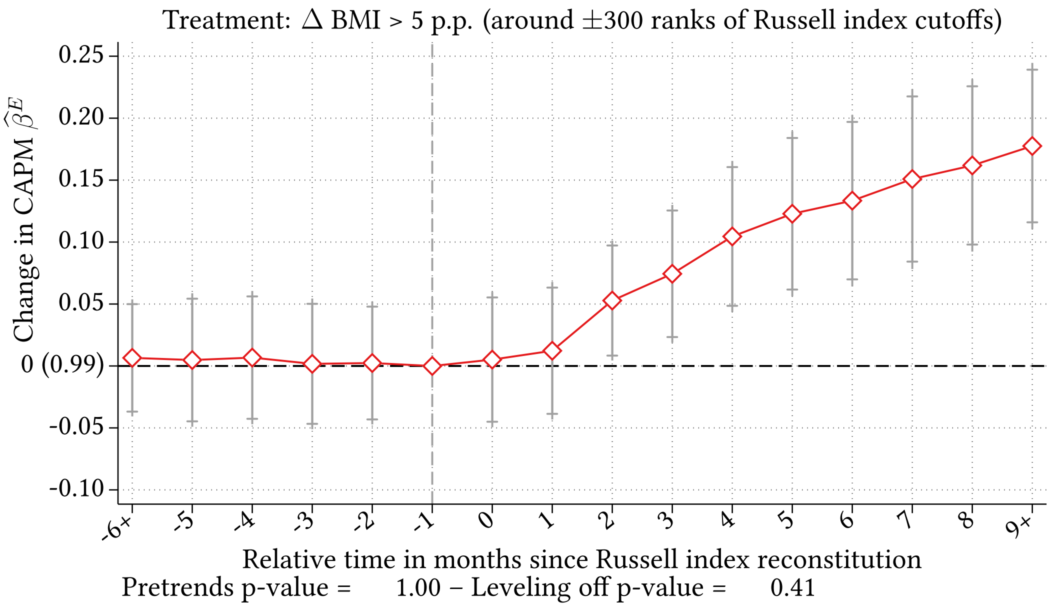
Notes: This figure shows binned scatter plots of consumption growth $\hat{\beta}$s from Kim et al. (2024) against May market capitalization ranks. Each bin reflects the equal-weighted average of approx. 100 ranks. We standardize the consumption growth $\hat{\beta}$s to have a mean and a standard deviation of one across the full sample period. Conditional means are identified absorbing yearly effects. Outlined bins use data from 1989 to 2002; filled bins from 2003 to 2018. Shaded areas show 95% confidence bands with standard errors clustered by stock and year-month.

Figure A8: Alternative Investment Rates Definitions

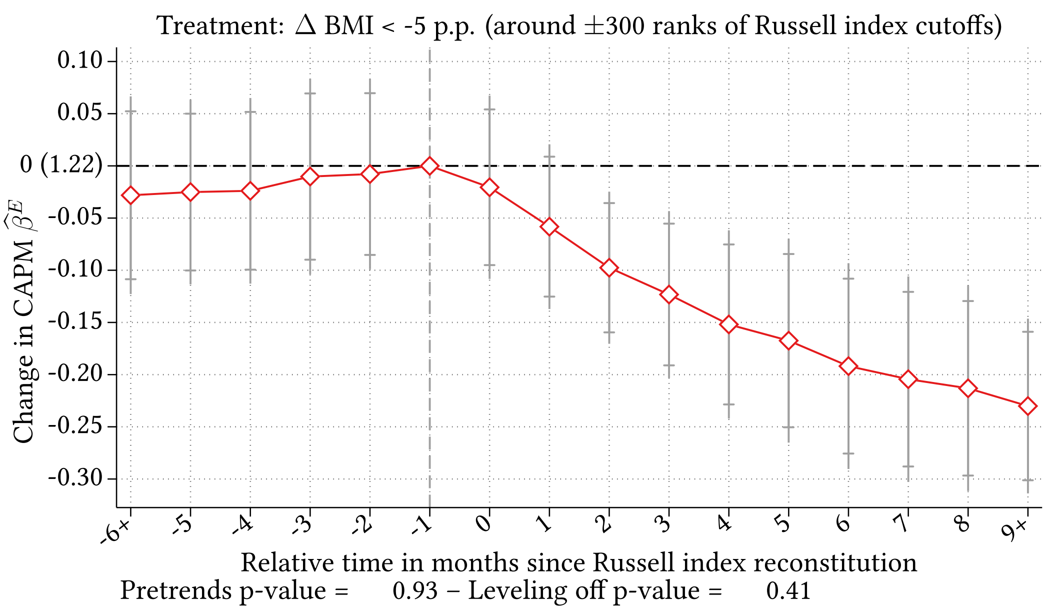


Notes: This figure plots binned scatters of 25 quantile-spaced bins of different investment rates against benchmarking intensity, constructed after absorbing year-by-rank-bucket fixed effects, with buckets defined every 250 market capitalization ranks. Sample period from 1998 2018 sample for which BMI is available.

Figure A9: Difference-in-differences Event Study of Changes in BMI on Changes in CAPM $\hat{\beta}^E$



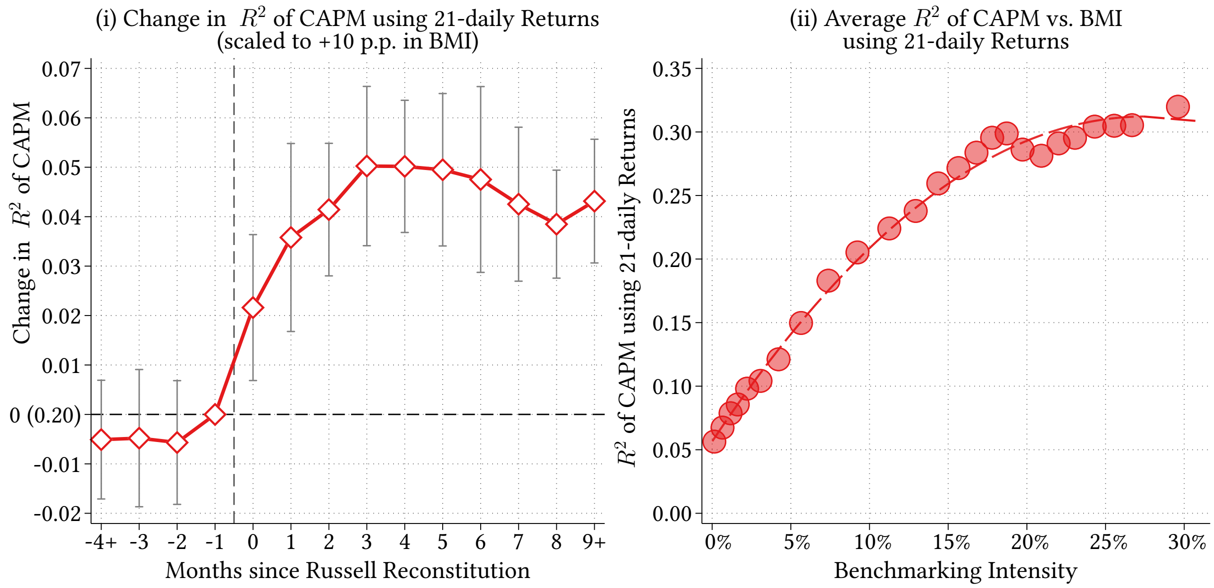
(a) Treated stocks with an increase in Δ BMI > 5 p.p. relative to control group.



(b) Treated stocks with a decrease in Δ BMI < -5 p.p. relative to control group.

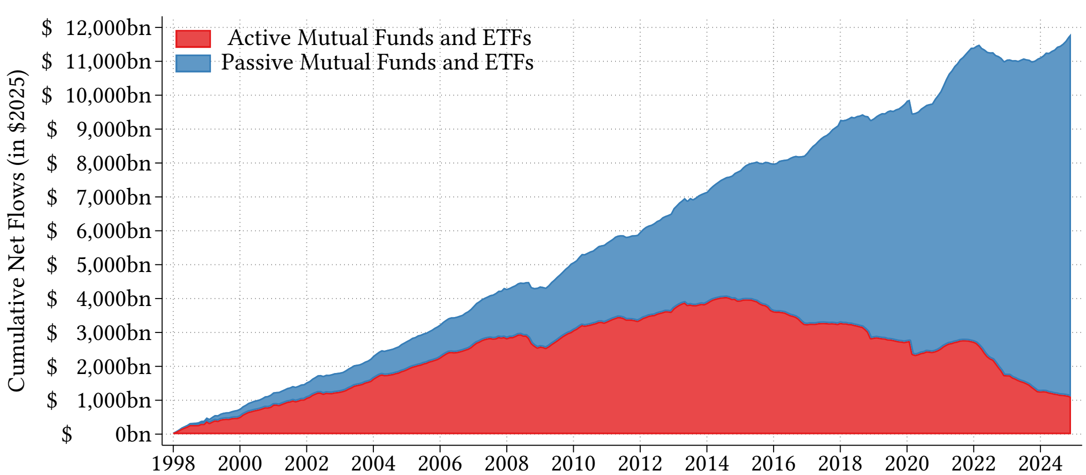
Notes: This figure shows difference-in-differences event study coefficients for a change in CAPM $\hat{\beta}^E$ of treated stocks with an increase or decrease in BMI of at least 5 p.p. relative to a control group, in which $|\Delta \text{ BMI}| < 1$ p.p.. Pointwise confidence intervals (95%) and sup-t confidence bands based on double-clustered standard errors. Values in parentheses on the Y-axis show the average CAPM $\hat{\beta}^E$ before treatment.

Figure A10: Effects of Benchmarking Intensity on the R^2 of the CAPM



Notes: Panel (i) in this figure shows the results of a difference-in-differences event study of a 10 p.p. increase in BMI due to Russell reconstitution on the R^2 of the CAPM in explaining realized daily returns. We restrict the sample to stocks within 300 ranks of each Russell cutoff. Pointwise confidence intervals (95%) based on double-clustered standard errors. Panel (ii) shows 25 quantile-spaced bins, constructed after absorbing year-month-by-FF49-industry fixed effects, of the monthly R^2 of the CAPM versus BMI.

Figure A11: Cumulative Net Flows into Passive and Active Mutual Funds and ETFs



Notes: This figure show cumulative monthly net flows into active and passive mutual funds and ETFs from 1998 to 2024 deflated by the Consumer Price Index. Source: Morningstar Direct.

Figure A12: Change in $\hat{\beta}$, Investment Semi-Elasticity, Aggregation Weights, and Equity Share

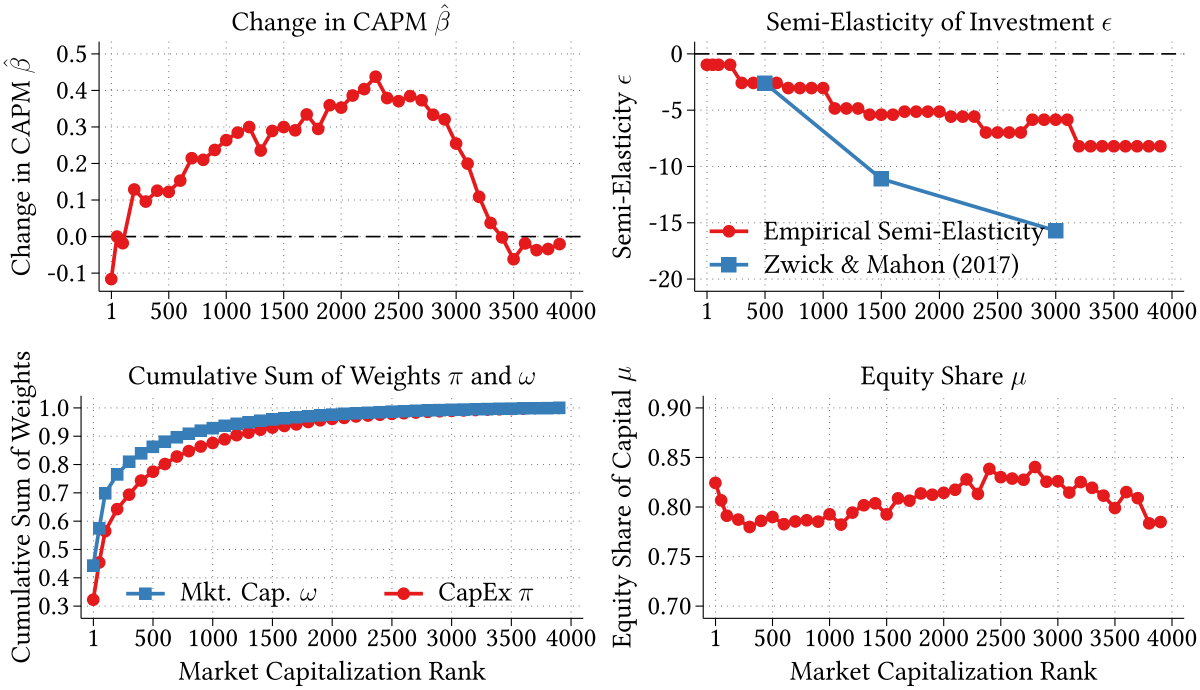
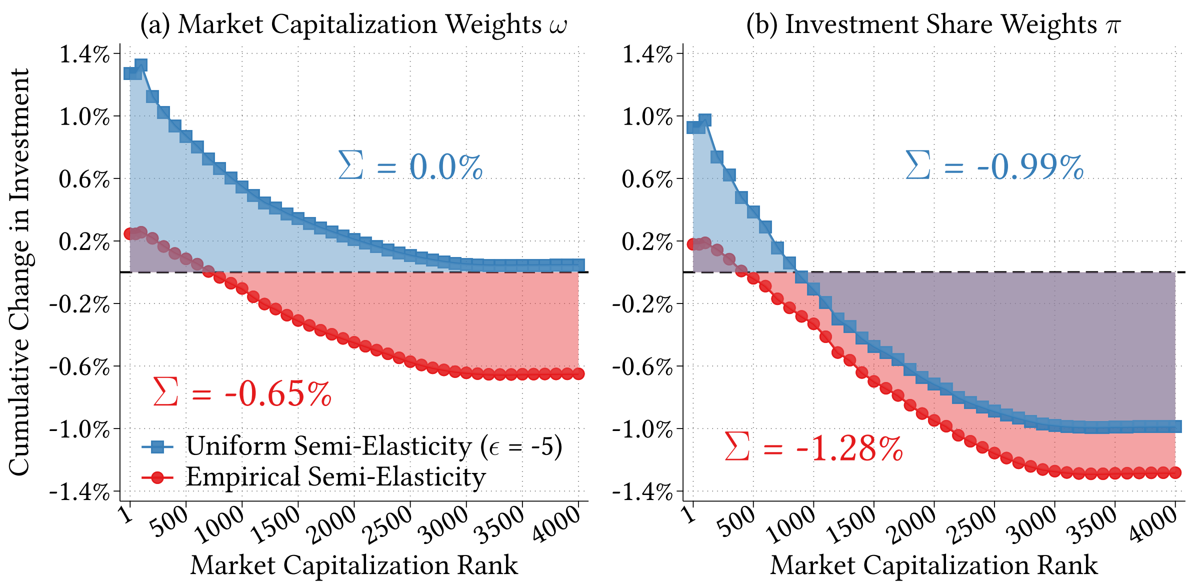
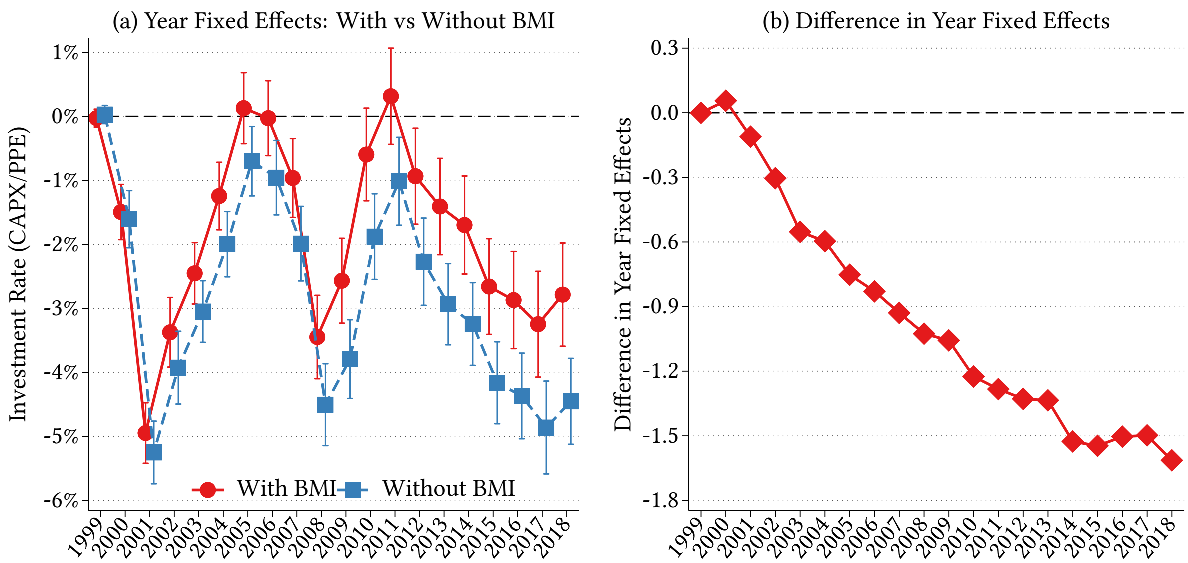


Figure A13: Cumulative Sum of Changes in Investment Across Market Capitalization Ranks



Notes: This figure shows the cumulative sum over the change in aggregate investment implied by Equation (19) across market capitalization ranks i: $\Delta I_t / I_{t-1} \approx q_t \lambda_t \sum_i \pi_{i,t-1}\, \epsilon^C_{i,t}\, \mu_{i,t}\, \Delta\beta_{i,t}$ in which 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 A12. 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 H).

Figure A14: Year Fixed Effects in Investment Rate with and without Benchmarking Intensity



Notes: Panel (a) shows estimates of δ_t from panel regressions of the form $\frac{\text{CAPX}_{i,t+1}}{\text{PPE}_{i,t}} = \alpha_i + \delta_t + \gamma_1 \text{Tobin's } q^{tot}_{i,t} + \gamma_2 \text{Cash Flow}_{i,t} + \gamma_3 \text{BMI}_{i,t} + \varepsilon_{i,t}$ with and without BMI included as a regressor. Panel (b) shows the difference, $\Delta_t = \hat{\delta}_t^{\text{(without BMI)}} - \hat{\delta}_t^{\text{(with BMI)}}$, between the two series in panel (a). Estimated time fixed effects are relative to the investment rate in base year 1998 ($\approx$ 21%). Pointwise confidence intervals (95%) based on double-clustered standard errors.

A.2 Appendix Tables

Table A1: 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 A2: 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 × Year FE				✓		
FF49 × Size × 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 $\hat{\beta}_{i,t} = \alpha_i + \alpha_t + \gamma \times \text{Avg. BMI over past 12 months}_{i,t} + \varepsilon_{i,t}$ 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 A3: Robustness to Alternative CAPM $\hat{\beta}$ Estimators

	(1) $\Delta\ \widehat{\beta}^{OLS}$	(2) $\Delta\ \widehat{\beta}^{WEL}$	(3) $\Delta\ \widehat{\beta}^{DIM}$	(4) $\Delta\ \widehat{\beta}^{BLU}$	(5) $\Delta\ \rho(r_i, r_m)$	(6) $\Delta\ \sigma^i$
Δ BMI (in p.p.)	0.0183***	0.0154***	0.0135***	0.0122***	0.00646***	-0.0000668*
	(0.001)	(0.001)	(0.002)	(0.001)	(0.000)	(0.000)
Firm Fixed Effects	✓	✓	✓	✓	✓	✓
Year Fixed Effects	✓	✓	✓	✓	✓	✓
Adj. R^2	0.15	0.16	0.11	0.15	0.41	0.59
Observations	28,514	28,514	28,514	28,514	28,514	28,514

Notes: This table reports coefficient estimates of specifications of the form: $\Delta\hat{\beta}_{i,t} = \alpha_i + \alpha_t + \gamma\Delta\text{BMI}_{i,t} + \varepsilon_{i,t}$. $\Delta\beta_{i,t}$ is between 1st and 4th quarter of each year. β^{WEL} is estimator of Welch (2022), β^{DIM} is estimator of Dimson (1979), β^{BLU} is estimator of Blume (1975) (also known as Bloomberg $\hat{\beta}$). We winsorize $\hat{\beta}$s changes at the 2% and 98% level. We restrict the estimation sample to stocks within 300 ranks around Russell index 1000/2000 and 3000 cutoffs. Standard errors in parentheses are double clustered at firm- and year level. * p<0.10, ** p<0.05, *** p<0.01.

Table A4: Effects of Benchmarking Intensity on Equal-Weighted Average CAPM $\hat{\beta}^E$

	(1) OLS	(2) ADL(1)	(3) DOLS(3)	(4) DOLS(4)	(5) DOLS(5)	(6) DOLS(7)
Average Benchmarking Intensity (in %)	0.038	0.030*	0.032***	0.031***	0.031***	0.029***
		(0.015)	(0.005)	(0.005)	(0.005)	(0.005)
Engle-Granger's Augmented Dickey-Fuller test (H_0: no cointegration)		-13.77***	-3.93***	-3.66**	-3.75**	-3.30*
Adj. R^2		0.99	0.71	0.72	0.74	0.78
Observations	225	225	225	225	225	225

Notes: This table estimates the long-run relationship between the equal-weighted average CAPM $\hat{\beta}$ and the average Benchmarking Intensity (BMI). To address the potential for spurious regression in the time series, we report results from several models. Column (1) shows the static OLS estimate. Column (2) presents an Autoregressive Distributed Lag, ADL(1), model. Columns (3)-(6) report long-run coefficients from Dynamic OLS (DOLS) (Stock & Watson, 1993) specifications with varying numbers of leads and lags. We report the Engle-Granger Augmented Dickey-Fuller test statistic for the residuals of the cointegrating regression, where the null hypothesis is no cointegration. Newey-West standard errors (21 lags) in parentheses. * 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: Panel Regression of Firm Investment Accounting for Measurement Error in Tobin's q

	(1)	(2)	(3)	(4)	(5)
	Dep. var.: Investment rate (CAPX/PPE)				
	OLS		IV: Industry q		EW (2012)
BMI (in %)	-0.147***	-0.105***	-0.099***	-0.070***	-0.067***
	(0.021)	(0.022)	(0.022)	(0.020)	(0.014)
Tobin's q^{tot}	3.434***	3.038***	5.043***	4.573***	6.078***
	(0.155)	(0.205)	(0.327)	(0.435)	(0.157)
Leverage	0.008*	0.012**	0.018***	0.006	0.001
	(0.005)	(0.006)	(0.006)	(0.006)	(0.005)
Firm FE		✓		✓	✓
Year × Rank-Bin FE	✓	✓	✓	✓	✓
FS F-stat.			143.16	33.95	
Within R^2	0.21	0.12	0.17	0.10	0.27
Observations	36,277	36,129	35,690	35,543	36,129

Notes: This table report 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. We address measurement error in Tobin's q (Peters & Taylor, 2017) in columns 3-5. Columns 3-4 use the NAICS-4 industry level leave-one-out mean of Tobin's q as an instrument for firm-level Tobin's q. Columns 5 use Erickson & Whited's (2012) cumulant estimator. We additionally control for leverage and cash flow to PPE. Standard errors in parentheses are clustered at the year- and firm-level. * p<0.10, ** p<0.05, *** p<0.01.

Table A7: Panel Regressions of Firm Investment on BMI (without imposing sample restrictions)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Dependent variable: CAPX_{t+1} / PPE_t (in %)						
BMI (in %)	-0.214***	-0.349***	-0.191***	-0.114***	-0.124***	-0.134***	-0.186***
	(0.044)	(0.033)	(0.033)	(0.020)	(0.022)	(0.027)	(0.036)
IOR (in %)				0.006	0.004	0.004	0.003
				(0.005)	(0.006)	(0.006)	(0.006)
Tobin's q^{tot}				2.192***	2.092***	2.087***	
				(0.145)	(0.142)	(0.142)	
Linear Time Trend	-0.423***						
	(0.071)						
Leverage				0.019***	0.018***	0.017***	0.022***
				(0.005)	(0.005)	(0.005)	(0.006)
Fixed Effects							
Firm FE	✓		✓	✓	✓	✓	✓
Year × Rank FE		✓	✓	✓			
Ind. × Year × Rank FE					✓	✓	✓
Russell 2000 Index FE						✓	✓
Adj. R^2	0.43	0.07	0.46	0.49	0.56	0.56	0.53
Mean Dep. Var.	14.6	14.7	14.6	14.6	14.6	14.6	14.6
SD BMI	9.2	9.2	9.2	9.1	9.1	9.1	9.1
Observations	53,017	53,763	53,015	50,796	49,553	49,553	49,567

Notes: In this table, we do not impose any sample restrictions on firm size, industry, or data availability. This table report 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.

Table A8: Reduced Form of Russell Reconstitution BMI Shock on Investment Rate (CAPX/PPE) - Robustness to Window Size

Panel A. Window around Russell 1000/2000 Cutoff = 150

	(1)	(2)	(3)	(4)	(5)	(6)
	t+1	t+2	t+3	t+4	t+5	t+6
Δ BMI	0.134	-0.394	-0.477	-0.815	-0.852	-1.219**
	(0.271)	(0.390)	(0.381)	(0.496)	(0.541)	(0.524)
Window	150	150	150	150	150	150
Adj. R^2	0.07	0.10	0.09	0.09	0.09	0.07
Observations	5,058	4,826	4,342	3,896	3,458	3,072

Panel B. Window around Russell 1000/2000 Cutoff = 250

	(1)	(2)	(3)	(4)	(5)	(6)
	t+1	t+2	t+3	t+4	t+5	t+6
Δ BMI	0.000	-0.490	-0.555	-0.970**	-1.016**	-0.809*
	(0.278)	(0.354)	(0.354)	(0.454)	(0.430)	(0.392)
Window	250	250	250	250	250	250
Adj. R^2	0.07	0.10	0.09	0.09	0.09	0.07
Observations	7,702	7,301	6,570	5,885	5,230	4,657

Panel C. Window around Russell 1000/2000 Cutoff = 350

	(1)	(2)	(3)	(4)	(5)	(6)
	t+1	t+2	t+3	t+4	t+5	t+6
Δ BMI	0.105	-0.338	-0.762*	-1.006**	-1.183**	-0.817*
	(0.263)	(0.384)	(0.388)	(0.466)	(0.488)	(0.449)
Window	350	350	350	350	350	350
Adj. R^2	0.06	0.09	0.10	0.10	0.09	0.07
Observations	9,851	9,344	8,429	7,560	6,770	6,044

Panel D. Window around Russell 1000/2000 Cutoff = 450

	(1)	(2)	(3)	(4)	(5)	(6)
	t+1	t+2	t+3	t+4	t+5	t+6
Δ BMI	0.203	-0.227	-0.738*	-0.898*	-1.077**	-0.590
	(0.257)	(0.368)	(0.416)	(0.500)	(0.493)	(0.394)
Window	450	450	450	450	450	450
Adj. R^2	0.06	0.10	0.10	0.10	0.08	0.06
Observations	12,067	11,456	10,342	9,308	8,346	7,472

Notes: This table reports estimates for regressions of the form: $\log\left(\frac{\text{CAPX}_{i,t+h}}{\text{PPE}_{i,t}}\right) - \log\left(\frac{\text{CAPX}_{i,t}}{\text{PPE}_{i,t-1}}\right) = \alpha_t + \gamma\Delta\ \text{BMI}_{i,t} + \log\left(\text{Market Cap.}\right)_{i,t} + \text{Banding Variables}_{i,t} + \varepsilon_{i,t+h}$ Standard errors in parentheses are 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 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 report estimates for panel regressions of the form: $\frac{\text{CAPX}_{i,t+1}}{\text{PPE}_{i,t}} = \alpha_{t,bin} + \alpha_i + \gamma\, \text{BMI}_{i,t} + \mathbb{1}\{\text{High Risk Exposure}\} \times \text{BMI}_{i,t} + X'_{i,t}\xi + \varepsilon_{i,t}$, 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 A10: 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 $\times$ 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 $\times$ Year $\times$ 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 report estimates for panel regressions of the form: $\frac{\text{CAPX}_{i,t+1}}{\text{PPE}_{i,t}} = \alpha_{t,bin} + \alpha_i + \gamma\ \text{BMI}_{i,t} + \mathbb{1}\{\text{High CO in Industry}\} \times \text{BMI}_{i,t} + X'_{i,t}\xi + \varepsilon_{i,t}$, 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 clustered at the year- and firm-level. * p<0.10, ** p<0.05, *** p<0.01.

Table A11: 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 $\times$ Industry $\times$ 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 report estimates for panel regressions of the form: $\frac{CAPX_{i,t+1}}{PPE_{i,t}} = \alpha_{t,bin} + \alpha_i + \gamma\, BMI_{i,t} + \mathbb{1}\{\text{High Private Info.}\} \times q^{tot} + \theta q^{tot} + X'_{i,t}\xi + \varepsilon_{i,t}$, 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 BMI on the private information proxies. Standard errors in parentheses are clustered at the year- and firm-level. * p<0.10, ** p<0.05, *** p<0.01.

Table A12: Reduced Form Effects of Benchmarking on Capital Accumulation at the Industry-level

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Dependent variable: log (Real Capital Stock in 2016/Real Capital Stock in 1998)						
Δ CAPM β	-0.258**	-0.140*			-0.132*		
(1998-2016)	(0.111)	(0.072)			(0.078)		
Δ BMI			-0.653**			-0.608**	
(1998-2016)			(0.259)			(0.269)	
Δ IOR				0.0632			0.0931
(1998-2016)				(0.111)			(0.107)
Capital Stock/Value-Added		-0.170***	-0.185***	-0.180***	-0.221***	-0.230***	-0.224***
(1998)		(0.042)	(0.035)	(0.035)	(0.052)	(0.050)	(0.048)
log (Employment)		0.00976	0.00936	0.0188	0.0536	0.0573	0.0492
(1998)		(0.029)	(0.029)	(0.028)	(0.035)	(0.035)	(0.034)
log (TFP)		0.372	0.448*	0.397	-0.119	-0.0442	-0.104
(1998)		(0.226)	(0.230)	(0.274)	(0.228)	(0.236)	(0.224)
Pre-trend Capital					-0.217**	-0.163*	-0.137
(1980-1996)					(0.094)	(0.089)	(0.102)
Pre-trend Employment					0.195*	0.158	0.155
(1980-1996)					(0.106)	(0.096)	(0.106)
Pre-trend Wage					0.664	0.494	0.769*
(1980-1996)					(0.399)	(0.405)	(0.407)
Constant	0.238***	0.308**	0.323**	0.211			
	(0.063)	(0.150)	(0.152)	(0.143)			
NAICS-3 Subsector FE					✓	✓	✓
Weights	VA_{1998}	VA_{1998}	VA_{1998}	VA_{1998}	VA_{1998}	VA_{1998}	VA_{1998}
Adj. R^2	0.10	0.34	0.35	0.31	0.52	0.52	0.50
Observations	103	103	103	103	103	103	103

Notes: This table reports coefficient estimates of regressions at the NAICS 5-digit industry-level of the form: $\Delta \log(\text{Real Capital Stock})_i = \alpha_j + \gamma \Delta Z_i + X_i' \xi + \varepsilon_i$ for changes from 1998 to 2016. Z is either CAPM $\hat{\beta}$, benchmarking intensity (BMI), or institutional ownership ratio (IOR). BMI, IOR, and CAPM $\hat{\beta}$ are market-value weighted averages at the industry level of Compustat firms. We exclude industries with less than 5 firms. Pre-trends measure log changes in variables from 1980 to 1996. We weight observations by industry value-added in 1998 and winsorize all variables at the 2% and 98% level. Robust standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

B Three period model with heterogeneous benchmarks

To illustrate our main mechanism, we develop a simple model of asset prices and investment in the presence of heterogeneous benchmarks. Our model introduces two new frictions into an otherwise standard model of benchmark-linked investing adapted from the literature (Brennan, 1993, Kashyap et al., 2021, Buffa et al., 2022, Pavlova & Sikorskaya, 2023). The first friction is uncertainty in the relative demand of benchmarked investors that proxies for fund flows. Exposure to benchmarked fund flows creates an additional source of comovement among benchmark constituent stocks that shifts the cross-section of CAPM βs. The second friction is a behavioral assumption about firm managers: we assume that firm managers do not observe the fundamental risk exposure of their firm and instead use the observed covariance of stock returns with the market to infer their cost of capital.

We proceed in two steps: First, we derive asset prices and the optimal investment policy with and without benchmarked investors. We illustrate that benchmarking distorts prices and expected returns relative to the CAPM and confirm the existence of a benchmark inclusion subsidy that lowers the costs of capital of firms included in a benchmark index. Next, we show that i) firm managers can infer the CAPM-optimal investment policy without knowledge of their fundamental risk exposure from the covariance of their stock returns with the market; ii) if assets are priced by benchmarked investors there is a two-factor structure in returns that increases the comovement of benchmark constituent stocks; iii) if firm managers erroneously implement the CAPM-optimal investment implied by the covariance of their stock returns with the market, they under-invest.

Setup There are three periods - denoted 0, 1, and 2 - and three types of agents: firm managers, investors and households. Each firm manager operates one of n fully equity-financed firms. Their objective function is to maximize firm value $\overline{x}_i S_{it}$ where S_{it} denotes the share price of the firm's equity and $\overline{x}_i$ denotes the number of outstanding shares normalized to $\overline{x} = \mathbf{1}$.

Investor demand The equity of each firm is priced by a unit mass of investors with absolute risk aversion γ. Their objective function is to maximize expected utility over next period wealth $U(W) = e^{-\gamma W}$ by investing in firms' (risky) equity and a risk-free bond that is in infinitely elastic supply with net interest rate normalized to 0. We follow the convention of the literature and denote the absolute returns of a portfolio $x_t = (x_t^1, \ldots, x_t^n)' \in \mathbb{R}^n$ by $R_{t+1}^x = x_t' R_{t+1}$, where $R_{t+1} = Y_{t+1} - S_t$ denotes the vector of absolute returns that is distributed with conditional covariance matrix Σ_t and $Y_{t+1} = S_{t+1} + D_{t+1}$ denotes the vector of total marketable cash flows.

Among investors, a fraction $\lambda_t^B \in [0,1)$ invests funds on behalf of a principal. Their income is contingent upon performance relative to a benchmark B represented by a benchmark portfolio vector $\mathbf{1}_B \in \{0,1\}^n$ with absolute returns $R_{t+1}^B = \mathbf{1}_B'(Y_{t+1} - S_t)$. Their compensation contract w is parameterized by constants $a \geq 0, c > 0$ and k.

$$w_t = aR_t^x + c(R_t^x - R_t^B) + k$$

The first and second term represent compensation for absolute performance R_t^x and performance relative to the benchmark portfolio R_t^B, respectively. The final term is a constant "base salary."[50]

The remaining $1 - \lambda_t^B$ investors are "fundamental" investors who invest directly and only care about absolute returns. The solution to their portfolio choice problem is standard:

$$x_t^D = \Sigma_t^{-1} \frac{\mathbb{E}_t \left[Y_{t+1}\right] - S_t}{\gamma} \tag{22}$$

The solution to the portfolio choice problem of a benchmarked investor is a combination of the mean-variance optimal portfolio x_t^D and the benchmark portfolio $\mathbf{1}_B$

$$x_t^B = \frac{1}{a+c} \Sigma_t^{-1} \frac{\mathbb{E}_t \left[Y_{t+1}\right] - S_t}{\gamma} + \frac{c}{a+c} \mathbf{1}_B \tag{23}$$

As first shown by Brennan (1993) benchmarking exposes investors to additional income risk that can be hedged by holding the benchmark portfolio. The more weight the compensation contract places on performance relative to the benchmark, the more weight a benchmarked investor places on the benchmark portfolio. In the limit, as $c \to \infty$, the portfolio of a benchmarked investor approaches the index itself (as in a passive fund evaluated on its tracking error).

Benchmarking Intensity We allow for heterogeneous benchmark portfolios across investors: There is a finite set of benchmark portfolios $\mathcal{B} = \{B_1, B_2, ...\}$, summarized by the matrix $\mathbf{1}_{\mathcal{B}} \in \{0,1\}^{n \times |\mathcal{B}|}$. The mass of benchmarked investors λ_t^B is partitioned into $|\mathcal{B}|$ disjoint masses $\lambda_t^{\mathcal{B}} = (\lambda_t^{B_1}, \lambda_t^{B_2}, ...) \in \mathbb{R}_{\geq 0}^{|\mathcal{B}|}$ with $\sum \lambda_t^{B_j} = \lambda_t^B$. This allows us to define the vector of benchmarking intensities across stocks as

$$BMI_t \equiv \sum_{B_j \in \mathcal{B}} \mathbf{1}_{B_j} \lambda_t^{B_j} = \mathbf{1}_{\mathcal{B}} \lambda_t^{\mathcal{B}}$$

[50] Kashyap et al. (2023) derive this specification as the solution to an agency problem. Studies of the mutual fund industry provide empirical support for this specification (Ma et al., 2019, Evans et al., 2024).

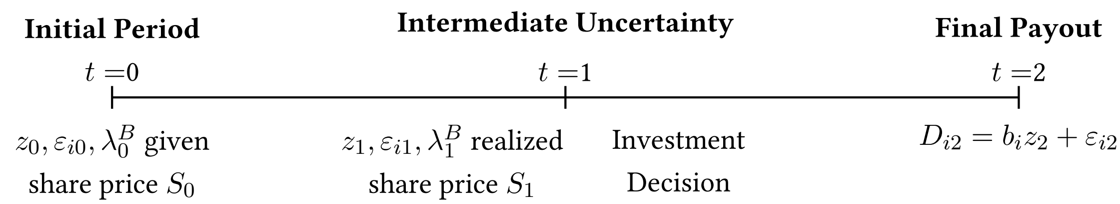


Figure B15: Model Timing

Timing The remaining setup is as follows: In period 2 all firms are liquidated with payout

$$D_{i2} = b_i z_2 + \varepsilon_{i2}$$

where $b \in \mathbb{R}^n_{\geq 0}$ is a vector of positive factor loadings on a common fundamental factor z_t, and ε_{it} is a firm specific idiosyncratic productivity process. Both the common factor and the idiosyncratic shock follow a square root process (as in Buffa et al., 2022, Kashyap et al., 2021),[51]

$$\begin{aligned} z_{t+1} &= z_t + \sqrt{z_t}\sigma_z u^z_{t+1}, \quad u^z_{t+1} \sim \mathcal{N}(0,1) \\ \varepsilon_{it+1} &= \varepsilon_{it} + \sqrt{\varepsilon_{it}}\sigma_e u^\varepsilon_{it+1}, \quad u^\varepsilon_{it+1} \sim \mathcal{N}(0,1) \end{aligned}$$

In period 0 the initial state of the economy $(z_0, \mathbf{e}_o, \lambda_0^B)$ is determined. Period 1 is divided into two subperiods: At the beginning of period 1 there is news about the state of the economy $(u_1^z, \mathbf{u}_1^\varepsilon)$ and a series of correlated shocks to the composition of investors $\lambda_0^{\mathcal{B}}$. Shocks to $\lambda^{\mathcal{B}}$ can be interpreted as net fund flows that induce correlated demand shocks – a positive shock to λ^B represents a flow of capital from active funds into benchmarked funds who invest the inflows according to their benchmark. The distribution of shocks to investor composition is governed by a correlation matrix $\Omega_\lambda \in [0,1]^{|\mathcal{B}| \times |\mathcal{B}|}$ and a scale parameter σ_λ.

$$\lambda_1^{\mathcal{B}} = \lambda_0^{\mathcal{B}} + \sigma_\lambda \mathbf{u}_1^\lambda, \quad \mathbf{u}_1^\lambda \sim \mathcal{N}(\mathbf{0}, \Omega_\lambda)$$

In response to the realization of shocks in period 1 firm managers are given the opportunity to invest in expanding the operations of their firm by a scalar μ such that their final payout is equal to $\widehat{D}_{i2}(\mu) = (1+\mu)D_{i2}$. Investment incurs a constant per-unit cost μC that firm managers finance by issuing δ additional shares of equity worth $\delta \widehat{S}_{i1}(\mu) = \mu C$, where $\widehat{S}_{i1}(\mu)$ denotes the

[51] The common caveat applies that the term in the square root cannot be negative (see Backus et al., 2001, for further discussion.). We assume that starting values $(z_0, \mathbf{e}_o, \lambda_0^B)$ and magnitude of shocks are such that the probability of either process dropping below zero is negligible.

value of the firm post-investment. The covariance matrix of payoffs post-investment is given by $\widehat{\Sigma}_1(\mu) = Var_1\left((1+\mu e_i)D_2\right)$ where e_i denotes the i-th unit vector.

Asset prices and optimal investment with benchmarking As shown by Kashyap et al. (2021) benchmarking distorts asset prices and investment policies so that the CAPM no longer holds. Imposing market clearing yields stocks prices

$$S_t = \mathbb{E}_t\left[Y_{t+1}\right] - \gamma\Lambda_t\Sigma_t\Big(\mathbf{1} - \frac{c}{a+c}BMI_t\Big) \tag{24}$$

where $\gamma\Lambda_t = \gamma\left[1-\lambda_t^B + \lambda_t^B/(a+c)\right]^{-1}$ modifies the market's effective coefficient of risk aversion. Equation (24) can be rearranged to construct an expression for expected returns

$$\mathbb{E}_t\left[R_{it+1}\right] = \beta_{it}^{CAPM}\mathbb{E}_t\left[\mu_{t+1}^M\right] - \beta_{it}^{\mathcal{B}}\mathbb{E}_t\left[\mu_{t+1}^{\mathcal{B}}\right] \tag{25}$$

where $\mathbb{E}_1\left[\mu_{t+1}^M\right] = \gamma\Lambda_t Var_t(\sum_j R_{jt+1})$ and $\beta_{it}^{CAPM} = \frac{Cov_t(R_{it+1},\sum_j R_{jt+1})}{Var_t(\sum_j R_{jt+1})}$ denote the market risk premium and CAPM β of firm i. Equations (24) and (25) cleanly illustrate the key frictions of our model: The inelastic demand of benchmarked investors raises the price of benchmark constituent stocks and lowers expected returns moving forward by introducing a second benchmarking subsidy factor in expected returns with factor loadings $\beta_{it}^{\mathcal{B}} = \frac{Cov_t(R_{it+1},\sum_j BMI_{jt}R_{jt+1})}{Var_t(\sum_j BMI_{jt}R_{jt+1})}$ and a negative risk premium $\mathbb{E}_t\left[\mu_{t+1}^{\mathcal{B}}\right] = \frac{c}{a+c}\gamma\Lambda_t Var_t(\sum_j BMI_{jt}R_{jt+1})$. This distorts the textbook single-factor CAPM relationship between expected returns and market risk exposure that otherwise holds if there is no benchmarking ($c = 0$).

Proposition 1. *There is a benchmark inclusion subsidy that is increasing in benchmarking intensity and lowers the required return on investment for firms included in a benchmark index.*

As in standard investment models, the optimal investment policy is to invest if this increases firm value. This requires that the expected returns to investment are above a threshold $\underline{R}(BMI_{i1})$ that is decreasing in benchmarking intensity. In the limit, as $n \to \infty$, the optimal policy is to invest if the expected return per unit of investment $\mathbb{E}_1\left[D_{i2}\right] - C$ satisfies

$$\mathbb{E}_1\left[D_{i2}\right] - C > \beta_{i1}^{CAPM}\mathbb{E}_1\left[\mu_2^M\right]\left(1 - \frac{c}{a+c}BMI_{i1}\right) \tag{26}$$

Intuitively, the inelastic demand of benchmarked investors lowers Benchmarking gives managers of benchmark constituent firms an additional incentive to invest and lowers the required return on investment. The higher the benchmarking intensity of a firm, the larger the subsidy.

Asset prices and investment policy without benchmarking In the absence of benchmarking all assets are priced by fundamental investors and firm managers no longer need to take into account the inelastic demand of benchmarked investors. Without the benchmark inclusion subsidy the investment policy in (26) simplifies to a textbook CAPM investment policy: Firm managers should invest if

$$\mathbb{E}_1\left[D_{i2}\right] - C > \tilde{\beta}_{i1}^{CAPM} \mathbb{E}_1\left[\tilde{\mu}_2^M\right] \tag{27}$$

where $\tilde{\beta}_{i1}^{CAPM}$ and $\mathbb{E}_2\left[\tilde{\mu}_2^M\right]$ denote the CAPM β of firm i and the market risk premium in the absence of benchmarked investors.

Assumption 1. *Firm managers cannot observe their fundamental factor loading b_i or the level of the common factor z_t and assume that assets are priced by fundamental investors (the CAPM holds).*

This assumption represents the key behavioral friction of our model. As in practice, managers have limited information and cannot directly observe their fundamental risk exposure. Instead, they need to infer the required return on capital for their investment decisions, in the same way that practitioners use observable stock returns to infer their cost of equity.

Proposition 2. *If assets are priced by fundamental investors, firm managers can implement the CAPM-optimal investment policy in* (27) *without knowledge of their fundamental factor loading b_i or the* level *of the common factor z_t by observing the past covariance of stock returns with the market, $Cov_0\left(\tilde{R}_{i1}, \sum_j \tilde{R}_{j1}\right)$, growth in fundamentals $\frac{z_1}{z_0}$, and their idiosyncratic productivity $\varepsilon_{i0}, \varepsilon_{i1}$.*

In appendix B.1 we prove that there are terms[52] $A_{i1}(\frac{z_1}{z_0}, e_{i1}, e_{i0})$ and $\Gamma_1(\frac{z_1}{z_0})$ that allow to express the required return on investment in (27) as an affine function of the past covariance of returns with the market $Cov_0(\tilde{R}_{i1}, \sum_j \tilde{R}_{j1})$. Consequently, even a manager without knowledge of their own common factor loading b_i or the *level* of the common factor z_t can implement the investment policy in (27). They should invest if

$$\mathbb{E}_1\left[D_{i2}\right] - C > \gamma\Big[A_{i1} + \Gamma_1 Cov_0(\tilde{R}_{i1}, \sum_j \tilde{R}_{j1})\Big] \tag{28}$$

CAPM β and investment policy with benchmarked investors A first order approximation of prices with benchmarked investors S_1 in (24) around $\lambda_0^{\mathcal{B}}$ shows that up to $\mathcal{O}(\sigma_\lambda^2(u_1^\lambda)^2)$ returns

[52]Specifically, $A_{i1} = \sigma_\varepsilon^2 \varepsilon_{i1} - \frac{[1-\gamma\sigma_\varepsilon^2]\sigma_\varepsilon^2}{[1-\gamma\sigma_z^2]\sigma_z^2}\frac{z_1}{z_0}\varepsilon_{i0}$ and $\Gamma_1 = \frac{1}{(1-\gamma\sigma_z^2)}\frac{z_1}{z_0}$

R_{i1} have a linear multi-factor structure.

$$R_{i1} \approx const. + \phi_i^z \Delta z_1 + \sum_{B_k \in \mathcal{B}} \phi_{B_k(i)}^{\lambda} \Delta \lambda_1^{B_k} + \nu_{i1} \tag{29}$$

The first factor with factor loadings ϕ_i^z reflects shocks to economic fundamentals. The second set of factors with loadings $\phi_{B_k(i)}^{\lambda}$ reflects shocks to the relative demand of benchmarked investors, such as fund flows. The loadings on the second factor consist of a systemic term that is independent of benchmark membership, and a benchmark-specific term that is increasing in benchmarking intensity.

Proposition 3. *Benchmarking shifts the distribution of CAPM βs and increases the variance of the market. An increase in benchmarking intensity raises (lowers) the CAPM β of benchmark constituents (non-constituents).*

Under the factor structure in (29) the CAPM β of a stock is equal to

$$\beta_{i0}^{CAPM} = \frac{Cov_0\left(\phi_i^z \Delta z_1 + \sum_k \phi_{B_k(i)}^{\lambda} \Delta \lambda_1^{B_k} + \nu_{i1}, \sum_j \phi_j^z \Delta z_1 + \sum_k \phi_{B_k(j)}^{\lambda} \Delta \lambda_1^{B_k} + \nu_{j1}\right)}{Var_0\left(\sum_j \phi_j^z \Delta z_1 + \sum_k \phi_{B_k(j)}^{\lambda} \Delta \lambda_1^{B_k} + \nu_{j1}\right)} \tag{30}$$

The introduction of a second factor that reflects the correlated demand shocks of benchmarked investors increases the variance of the market in the denominator for all stocks equally. However, the covariance term in the numerator varies with stocks benchmarking intensity. Benchmarking raises the covariance with the market for *all* stocks, but it has a larger effect for stocks with higher benchmarking intensities. On net, the CAPM β of stocks with the highest benchmarking intensity increases, while the CAPM β of stocks with lower benchmarking intensity decreases.[53]

Corollary 3.1. *All else equal, if firm managers pursue the CAPM-optimal investment policy in (28), compared to a setting without benchmarking i) all firms underinvest; ii) a firm inside the benchmark underinvests more than an otherwise identical firm outside the benchmark.*

If the CAPM holds firm managers can use the past covariance of stock returns with the market to implement the CAPM-optimal investment policy. The introduction of additional factors that amplify comovement, such as the demand of benchmarked investors, is perceived by firm managers as an increase on the required return on investment and induces them to under-invest relative to the CAPM. Because comovement increases more strongly for benchmark constituent stocks, this effect is particularly pronounced for stocks with high benchmarking intensity.

[53]By construction, the average CAPM β is constant and equal to 1.

B.1 Proofs

Combining the expressions for fundamental and benchmarked investor demand in (22) and (23) and imposing market clearing yields the expression for prices in (24). The aggregate demand of benchmarked and fundamental investors is equal to

$$\sum_{b\in\mathcal{B}} \lambda_t^B x_t^B + (1-\lambda_t^B)x_t^D = \Sigma^{-1}\left(1-\lambda_t^B+\frac{\lambda_t^B}{a+c}\right)\frac{\mathbb{E}_t\left[Y_{t+1}\right]-S_t}{\gamma} + \sum_{B_k\in\mathcal{B}}\frac{c}{a+c}\mathbf{1}_{B_k} \tag{31}$$

Imposing market clearing yields the expression for prices in (24).

Proposition 1. The total value of the firm post-investment is equal to

$$(1+\delta)\widehat{S}_{i1}(\mu) = (1+\mu)\mathbb{E}_1\left[D_{i2}\right] - \gamma\Lambda_1 e_i'\widehat{\Sigma}(\mu)\left(\mathbf{1}-\frac{c}{a+c}BMI_1\right)$$

which means that the change in firm value from investment is

$$\Delta\widehat{S}_{i1}(\mu) = \mu\left(\mathbb{E}_1\left[D_{i2}\right]-C\right) - e_i'\gamma\Lambda_1\left[\widehat{\Sigma}_1(\mu)-\Sigma_1\right]\left(\mathbf{1}-\frac{c}{a+c}BMI_{i1}\right)$$

Investment is profitable if a marginal unit of investment increases firm value, which requires that $\frac{\partial\Delta\widehat{S}_{i1}(0)}{\partial\mu} > 0$. This implicitly defines a lower bound on the required return on investment $\underline{R}(BMI_{i1})$ equal to

$$\mathbb{E}_1\left[D_{i2}\right] - C > \gamma\Lambda_1 \underbrace{\left[(b'\mathbf{1}b_i + b_i^2)z_1\sigma_z^2 + 2\sigma_\varepsilon^2\varepsilon_{i1}\right]}_{=Cov_1\left(R_{i2},\sum_j R_{j2}\right)+Var_1(R_{i2})}\left(1-\frac{c}{a+c}BMI_{i1}\right) = \underline{R}(BMI_{i1})$$

To derive the limit result in (26) we consider a sequence of economies indexed by the number of firms n and investors' coefficient of absolute risk aversion $\gamma(n) = \frac{\gamma}{n}$ that scales with the size of the economy.[54] Firms' factor loadings b_i are drawn from a distribution $F(b)$ with positive support, finite variance and mean $\mu(b)$. As $n\to\infty$ the threshold on the right hand side converges to

$$\lim_{n\to\infty}\underline{R}(BMI_{i1}) = \beta_{i1}^{CAPM}\mathbb{E}_1\left[\mu_2^M\right]\left(1-\frac{c}{a+c}BMI_{i1}\right)$$

[54] This ensures that if we were to duplicate an economy with n firms the price of each firm is unaffected.

where

$$
\begin{aligned}
\beta_{i1}^{CAPM} &= \lim_{n\to\infty} \frac{\frac{1}{n}Cov_1(R_{i2}, \sum_j R_{j2})}{\frac{1}{n}Var_1(\sum_j R_{j2})} = \frac{b_i\mu(b)\sigma_z^2 z_1}{\mu(b)^2\sigma_z^2 z_1} \\
\mathbb{E}_1\left[\mu_2^M\right] &= \lim_{n\to\infty} \gamma(n)\Lambda_1 Var_1(\sum_j R_{j2}) = \gamma\Lambda_1\mu(b)^2\sigma_z^2 z_1
\end{aligned}
$$

Proposition 2. If there is no benchmarking assets are priced by fundamental investors with mean-variance preferences and prices simplify to a standard textbook solution.

$$
\tilde{S}_t = \mathbb{E}_t\left[\tilde{Y}_{t+1}\right] - \gamma Var_t\left(\tilde{Y}_{t+1}\right)\mathbf{1} \tag{32}
$$

Rearranging (32) yields the textbook expression for the CAPM (in absolute returns):

$$
\mathbb{E}_t\left[R_{it+1}\right] = \underbrace{\frac{Cov_t(\tilde{Y}_{it+1} - \tilde{S}_{it}, \sum_j \tilde{Y}_{jt+1} - \tilde{S}_{jt})}{Var_t\left(\sum_j \tilde{Y}_{jt+1} - \tilde{S}_{jt}\right)}}_{=\tilde{\beta}_{it}^{CAPM}} \underbrace{\gamma Var_t\left(\sum_j \tilde{Y}_{jt+1} - \tilde{S}_{jt}\right)}_{=\mathbb{E}_t\left[\tilde{\mu}_{t+1}^M\right]}
$$

The optimal investment policy without benchmarking follows directly from (26) and setting $\lambda^B = 0$. In order to implement the investment policy in (27) it is sufficient for managers to have knowledge of $Cov_1(\tilde{R}_{i2}, \sum_j \tilde{R}_{j2}) = \tilde{\beta}_{i1}^{CAPM}\mathbb{E}_1\left[\tilde{\mu}_2\right]$ as opposed to both $\tilde{\beta}_{i1}^{CAPM}$ and $\mathbb{E}_1\left[\tilde{\mu}_2\right]$. In order to express $Cov_1(\tilde{R}_{i2}, \sum_j \tilde{R}_{j2})$ as an affine function of $Cov_0(\tilde{R}_{i1}, \sum_j \tilde{R}_{j1})$ note that if assets are priced by fundamental investors time 1 and time 0 prices are

$$
\begin{aligned}
S_1 &= bz_1 + \varepsilon_1 - \gamma\Sigma_1\mathbf{1} \\
S_0 &= b(1 - \gamma\sigma_z^2)z_0 + \varepsilon_0(1 - \gamma\sigma_\varepsilon^2) - \gamma\Sigma_0\mathbf{1}
\end{aligned}
$$

where $\Sigma_1 = bb'\sigma_z^2 z_1 + \sigma_\varepsilon^2 Diag(\varepsilon_1)$ and $\Sigma_0 = bb'\left(1 - \gamma\sigma_z^2\right)\sigma_z^2 z_0 + \left(1 - \gamma\sigma_\varepsilon^2\right)\sigma_\varepsilon^2 Diag(\varepsilon_0)$. The conditional covariance of returns with the market in each period is equal to

$$
\begin{aligned}
Cov_1(D_{i2} - S_{i1}, \sum D_{j2} - S_{j1}) &= \sigma_z^2 b'\mathbf{1}b_i z_1 + \sigma_\varepsilon^2\varepsilon_{i1} \\
Cov_0(S_{i1} - S_{i0}, \sum S_{j1} - S_{j0}) &= \left[1 - \gamma\sigma_z^2\right]\sigma_z^2 b'\mathbf{1}b_i z_0 + \left[1 - \gamma\sigma_\varepsilon^2\right]\sigma_\varepsilon^2\varepsilon_{i0}
\end{aligned}
$$

Rearranging and pre-multiplying the second line by $\frac{z_1}{z_1}$ illustrates that the time 1 covariance of future returns can be expressed in terms of the past covariance of stock returns with the market, $Cov_0\left(S_{i1} - S_{i0}, \sum_j S_{j1} - S_{j0}\right)$, growth in the common factor $\frac{z_1}{z_0}$, and idiosyncratic productivity

$\varepsilon_{i0}, \varepsilon_{i1}$:

$$Cov_1(D_{i2} - S_{i1}, \sum_j D_{j2} - S_{j1}) = A_{i1} + \Gamma_1 Cov_0(S_{i1}, \sum_j S_{j1}) \tag{33}$$

where

$$\begin{aligned} A_{i1} &= \sigma_\varepsilon^2 \varepsilon_{i1} - \frac{[1-\gamma\sigma_\varepsilon^2]\sigma_\varepsilon^2}{[1-\gamma\sigma_z^2]\sigma_z^2}\frac{z_1}{z_0}\varepsilon_{i0} \\ \Gamma_1 &= \frac{1}{(1-\gamma\sigma_z^2)}\frac{z_1}{z_0}. \end{aligned}$$

Proposition 3. Given the expression for period 1 prices in (24) we can express S_{i1} as an affine function of z_1 and ε_{i1}

$$S_{i1} = \Theta_z(\lambda_1^{\mathcal{B}}) b_i z_1 + \Theta_\varepsilon(\lambda_1^{\mathcal{B}})\varepsilon_{i1}$$

with coefficients $\Theta_z(\lambda_1^{\mathcal{B}})$, $\Theta_{\varepsilon i}(\lambda_1^{\mathcal{B}})$ equal to

$$\begin{aligned} \Theta_z(\lambda_1^{\mathcal{B}}) &= 1 - \gamma\Lambda(\lambda_1^{\mathcal{B}})\sigma_z^2\left(1 - \frac{c}{a+c} b' BMI_1(\lambda_1^{\mathcal{B}})\right) \\ \Theta_{\varepsilon i}(\lambda_1^{\mathcal{B}}) &= 1 - \gamma\Lambda(\lambda_1^{\mathcal{B}})\sigma_\varepsilon^2\left(1 - \frac{c}{a+c} BMI_{1i}(\lambda_1^{\mathcal{B}})\right) \end{aligned}$$

A first order Taylor approximation of S_{i1} around λ_0^B shows that up to order $\mathcal{O}(\sigma_\lambda^2(u_1^\lambda)^2)$

$$\begin{aligned} S_{i1} &\approx [\Theta_z(\lambda_0^{\mathcal{B}}) + (\Delta\lambda_1^{\mathcal{B}})^T\nabla_\lambda^z] b_i (z_0 + \Delta z_1) + [\Theta_{\varepsilon i}(\lambda_0^{\mathcal{B}}) + (\Delta\lambda_1^{\mathcal{B}})^T\nabla_\lambda^{\varepsilon i}](\varepsilon_{i0} + \Delta\varepsilon_{i1}) \\ \text{with } \nabla_\lambda^z(\lambda_0^{B_k}) &= \gamma\Lambda_0\sigma_z^2\left[\frac{c}{a+c} b'\mathbf{1}_{B_k} - \Lambda_0\left(1 - b'\frac{c}{a+c}BMI_0\right)\left(1 - \frac{1}{a+c}\right)\right] \\ \nabla_\lambda^{\varepsilon i}(\lambda_0^{B_k}) &= \gamma\Lambda_0\sigma_\varepsilon^2\left[\frac{c}{a+c}\mathbf{1}_{B_k}(i) - \Lambda_0\left(1 - \frac{c}{a+c}BMI_{0i}\right)\left(1 - \frac{1}{a+c}\right)\right] \end{aligned}$$

which means that for small values of σ_λ^2 returns $S_{i1} - S_{i0}$ have a linear multi-factor structure in fundamental shocks Δz_1 and fund flows $\Delta\lambda_1^{B_k}$

$$S_{i1} - S_{i0} \approx const. + \ \phi_i^z \Delta z_1 + \sum_k [\phi_{k,S(i)}^\lambda + \phi_{k,B(i)}^\lambda]\Delta\lambda_1^{B_k} + \nu_{i1} \tag{34}$$

with factor loadings ϕ_i^z and $\sum_k [\phi_{k,S(i)}^\lambda + \phi_{k,B(i)}^\lambda]$.

$$\phi_i^z = b_i \left(1 - \gamma\Lambda(\lambda_0^{\mathcal{B}})\sigma_z^2 \left(1 - \frac{c}{a+c} b' BMI_0\right)\right)$$

$$\phi_{k,S(i)}^\lambda = \gamma\Lambda_0 \left\{ \frac{c}{a+c} \left[b'\mathbf{1}_{B_k} + \Lambda_0 \left(1 - \frac{c}{a+c} b' BMI_0\right)\right] b_i z_0 \sigma_z^2 - \Lambda_0 \left(1 - \frac{c}{a+c}\right) \left(b_i z_0 \sigma_z^2 + \varepsilon_{i0}\sigma_\varepsilon^2\right) \right\}$$

$$\phi_{k,B(i)}^\lambda = \gamma\Lambda_0 \left\{ \frac{c}{a+c} \left[b'\mathbf{1}_{B_k}(i) + \Lambda_0 \left(1 - \frac{c}{a+c}\right) BMI_{0i}\right]\right\} \varepsilon_{i0}\sigma_\varepsilon^2$$

Benchmarking not only introduces a second factor but also changes the loadings on the fundamental factor. Plugging these expressions into the CAPM β that an econometrician would estimate yields

$$\begin{aligned}\beta_{i0}^{CAPM} &= \frac{Cov_0\left(\phi_i^z \Delta z_1 + \sum_k [\phi_{k,S(i)}^\lambda + \phi_{B_k(i)}^\lambda]\Delta\lambda_1^{B_k} + \nu_{i1}, \sum_j \phi_j^z \Delta z_1 + \sum_k [\phi_{k,S(j)}^\lambda + \phi_{B_k(j)}^\lambda]\Delta\lambda_1^{B_k} + \nu_{j1}\right)}{Var_0\left(\sum_j \phi_j^z \Delta z_1 + \sum_k [\phi_{k,S(j)}^\lambda + \phi_{B_k(j)}^\lambda]\Delta\lambda_1^{B_k} + \nu_{j1}\right)} \\ &= \frac{\phi_i^z (\mathbf{1'}\phi^z)\sigma_z^2 + [\phi_{S(i)}^\lambda + \phi_{B(i)}^\lambda]'\Omega_\lambda [\phi_S^\lambda + \phi_B^\lambda]\sigma_\lambda^2 + \sigma_{\nu,i}^2}{(\mathbf{1'}\phi^z)^2\sigma_z^2 + [\phi_S^\lambda + \phi_B^\lambda]'\Omega_\lambda [\phi_S^\lambda + \phi_B^\lambda]\sigma_\lambda^2 + \sum_j \sigma_{\nu,j}^2}\end{aligned}$$

Compared to a setting without benchmarked investors we observe that

1. The covariance of all stocks with the market increases
2. The covariance of stocks inside a benchmark index increases additionally by $\beta_{ik}^{\lambda_k,i}$
3. The variance of the market increases
4. A shift in initial exposure to investor composition shocks $\Delta\lambda_1^B$, for example due to adding an additional index or an increase in c shifts the initial cross-section of β_{i0}^{CAPM}.

C Simulated CAPM βs in a Two-Factor Model

This appendix uses a simulation to show that the emergence of a passive flow factor can explain the evolution of CAPM $\hat{\beta}$s between 1998 and 2018. We specify a parsimonious two-factor model where stock returns depend on: (1) a fundamental factor derived from macro-financial variables, with loadings fixed to the pre-benchmarking era (May 1990), and (2) a flow factor constructed from passive fund flows, with exposures proportional to stocks' benchmarking intensity.

The simulation yields three key findings: (i) The model successfully replicates both the cross-sectional distribution and time-series evolution of empirical CAPM $\hat{\beta}$s. (ii) Calibrating the model with actual passive fund flows accurately reproduces the observed conditional covariance structure and time series of $\hat{\beta}$s. (iii) In contrast, a model using active fund flows fails to match these empirical patterns, especially after 2003.

Model Suppose excess returns on stock i obey the following factor structure

$$R_{i,t+1} - R_t^f = a_{i,t} + b_{i,t}\lambda_{t+1} + u_{i,t+1} \tag{35}$$

where $\lambda_{t+1} = (z_{t+1}\ f_{t+1})'$ denotes "fundamental" and flow factors, and $(b_{it}^1\ b_{it}^2)$ denotes the loadings on the factors where b_{it}^2 is proportional to the benchmarking intensity of stock i. The covariance structure of the factors Σ_λ may contain positive off-diagonal elements, the covariance structure of idiosyncratic shocks Σ_u does not.

An econometrician estimating the CAPM β of a stock as $\hat{\beta} = \frac{Cov_t(R_{i,t+1}, R_{m,t+1})}{Var_t(R_{m,t+1})}$ where $R_{m,t+1} = \sum_j w_{j,t} R_{j,t+1}$ denotes the market capitalization weighted average return on the universe of securities j. Plugging (35) into the CAPM β formula, one finds that

$$\begin{aligned}
\hat{\beta}_{it} &= \frac{Cov_t\left(b_{i,t}\lambda_{t+1} + u_{i,t+1}, \sum_j w_{jt}\left(b_{j,t}\lambda_{t+1} + u_{j,t+1}\right)\right)}{Var_t\left(\sum_j w_{jt}(b'_{j,t}\lambda_{t+1} + u_{j,t+1})\right)} \\
&= \frac{w'_t b_t \Sigma_\lambda b'_t e_i + w_{i,t}\sigma^2_{u,i}}{w'_t b_t \Sigma_\lambda b'_t w_t + w'_t \Sigma_u w_t}
\end{aligned} \tag{36}$$

where e_i denotes the i-th unit vector.

To replicate Figure 1 in our simulation, we simulate Eq. (36) using the conditional means of CAPM $\hat{\beta}s$ across market capitalization ranks rather than individual stocks $\hat{\beta}_{it}$. We model conditional means of CAPM $\hat{\beta}$ and BMI as flexible fifth-order polynomial functions of market capitalization ranks.[55] We then compare the simulated conditional means to the empirical conditional means of CAPM $\hat{\beta}$s across market capitalization ranks. To evaluate model fit, we compute root mean square error (RMSE) and Spearman rank correlations in each cross-section. Finally, we examine various model calibrations to assess how the flow factor and covariance structure between factors affect the simulation outcomes.

Baseline Calibration To simulate Eq. (36), we need estimates of the factor loadings b_t, factor covariance matrix Σ_λ, idiosyncratic variances Σ_u, and weights w_{it}.

We start by calibrating b_t. We fix the fundamental factor exposures to $b^1_{it} =$ CAPM $\hat{\beta}_{i1990m5}\ \forall\, t$. This ensures that time-variation in our simulated CAPM $\hat{\beta}$s is driven by exposure to the flow factor. We specify the flow factor loadings as proportional to the stock's benchmarking intensity : $b^2_{it} \propto \text{BMI}_{it}$. This reflects our hypothesis that stocks with higher benchmarking intensity experience greater exposure to benchmark-driven capital flows. The proportionality constant is difficult to precisely determine empirically. However, Table 3 provides evidence that net flows into passive funds predict changes in CAPM $\hat{\beta}$s. We thus set the proportionality constant to 0.3, matching the coefficient of the BMI-passive flow interaction term from Column 5 of Table 3.

We next calibrate the factor covariance matrix, Σ_λ. To do so, we first need to specify what the fundamental factor and flow factor are. We proxy the fundamental factor using the first principal component (PC) derived from various macro-financial variables: log changes in industrial production (Cochrane, 1991), the 3-month Treasury bill rate (Bernanke & Kuttner, 2005), unemployment rate (Kilic & Wachter, 2018), WTI oil price (Kilian & Park, 2009), the University of Michigan consumer sentiment index (Baker & Wurgler, 2006), and the consumer price index (Campbell & Ammer, 1993). The first PC explains 39.2% of the variation in these variables between 1990 and 2024. We scale the PC by 10^{-1} to align its scale to the $\hat{\beta}$s from May 1990.[56]

We specify the flow factor as net flows into passive mutual funds and ETFs, scaled by their total net assets. We compare the net flows into passive funds with net flows into active funds to determine whether flows in general or passive flows in particular drive changes in CAPM $\hat{\beta}$s. We estimate each component of the factor covariance matrix using 60-month rolling windows,

$$\widehat{\Sigma}_{\lambda,t} = \begin{pmatrix} \widehat{\sigma}^2_{z,t} & \widehat{\rho}_{zf,t}\widehat{\sigma}_{z,t}\widehat{\sigma}_{f,t} \\ \widehat{\rho}_{zf,t}\widehat{\sigma}_{z,t}\widehat{\sigma}_{f,t} & \widehat{\sigma}^2_{f,t} \end{pmatrix},$$

and set $\sigma_{u,it} = 0.07\ \forall\, i, t$.

[55] Specifically, we the estimate conditional means each month as $y_i = \gamma_0 + \sum_{j=1}^{5} \gamma_j (\text{ME rank}_i)^j + \varepsilon$.

[56] Using changes in industrial production or the excess return on the market itself as the factor yields similar results.

Table C13: Model Evaluation – RMSE and Rank Correlation

	RMSE		Rank Correlation		Monthly
Model Calibration	Passive Flows	Active Flows	Passive Flows	Active Flows	Obs.
Baseline	**0.162**	**0.294**	**0.49**	**-0.02**	**249**
Full Sample $\widehat{\Sigma}_\lambda$	0.161	0.273	0.48	0.05	249
Fixed Weights ($w_{it} = w_{i1990m5}\ \forall i$)	0.159	0.286	0.49	-0.02	249
Flow Factor Off ($\sigma_f = 0$)	0.531	0.531	-0.07	-0.07	249

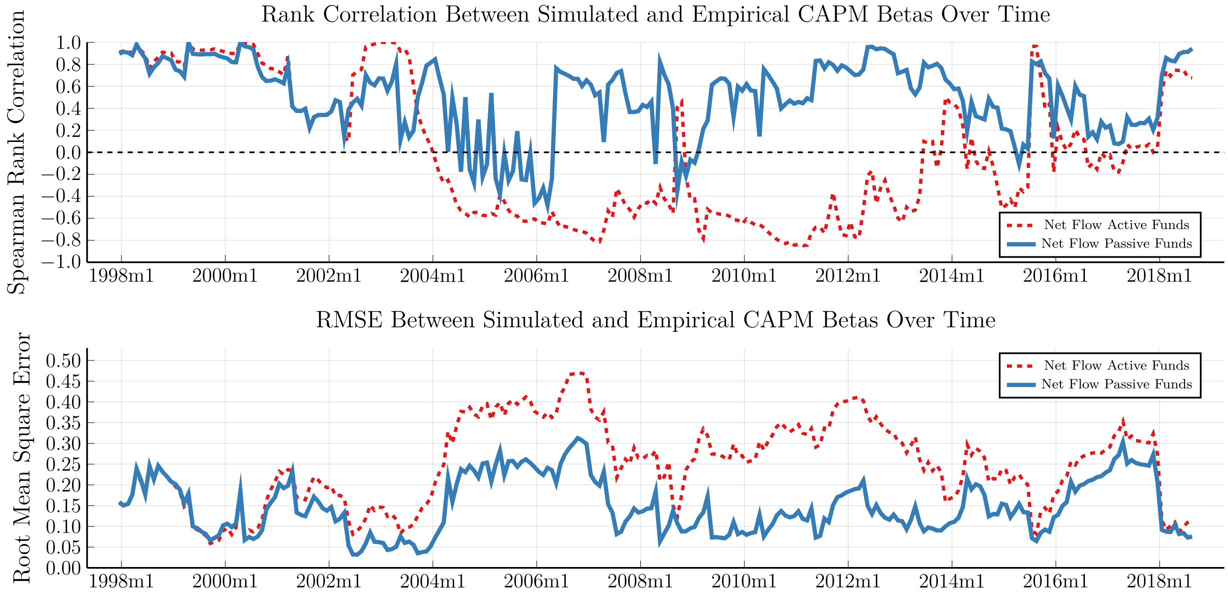
Notes: This table reports the average root mean square error (RMSE) and Spearman rank correlation between simulated and empirical CAPM $\hat{\beta}$s from January 1998 to September 2018. Each month, we simulate conditional means of CAPM $\hat{\beta}$ across market capitalization ranks and compare them with empirical conditional means. We report results for calibrations using active and passive net flows under different model configurations.

Results Our simulation yields three key insights: (i) Introducing a flow factor, whose loadings are proportional to benchmarking intensity, explains both the cross-sectional distribution and the temporal evolution of CAPM $\hat{\beta}$s from 1998 to 2018. (ii) Calibrating the flow factor using passive net flows allows us to match the observed cross-section and time-series of CAPM $\hat{\beta}$s. (iii) In contrast, calibration using active fund flows fails to reproduce these observed conditional moments. These findings support our hypothesis that passive flows are a key driver behind the observed increases in CAPM $\hat{\beta}$s.

Table C13 reports the average RMSE and Spearman rank correlations between simulated and empirical CAPM $\hat{\beta}$s for each month from January 1998 to September 2018. Comparisons across model calibrations highlight that active fund flows yield RMSE nearly twice as large as those from passive flows. The baseline calibration has an average RMSE of 0.16 (passive) versus 0.29 (active). Additionally, simulated cross-sectional distributions of CAPM $\hat{\beta}$s correlate strongly with actual distributions when calibrated to passive flows (avg. correlation of 0.49), whereas correlations using active flows are close to zero. Comparing different model specifications, results for passive flows remain robust. Eliminating the flow factor ($\sigma_f = 0$) worsens model performance, increasing RMSE dramatically and implies negative correlations between simulated and observed $\hat{\beta}$s. Figure C16 shows the time-series evolution of rank correlations and RMSE between simulated and empirical CAPM $\hat{\beta}$s from 1998 to 2018. The passive-flow calibration consistently outperforms the active-flow calibration, particularly after 2007. This aligns with Table 3, which indicates a stronger correlation between passive flows, benchmarking intensity, and $\hat{\beta}$s post-2010.

Figure C17 illustrates our two-factor model's ability to replicate CAPM $\hat{\beta}$ evolution across market capitalization ranks from 2000 to 2018. The solid blue line represents simulated conditional means, while the dashed red line shows empirical conditional means of CAPM $\hat{\beta}$s. Despite its simplicity, the model successfully captures key empirical patterns in the data. It is able to repli-

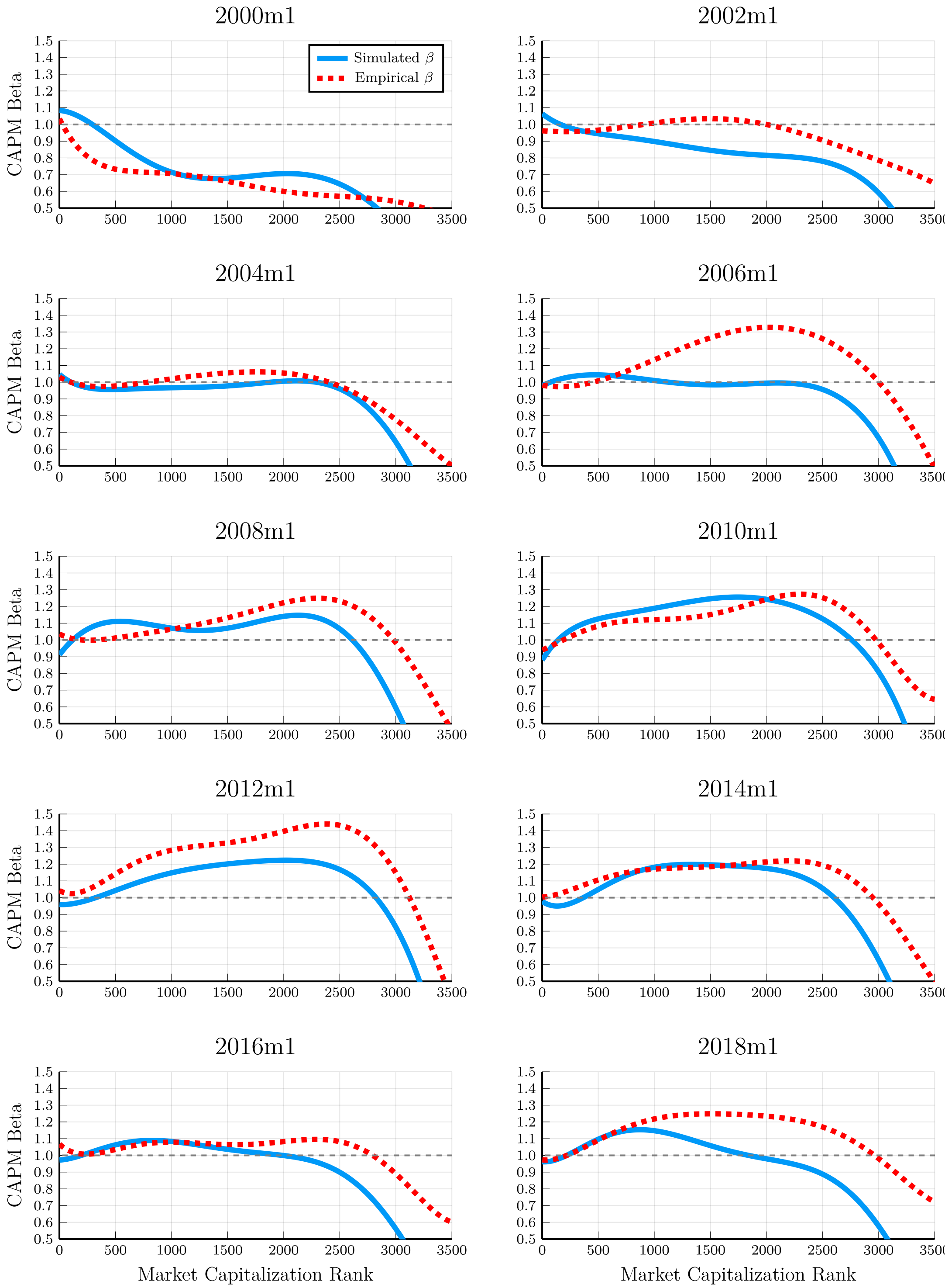
Figure C16: Time Series of Correlation and RMSE Between Simulated and Empirical CAPM $\hat{\beta}$s



Notes: This figure plots Spearman rank correlation and root mean square error between the empirical and simulated conditional means of CAPM $\hat{\beta}s$ from 2000 to 2018. Solid blue lines are report results from a calibration using net flows into *passive* mutual funds and ETFs. Dashed red lines are report results from a calibration using net flows into *active* mutual funds.

cate the cross-sectional distribution well. Moreover, the model is able to replicate the time-series increase in CAPM $\hat{\beta}$s across market capitalization ranks from 2000 to 2018.

Figure C17: Simulated and Empirical CAPM $\hat{\beta}$s Across Market Capitalization Ranks



Notes: This figure plots the empirical and simulated conditional means of CAPM $\hat{\beta}s$ from 2000 to 2018. We calibrate the flow factor to the net flows into passive mutual funds and ETFs. Dashed red line is the conditional mean of the empirical distribution across market capitalization ranks. Solid blue line is the conditional mean of the simulated distribution across market capitalization ranks.

D Qualitative Evidence from Earnings Call Transcripts

This appendix presents qualitative evidence from earnings calls on how corporate executives discuss Russell benchmark inclusion and their use of the CAPM to estimate the cost of equity.

D.1 Executives Commenting on Russell Benchmark Inclusion

To understand how corporate executives frame the importance of benchmark inclusion, we analyze earnings call transcripts from Capital IQ (via WRDS) between 2008 and 2024. Our search for terms related to Russell reconstitution yields 165 unique transcripts.[57] After excluding one transcript from the London Stock Exchange Group (owner of the Russell brand) and two from BlackRock (discussing index products), our sample consists of 163 transcripts. We classify these transcripts into four mutually exclusive categories based on the context of the mention. To ensure a conservative classification, we assign transcripts sequentially based on the following hierarchy:

1. **Equity Offerings (*5 transcripts*):** Discussion of an at-the-market, seasoned equity, follow-on, shelf takedown, or other equity offering associated with inclusion.
2. **Liquidity (*26 transcripts*):** Mention of increased stock liquidity or trading volume.
3. **Visibility (*34 transcripts*):** Reference to increased visibility or a broader investor base.
4. **Passing Mention (*98 transcripts*):** A brief statement of inclusion with no further context.

This analysis shows that executives rarely link Russell benchmark inclusion to capital-raising activities. Only 3% of transcripts mention equity offerings associated with the reconstitution. In contrast, the most common context is a passing mention (60% of cases), where the managers note inclusion as a recent corporate achievement without further elaboration. For example,

> "Top line data from our PEDFIC-1 Phase III trial is expected at the end of 2019 or early 2020. **And finally, we were selected for inclusion in the Russell 2000 Index Russell as part of the annual reconstitution of the Russell stock indexes.** And with that, let me turn the call back over to Ron for some concluding remarks."
>
> — CFO, Albireo Pharma Inc. (Q2 2018)

> "The first half of this year has been extremely productive, and we are driving continued progress, sustainable and profitable growth as a leader and the disruptor of the B2B e-commerce technology solution. **We were honored to be added to the Russell 2000 Index through their recent reconstitution**. Now I will turn the call over to Iman to provide more color and – on our operational highlights."
>
> — CEO, GigaCloud Technology Inc. (Q2 2024)

[57] We query: "russell+index+inclusion+(1000|2000|3000)" and "russell+index+reconstitution+(1000|2000|3000)."

In 26 instances, executives connect the benchmark inclusion to expected or realized improvements in stock liquidity and trading volume. For example,

> "All this happened while we were distracted by hurricanes, wildfires and mudslides. In addition, **we were relisted on the Russell 2000 Index, increased our average daily share volume by over 200%** and outperformed both our peers and the S&P 500. For the full year 2017, our revenue was up 39% [...]"
>
> —CEO, Sterling Construction Company (Q4 2017)

> "Before we move into our financial results, I want to quickly update you on some exciting corporate developments. First, we were notified in the end of June that **we were added to the Russell 3000 and Russell Global Indexes as part of Russell Investments' annual reconstitution**. We always prioritize building shareholder value and **we hope that this inclusion may improve general liquidity in our stock.** We also announced last week some changes to our Board of Directors [...]"
>
> — President, BioSpecifics Technologies Corp (Q2 2014)

A third prominent theme, found in 34 transcripts, is the belief that benchmark inclusion serves as a catalyst for increased corporate visibility. For example,

> "As you may have seen in June, we have been added to the Russell 2000 index at the conclusion of the indexes' annual reconstitution. We are proud to have come this far as a public company and expect this new index addition to provide **increased awareness to the broader investment community going forward."**
>
> —CEO, StarTek, Inc. (Q2 2019)

> "Working with our leadership team Carol will implement our company's strategic initiatives and increase operational execution across all our business channels. And **we are very pleased to rejoin the Russell 2000 index following a reconstitution on June 24. We believe this addition will bring additional visibility to our company and our strategic initiatives.** Now I'd like to turn the call over to David C., to provide more details on our financial performance for the second quarter."
>
> — CEO, Hickory Tech Corp. (Q2 2011)

D.2 Executives Referencing The CAPM to Calculate Cost of Equity

We perform a similar analysis and search earnings call transcripts from Capital IQ for mentions of "capital asset pricing model" or "CAPM." Corporate executives frequently reference the CAPM in response to analysts' questions about their firm's cost of equity and capital budgeting decisions:

> "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. [...] this is really how we view our weighted average 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, LKQ Corp. (Q1 2016)

> "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)

> "And for those of us that took financial classes, undergrad or graduate, we all understand **CAPM** and WACC and so on and so forth, and we've done a good job, we believe, of managing our capital structure to minimize our cost of capital."
>
> — CFO, L Brands (Q4 2016)

> "This is our way of calculating the cost of equity. So this is very textbook like **CAPM** type of methodology. We start with the risk-free rate [...]. Then we look at the group's beta."
>
> — CFO, Talanx (Q4 2019)

> "If you don't push your ROE target up when interest rates go up, and that's for every company to decide, it depends if you believe in the **capital asset pricing model** or not. I won't take you back to school. [...] I think you should [expect a higher ROE]."
>
> — CFO, Intact Financial (Q3 2024)

> "So the investment is about $240 million. We expect to project finance the deal so we will be, I think, around $130 million equity investment. [...] I'm not going to get in to what our cost of capital is but most people can probably — I mean everybody knows **CAPM** and can kind of back into what it is."
>
> — CEO, Vistra Energy (Q1 2017)

> "Looking at WACC, we have both an equity component and a debt component. On the equity component, we calculate cost of equity using the **capital asset pricing model** using historical data and market risk premiums. Our current cost of equity is running around 9%."
>
> — CFO, Archer Daniels Midland (Q1 2012)

> "From a cost of capital perspective, we update our cost of capital estimates monthly. So yes, there are changes that go on a monthly basis looking at interest rates and looking at local country risk, as well as betas and all of the things that go into kind of the **CAPM** model."
>
> — CEO, American Tower Corp. (Q4 2013)

“We haven’t historically disclosed our cost of equity, but it’s actually fairly straightforward calculation from a **CAPM** model, so in terms of where we’re coming out. But I think from that, you’re going to get around a 10%-ish type range cost.”

— CEO, E-Trade (Q1 2016)

“So the way I think about and we think about our cost of capital is, it’s our long-term weighted average cost of capital. And with a balance sheet that’s about a 75% equity, 25% debt spread. When you do a sort of a **capital asset pricing model** analysis of what is Camden’s cost of capital, it’s slightly higher than 6%.”

— CEO, Camden (Q4 2019)

“Basically, we — across the portfolio, we apply hurdle rates based on market data and applying the usual **capital asset pricing model**, so we have specific targets.”

— CFO, CLP Holdings (Q1 2022)

“We’ve also made progress on our weighted average cost of capital primarily through our refinancing, which resulted in about an 80-basis-point reduction in our weighted average cost of capital. In measuring that, we used kind of the classic **CAPM** type of calculation, which I’m sure we’re all familiar with.”

— CFO, Dynegy Inc. (Q1 2014)

“We estimate our cost of capital using a **CAPM** pricing model both on debt and equity, in a pretty traditional model. And we come up to about a 12% cost of capital.”

— CEO, Eclipse Resources (Q1 2018)

“We’ve done analysis, and we’ve looked at a **CAPM** pricing model. We’ve looked at our WACC curve.”

— Assistant Treasurer, Iron Mountain Inc. (Q2 2016)

“I know a year ago when I did the **capital asset pricing model** figure at our cost of equity it was about 13%.”

— CEO, Pinnacle Entertainment (Q4 2007)

“[...] to determine the equity costs, there are no binding regulations or standards, but there is a number of different methodologies that can result in different results. Based on the so-called **capital asset pricing model**, we, at present, see our equity costs at group level at around 10% after tax.”

— CFO, Deutsche Bank (AGM 2021)

“I mean we look at our cost of capital every quarter. We use **CAPM**. When we ran it at the balance sheet date it’s about 6.2%”

— CFO, Great Portland (Q2 2019)

E Other Measures of Perceived Cost of Equity

This section outlines alternative measures of the perceived cost of equity. We use these measures to validate our main result that the perceived cost of capital rises with benchmarking. Specifically, we show that benchmarking-induced changes in a stock's CAPM $\hat{\beta}$ translate into higher perceived costs of equity reported by stock analysts and by regulators of public utilities and railroads.

E.1 Stock Analysts' Perceived Cost of Equity

We collect stock analysts' perceived cost of equity from three independent research providers: I/B/E/S, Morningstar, and Value Line. These firm sell their reports and advice to investors, creating an incentive to assign cost of equity that match investors' perceptions of a stock's risk. However, the providers use different methodologies to estimate the cost of equity which provides us with independent variation which we exploit to corroborate our main finding.

Morningstar Analysts' Cost of Equity We obtain Morningstar analysts' cost of equity directly from Morningstar Direct for the period from 2001 to 2018 for stocks in Morningstar's coverage universe listed on the NYSE, NASDAQ, and Amex. Morningstar's cost of equity consists of a common risk-free rate and a stock-specific risk premium, which reflects the stock's systematic risk as qualitatively assessed by an analyst. This approach means that cross-sectional variation in the cost of equity depends solely on Morningstar's perception of systematic risk. While Morningstar draws inspiration from the CAPM, it differs by using a qualitative, forward-looking assessment rather than simply applying the CAPM directly (for details see Morningstar, 2022, page 4f)).

Value Line Safety Rank We hand-collect and digitize Value Line Investment Survey reports for Small & Mid-Cap stocks from 1998 to 2006 to obtain Value Line's safety rank measure, using the last available rank in each calendar year. The safety rank, ranging from 1 (safest) to 5 (riskiest), reflects Value Line analysts' subjective assessment of a stock's price stability and the financial strength of the underlying firm. Jensen (2024) shows that the CAPM best describes the subjective risk assessment of Value Line (see also Brav et al., 2005).

In the main text, we use the safety rank as a proxy for the perceived cost of equity and follow Eskildsen et al. (2024) in converting the ordinal rank to a required return on equity by multiplying it by 1.5 p.p.. We show below that instead working directly with the original ordinal rank yields qualitatively similar results.

Table E14 reports the marginal effects from an ordered logit regression of the Value Line

Table E14: Change in Probability of Each Value Line Safety Rank in Response to Δ BMI = 10 p.p.

	Safe		Average	Risky	
Value Line Safety Rank	1	2	3	4	5
Δ BMI = 10 p.p.	-1.52***	-4.00***	-8.48***	11.77***	2.23***
	(0.35)	(1.10)	(1.71)	(2.37)	(0.68)
Baseline Probability	2.7%	8.0%	48.3%	37.0%	4.0%
Observations	2,524				
Brant-Test p-value	0.61				

Notes: This table reports marginal effects of an ordered logit regression of Value Line safety rank on changes in benchmarking intensity due to Russell index reconstitution. We restrict the sample to stocks within 400 ranks around the Russell index cutoffs. Standard errors in parentheses are clustered by year. * p<0.10, ** p<0.05, *** p<0.01.

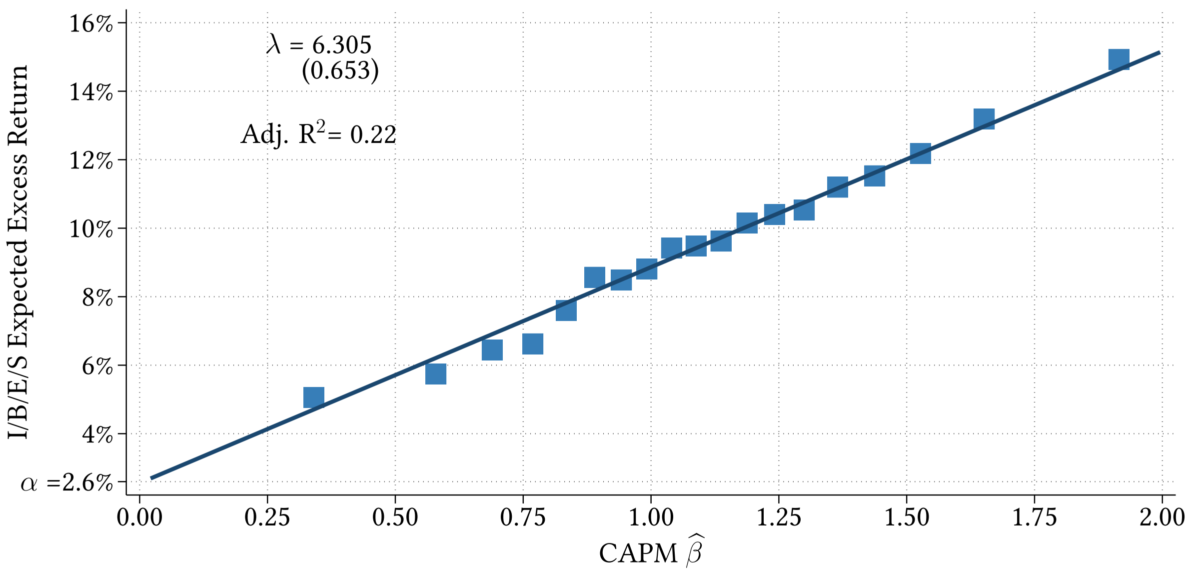
safety rank on exogenous changes in benchmarking intensity due to Russell reconstitution. We restrict the sample to stocks within 400 ranks around the Russell index cutoffs. The coefficients indicate the change in the probability of each outcome category due to a 10 p.p. increase in BMI (from May to June) because of Russell index reconstitution. The results show that an exogenous increase in BMI lead to a significant increase in the Value Line safety rank. The probability that a stock's riskiness is classified as above average increases by more than 11 p.p. at benchmark inclusion. This suggests that Value Line's stock analysts perceive an increase in the required rate of return on equity when benchmarking intensity increases.

I/B/E/S Stock Analysts' Subjective Expected Returns I/B/E/S does not directly provide cost of equity estimates. However, we can infer stock analysts' perceived cost of equity from their subjective expected returns. To do this we use data on the consensus forecasts of stock analysts from I/B/E/S for the period from 2002 to 2018. We construct stock analysts' subjective expected returns from I/B/E/S as

$$\mathbb{E}_t^\star \left[R_{i,t+1}\right] = \frac{\mathbb{E}_t^\star \left[p_{i,t+1}\right] + \mathbb{E}_t^\star \left[d_{i,t+1}\right]}{p_{i,t}} \tag{37}$$

in which $\mathbb{E}_t^\star \left[p_{i,t+1}\right]$ and $\mathbb{E}_t^\star \left[d_{i,t+1}\right]$ are the median consensus one-year price target and dividend forecast over the next fiscal year, respectively, and $p_{i,t}$ is the stock's price at the day of the forecast from CRSP. The subjective expected returns constructed in Eq. (37) are based on analysts' forecasts of future stock prices and thus incorporate both perceived discount rates and perceived mispricing, that is, whether analysts think the stock is over- or undervalued (see Jensen, 2024).

Figure E18: Security Market Line using I/B/E/S Analysts' Subjective Expected Exc. Returns



Notes: This figure shows monthly binned scatter plots of stock analysts' subjective expected excess returns versus CAPM $\hat{\beta}$. We estimate the conditional means of each bin using only cross-sectional variation by absorbing year-month fixed effects. α is the average of the year-month fixed effects. The slope of the security market line is given by λ. CAPM $\hat{\beta}$ from Welch (2022). $N =$ 261,795 observations.

Figure E18 plots the CAPM security market line using stock analysts' subjective expected returns using the CAPM $\hat{\beta}$s. The adj. R^2 is 0.22 and the slope implies a 6.3% annual equity risk premium. We find an annual α of 2.6%. The α likely reflects the unconditional upward bias in analysts' target prices that Brav & Lehavy (2003) document.

E.2 Authorized Cost of Equity of Regulated Monopolies

This subsection provides further evidence that increased benchmarking affects the perceived cost of equity. Our analysis, which draws on Kontz (2025), uses comprehensive data on requested and authorized costs of capital for all major U.S. investor-owned utilities from 1998 to 2018, covering over three-quarters of U.S. consumers. Kontz (2025) analyzes how the growth of index investing impacts regulated monopolies' cost of equity and consumer energy prices. Specifically, we test whether regulated monopolies perceive a higher cost of equity when their CAPM $\hat{\beta}$ increases due to benchmarking.

Background Electricity and natural gas utilities operate as regulated monopolies, granted geographic exclusivity in exchange for rate oversight by government utility commissions. Because these utilities do not face market-based pricing, regulators use a cost-of-service approach: they evaluate the utility's costs and investments, assess their prudence, and apply a risk-adjusted return to determine the revenue requirement that sets customer rates.

A central regulatory challenge is setting a fair return on equity (RoE). The legislative basis for this is U.S. Supreme Court (1944) in *Federal Power Commission v. Hope Natural Gas Co.* which ruled that a regulated monopoly's "[...] return to the equity owner should be commensurate with returns on investments in other enterprises having corresponding risks." Today, state and federal regulators usually implement the CAPM or a version of the DCF model to estimate the cost of equity.

Public Utilities We study utility rate cases from 1998 to 2018, covering all major investor-owned electricity and natural gas utilities in the U.S., which collectively serve over three-quarters of U.S. consumers. We collect data on requested and authorized costs of equity (CoE) from Regulatory Research Associates. We test whether benchmarking affects the authorized CoE using IV specifications of the following form:

$$\text{Authorized CoE}_{i,t} - r_t^f = \alpha_i + \lambda\, \widehat{\text{CAPM}\,\beta}_{i,t} + \varphi \left(\text{DCF Implied CoE } - r^f\right) + \varepsilon_{i,t}, \qquad (38)$$

in which $\widehat{\text{CAPM}\,\beta}_{i,t}$ is instrumented with the firm's benchmarking intensity, and the DCF-implied CoE term enters as a control. We include utility-by-state fixed effects, α_i, which absorb time-invariant unobserved heterogeneity across utility-state pairs. Identification of λ and φ thus relies on within-utility time-series variation.

Table E15 reports coefficient estimates of Eq. (38). Columns 1 and 2 show that a higher benchmarking intensity results in a higher authorized cost of equity. A 10 p.p. higher benchmarking

Table E15: Regulated Monopolies' Cost of Equity and Benchmarking Intensity

	Dependent Variable: Authorized Cost of Equity $- r^f$							
	Public Utilities				Railroads			
	RF		IV		RF		IV	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
BMI (in %)	0.069***	0.071***			0.481***	0.454***		
	(0.011)	(0.011)			(0.099)	(0.088)		
$\widehat{\text{CAPM } \beta^E}$			6.064***	6.189***			6.462***	6.481***
			(1.386)	(1.375)			(0.331)	(0.361)
DCF implied Cost of Equity $- r^f$		0.281***		0.170**		0.654**		-0.035
		(0.051)		(0.083)		(0.327)		(0.072)
Fixed Effects								
Utility × State FE	✓	✓	✓	✓				
Adj. R^2	0.26	0.43			0.48	0.60		
FS F-stat.			42.5	45.4			23.1	25.4
Observations	1,052	1,052	1,052	1,052	21	21	21	21

Notes: This table reports coefficient estimates of the form: Authorized $\text{CoE}_{i,t} - r^f_t = \alpha_i + \lambda \, \widehat{\text{CAPM } \beta}_{i,t} + \varphi \left(\text{DCF Implied CoE } - r^f\right) + \varepsilon_{i,t}$ for rate regulated public utilities' and railroads' authorized cost of equity. Data for authorized cost of equity for public utilities and railroads are from Regulatory Research Associates and from the Surface Transportation Board, respectively. CAPM $\hat{\beta}$ estimated from weekly returns data as usual in regulatory proceedings. Standard errors in parentheses clustered at utility-level for public utilities and Newey-West with 5 lags for railroads. * p<0.10, ** p<0.05, *** p<0.01

intensity translates into a 70 bps higher authorized cost of equity. Columns 3 and 4 translate the reduced form coefficient into the perceived CAPM-implied equity risk premium by instrumenting $\hat{\beta}$ with BMI. The IV estimates imply a risk premium of around 6.1%. Our estimate is close to the historical equity risk premium observed in the U.S. which is often used in regulatory proceedings.

Regulators often require analysts to estimate a public utility's cost of equity using a discounted cash flow (DCF) method in addition to the CAPM. The even-numbered columns in Table E15 show that our results remain robust when accounting for the DCF-implied risk premium. While the DCF risk premium explains a large share of the variation in authorized risk premia, its inclusion has only a negligible effect on the BMI coefficient. This suggests that omitted variable bias is unlikely to be a concern (Oster, 2017).

Appendix Table E16 shows that benchmarking intensity does not correlate with the authorized cost of debt of public utilities. In contrast, controls for aggregate credit market conditions, such as the BBB option-adjusted spread, exhibit a highly significant correlation with both requested and authorized cost of debt. This provides confidence that BMI serves as a valid instrument for the cost of equity by influencing CAPM $\hat{\beta}$s while not affecting the cost of capital through other channels.

Table E16: Effect of Benchmarking on Utilities Requested and Authorized Return on Debt

	(1)	(2)	(3)	(4)	(5)	(6)
		Requested			Authorized	
		Return on Debt — R^f			Return on Debt — R^f	
Benchmarking Intensity (in %)	0.016	0.008	0.009	-0.002	-0.013	-0.020
	(0.012)	(0.011)	(0.011)	(0.014)	(0.013)	(0.015)
BBB Option-Adjusted spread		0.264***	0.259***		0.310***	0.296***
		(0.048)	(0.049)		(0.053)	(0.057)
Requested E/(D+E)		0.075***	0.071***			
		(0.016)	(0.018)			
Authorized E/(D+E)					0.072***	0.066***
					(0.018)	(0.016)
Constant	2.218***	-1.979*		3.502***	-0.487	
	(0.267)	(0.753)		(0.295)	(0.878)	
Utility-by-State Fixed Effect			✓			✓
Adj. R^2	0.00	0.14	0.38	0.00	0.13	0.39
Observations	1,381	1,381	1,347	1,022	1,022	987

Notes: This table shows coefficient estimates for Return on $\text{Debt}_{i,t} = \alpha_i + \text{BMI}_{i,t} + \xi X'_{i,t} + \nu_{i,t}$ Risk-free rate (R^f_t) is the nominal yield on 10-year Treasurys. Standard errors clustered at utility and year-quarter in parenthesis. * p<0.10, ** p<0.05, *** p<0.01.

Railroads We use data on the cost of equity for regulated railroads from the Surface Transportation Board (STB). The STB sets an industry-wide annual cost of equity, rather than firm-specific rates. We thus only have a limited number of yearly observations. However, the STB data offers a granular view of the regulatory rate-setting process: the STB reports the risk-free rate, CAPM $\hat{\beta}$, and equity risk premium used to determine the industry-wide cost of equity. Importantly, the STB's equity risk premium enables us to assess the accuracy of our IV-implied estimates. We combine the STB data with the average BMI of publicly traded railroad companies.

Columns (5) to (8) of Table E15 report results for the railroad industry. Benchmarking intensity strongly predicts the authorized cost of equity, even after controlling for the DCF-implied cost. The IV estimates imply a perceived CAPM equity risk premium of 6.4% annually—statistically indistinguishable from the average 6.85% applied by the STB over the sample period.

F Additional Tests and Instrument Validity

F.1 Russell 1000/2000/3000 Index Methodology

The Russell Index Reconstitution Process The Russell 1000, 2000, and 3000 indices are reconstituted annually in June based on a two-step process.

First, index assignment is determined by ranking eligible securities by their total market capitalization on the designated "rank day" in May.[58] Before 2007, the assignment rule was simple: firms ranking in the top 1,000 formed the Russell 1000, while firms ranking from 1,001 to 3,000 formed the Russell 2000. This created a sharp cutoff at rank 1,000, where assignment is considered quasi-random.

In 2007, FTSE Russell introduced a "banding" policy around the 1,000th rank to reduce index turnover. Under this policy, a stock's assignment also depends on its index membership in the prior year, creating a band around the cutoff. Under the banding policy, a stock's assignment depends on its prior-year index membership:

- A stock from the previous year's Russell 2000 is assigned to the Russell 1000 if its market cap rank is between 1 and $1000 - c_1$.
- A stock from the previous year's Russell 1000 is assigned to the Russell 2000 if its market cap rank is between $1000 + c_2$ and 3,000,

otherwise the stock remains in its current index.

The band of stocks between ranks 1000 - c_1 and 1000 + c_2 constitutes a 5% band around the cumulative market cap of the largest 1000 stocks in the Russell 3000E universe. And then c_1 and c_2 are chosen such that the cumulative market cap of stocks ranked 1 through 1000 - c_1 is 95% of the cumulative market cap of the largest 1000 stocks, and the cumulative market cap of stocks ranked 1 through 1000 + c_2 is 105% of the cumulative market cap of the largest 1000 stocks. Note that even after the introduction of the banding policy, assignment to the Russell 1000 or 2000 is still based on a mechanical rule that changes each year with the distribution of firm sizes.

We emphasize that there is no banding policy at the 3,000th rank cutoff (see, e.g., Section 6.10.3 on p. 19 of Russell (2025) US Equity Indexes Construction and Methodology).

Second, index weighting is based on each stock's float-adjusted market capitalization. Russell applies a proprietary, non-public float factor to determine the final weight. A larger float

[58] For most years, rank day is the last trading day in May. The full list of rank days from 1989 to 2019 is available in Appendix A of Ben-David et al. (2019).

Table F17: Predicting Russell 2000 Membership in June using Market Capitalization Rank Proxy

	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent variable: Russell 2000 Membership in June					
	Window width: 300 ranks			Window width: 150 ranks		
	1998-2018	1998-2006	2007-2018	1998-2018	1998-2006	2007-2018
$\mathbb{1}\{\text{Rank} > \text{cutoff in May}\}$	0.843***	0.924***	0.771***	0.830***	0.867***	0.751***
	(0.056)	(0.016)	(0.036)	(0.058)	(0.031)	(0.035)
Year Fixed Effect	✓	✓	✓	✓	✓	✓
Baseline Controls	✓	✓	✓	✓	✓	✓
Banding Controls	✓		✓	✓		✓
Adj. R^2	0.91	0.95	0.94	0.88	0.92	0.92
Observations	15,032	4,456	10,130	8,721	2,183	6,268

Notes: This table reports estimates from regressions of the form:

$$\text{Russell 2000 Member in June}_{i,t} = \alpha_t + \mathbb{1}\{\text{Rank} > \text{cutoff in May}\}_{i,t} + \text{Baseline controls}_{i,t} + \text{Banding controls}_{i,t} + \varepsilon_{i,t}.$$

The dependent variable is an indicator for whether stock i is a member of the Russell 2000 index in June of year t. Baseline controls are the log of market capitalization and bid-ask spread measured in May of year t. Banding controls are indicator variables for having rank-date market cap in the band, an indicator for being in the Russell 2000 in May before reconstitution, and the interaction of these indicators. All regressions include year-fixed effects. We construct the market capitalization rank variable following Ben-David et al. (2019). Columns (1)-(3) use a window width of 300 ranks around the Russell 1000/2000 cutoff, while columns (4)-(6) use a window width of 150 ranks. We are grateful to Aditya Chaudhry for sharing his code and data which greatly helped us in constructing the market capitalization rank variable. * p<0.10, ** p<0.05, *** p<0.01.

adjustment leads to a lower index weight, which corresponds to a lower BMI.

Empirical Strategy and Validation The official market capitalization ranks used for assignment are proprietary. We therefore construct a proxy for each firm's rank using public data, following the methodology of Ben-David et al. (2019). To account for the post-2007 rule changes, our regression models include a set of banding controls as proposed by Appel et al. (2019). These controls include indicator variables for a firm's rank falling within the band, its membership in the Russell 2000 in the year prior, and the interaction between these two.

We validate our constructed rank proxy by confirming its ability to predict official Russell 2000 membership. As shown in Table F17, our proxy performs remarkably well. Our results are consistent with those of Pavlova & Sikorskaya (2023, Table 12), who conduct a similar analysis using the proprietary Russell ranks. Specifically: For the pre-banding period (1998–2006), our estimates are within one standard error of their findings. For the post-banding period (2007–2018), our estimates are lower but closely track theirs. Notably, even Pavlova & Sikorskaya (2023) report a predictive coefficient of only 0.85 in their post-banding regressions, underscoring that our proxy captures the vast majority of the explainable variation. Our results also align with

Table F18: Replication of Pavlova & Sikorskaya's (2023) Price Pressure Result – BMI Change and Returns in April-July

	Total stock return in period				
Period	April	May	**June**	July	April-July
Panel A: Original Estimates of Pavlova & Sikorskaya (2023) from their Table A.19					
ΔBMI	0.151*	0.192***	**0.271****	0.037	0.677***
	(0.075)	(0.055)	**(0.102)**	(0.116)	(0.184)
Observations	14,547	14,547	14,547	14,547	14,547
Panel B: Replication of Estimates Using Ben-David et al. (2019) Ranking Variable Proxy					
ΔBMI	0.241**	0.186***	**0.267*****	0.035	0.787***
	(0.117)	(0.068)	**(0.102)**	(0.140)	(0.260)
Observations	13,232	13,233	13,232	13,157	13,266
p-value (Panel B = Panel A)	0.45	0.94	**0.97**	0.99	0.68

Notes: Panel A reproduces Pavlova & Sikorskaya (2023, Table A.19), which contains the main result for the month of June and provides additional evidence for anticipatory price pressures in months before the reconstitution. Panel B replicates these results in our sample using our constructed market capitalization rank variable based on Ben-David et al. (2019). The p-values test the null hypothesis that our coefficient estimates on ΔBMI in Panel B equal those reported by Pavlova & Sikorskaya (2023, Table A.19) in Panel A. Panel B reports estimates from regressions of the form:

$$\text{Return}_{i,t}^{\text{Month}} = \alpha_t + \gamma \Delta\text{BMI}_{i,t} + \text{Baseline controls}_{i,t} + \text{Banding controls}_{i,t} + \varepsilon_{i,t}.$$

Baseline controls are the log of market capitalization and bid-ask spread measured in May of year t. Banding controls are indicator variables for having rank-date market cap in the band, an indicator for being in the Russell 2000 in May before reconstitution, and the interaction of these indicators. All regressions include year fixed effects. We construct the market capitalization rank variable following Ben-David et al. (2019) and estimate the regressions using a window width of 300 ranks around the Russell 1000/2000 cutoff. Standard errors in parentheses are double-clustered by stock and year. * p<0.10, ** p<0.05, *** p<0.01.

similar validation exercises in Chaudhry (2025) and Ben-David et al. (2019).

To further validate our identification strategy, we replicate key results from Pavlova & Sikorskaya (2023). Specifically, we examine whether stocks with larger changes in BMI experience differential returns around the Russell reconstitution period. Following their approach, we estimate regressions of the form:

$$\text{Return}_{i,t}^{Month} = \alpha_t + \gamma \Delta BMI_{i,t} + \text{Baseline controls}_{i,t} + \text{Banding controls}_{i,t} + \varepsilon_{i,t}$$

where $\text{Return}_{i,t}^{\text{Month}}$ is the stock return for firm i in a given month, and $\Delta\text{BMI}_{i,t}$ is the change in benchmarking intensity.

Table F18 presents our replication results. Panel A reproduces the main findings from Pavlova & Sikorskaya (2023): stocks with larger increases in BMI experience significantly higher returns in May and June, with cumulative returns of 0.677% per 1 p.p. increase in ΔBMI over the April-

July period. These results are consistent with price pressures from index fund rebalancing around the June reconstitution date.

Panel B shows our estimates using the market capitalization rank variable we constructed. To formally assess the accuracy of our replication, we test the null hypothesis that our coefficients equal theirs. The resulting p-values (all exceeding 0.45) indicate that we cannot reject equality between the two sets of estimates. This close replication validates our data construction methodology and confirms that our BMI measure accurately captures benchmark assignment dynamics.

These findings also align with the suggestive evidence in Pavlova & Sikorskaya (2023) (Appendix A.19) of anticipatory price pressures in months before reconstitution, demonstrating that at least some part of the total change in BMI is expected by markets prior to the official June reconstitution date.

F.2 Changes in BMI and Measures of Risk Exposure

Changes in BMI that correlate with changes in exposure to aggregate or idiosyncratic risk pose a threat to our identification strategy. Industry's exposure to aggregate risk (Karolyi, 1992) and firm fundamentals (Gomes et al., 2003) should in theory determine firm-level exposure to aggregate risk. We thus test whether the aggregate risk exposure of treated firms changes by estimating whether the CAPM $\hat{\beta}$ of comparable peer firms changes when a firm's BMI changes. We also test whether measures of idiosyncratic firm-level risk exposure change with BMI. However, we find no evidence that changes in BMI correlate with changes in risk exposure.

Data We collect peer group information from data on executive compensation by Institutional Shareholder Services (ISS). We use measures of firm-level intangible capital from Peters & Taylor (2017). We use firm-level risk measures from Hassan et al. (2019) and data on financial frictions from Hoberg & Maksimovic (2015) and Linn & Weagley (2024).

Changes in CAPM $\hat{\beta}$s of Peer Firms We collect information about a firm's peer group from ISS. For each firm, we randomly select three peer firms and test whether the firm's change in BMI correlates with changes in the CAPM $\hat{\beta}$ of peers. To avoid confounding our estimates, we exclude peers that also experience a change in BMI. Appendix Table F19 reports the peer-based test. Column (1) shows that regressing changes in a firm's CAPM $\hat{\beta}$ on changes in its peers' $\hat{\beta}$s yields a significant positive coefficient, consistent with common exposure to aggregate risk.[59] Column (2) shows that changes in a firm's BMI change the firm's $\hat{\beta}$. By contrast, changes in a

[59] Levi & Welch (2017) similarly show that peer firms' CAPM $\hat{\beta}$s strongly predict own-firm $\hat{\beta}$s.

Table F19: Placebo test using the CAPM $\hat{\beta}$ of peer firms

	(1) Firm's Δ CAPM β^E	(2) Firm's Δ CAPM β^E	(3) All Peers' Δ CAPM β^E	(4) Peer n=1 Δ CAPM β^E	(5) Peer n=2 Δ CAPM β^E	(6) Peer n=3 Δ CAPM β^E
Δ CAPM β^{Peer}	0.232***					
	(0.010)					
Δ BMI		0.814***	0.037	0.075	-0.009	0.043
		(0.054)	(0.029)	(0.046)	(0.043)	(0.045)
Fixed Effects						
Firm FE	✓	✓	✓	✓	✓	✓
Peer FE	✓		✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Adj. R^2	0.421	0.249	0.472	0.466	0.471	0.479
Observations	46,689	16,995	47,749	16,470	16,022	15,257

Notes: This table reports coefficient estimates for a placebo test using N=3 firm peers' change in CAPM $\hat{\beta}$ and assigns them the Δ BMI of the firm: $\Delta\text{CAPM }\beta^{\text{Peer}}_{j,t} = \alpha_i + \alpha_j + \alpha_t + \Delta\text{BMI}^{\text{Firm}}_{i,t} + \varepsilon_{j,i,t}$ for firm i and peer j in year t. Standard errors in parentheses clustered at the firm-level in column (2) and double-clustered at firm and peer level in other columns. + p<0.10, * p<0.05, ** p<0.01, *** p<0.001.

firm's BMI do not correlate with changes in its peers' $\hat{\beta}$s, with insignificant coefficients near zero. This pattern suggests that benchmarking changes a firm's CAPM $\hat{\beta}$ rather than reflecting changes in aggregate risk exposure.

Table F20: Changes in CAPM $\hat{\beta}$ and firm-level risk measures of Hassan et al. (2019)

(in σ units)	(1) Δ Risk	(2)	(3) Δ Pol. Risk	(4)	(5) Δ Pol. Risk - Econ.	(6)	(7) Δ Pol. Risk - Secu.	(8)	(9) Δ Pol. Risk - Tech.	(10)	(11) Δ Pol. Risk - Trade	(12)
Δ CAPM β^E	0.0192**		0.0170*		0.0163*		0.0149*		0.0087		-0.0002	
	(0.007)		(0.007)		(0.007)		(0.007)		(0.007)		(0.007)	
Δ BMI		-0.0086		0.0080		-0.0011		0.0097		0.0115		-0.0088
		(0.009)		(0.009)		(0.009)		(0.009)		(0.009)		(0.009)
Fixed Effects												
Firm FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Adj. R^2	0.14	0.14	0.13	0.13	0.13	0.13	0.13	0.13	0.12	0.12	0.13	0.13
Observations	29,970	29,970	29,985	29,985	29,963	29,963	29,978	29,978	29,982	29,982	29,976	29,976

Notes: This table reports coefficients estimates for regression specifications of the form: $\Delta\text{Firm-level Risk}_{i,t} = \alpha_i + \alpha_t + \gamma\,\Delta\text{BMI}_{i,t} + \nu_{i,t}$. Changes in firm-level risk (Hassan et al., 2019) calculated between 1st and 4th quarter of the year. Coefficients are standardized to unit variances. Changes in firm-level risk measures, CAPM $\hat{\beta}$s, and BMI are trimmed at the 1% and 99% level. Standard error in parentheses are clustered at the firm-level. + p<0.10, * p<0.05, ** p<0.01, *** p<0.001.

Firm-level Risk Measures We analyze six firm-level risk measures derived from earnings calls by Hassan et al. (2019): the overall risk exposure of firms, exposure to overall political risk, and exposure to political risk stemming from economic policy, security policy, technological policy, and trade policy. Appendix Table F20 reports estimates of OLS regressions of changes in firm-level risk measures on changes in CAPM $\hat{\beta}$ and changes in BMI. Two things are worth noting.

First, changes in the CAPM $\hat{\beta}$ correlate with changes in the firm-level risk measures. Four of six firm-level risk-measure show a statistically significant positive relationship with changes in the CAPM $\hat{\beta}$ of firms. Second, changes in BMI do not correlate with changes in firm-level risk measures. The estimated coefficients across all risk measures are close to zero and not statistically significant.

F.3 Changes in BMI and Measures of Financial Constraints

Changes in BMI could correlate with changes in financial constraints, potentially violating the exclusion restriction of our IV strategy. We test this by examining the correlation between changes in a firm's BMI and measures of financial constraints and CDS spreads. If changes in BMI correlated with changes in financing costs due to factors other than CAPM $\hat{\beta}$, the exclusion restriction would be violated. However, we find no evidence of such correlations.

Table F21: Changes in measures of text-based financial frictions (Hoberg & Maksimovic, 2015)

(in σ units)	(1) Δ Inv. Delay	(2) Δ Inv. Delay & Equity Issue	(3) Δ Inv. Delay & Debt Issue	(4) Δ Inv. Delay & Private Issue	(5) Δ Inv. Delay & Equity (LW, '24)	(6) Δ Inv. Delay & Debt (LW, '24)
Δ BMI	-0.0008	-0.007	-0.0004	-0.005	-0.010	0.004
	(0.009)	(0.009)	(0.009)	(0.009)	(0.008)	(0.007)
Fixed Effects						
Firm FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Adj. R^2	0.08	0.07	0.06	0.07	0.07	0.04
Observations	23,463	23,463	23,463	23,463	32,275	32,275

Notes: This table reports coefficients estimates for regression specifications of the form: $\Delta\text{Measure of Financial Constraint}_{i,t} = \alpha_i + \alpha_t + \gamma\, \Delta\text{BMI}_{i,t} + \nu_{i,t}$. Changes in text-based financial constraint measures from Hoberg & Maksimovic (2015) and Linn & Weagley (2024). Coefficients are standardized to unit variances. Changes in financial constraints measures, CAPM $\hat{\beta}$s, and BMI are trimmed at the 1% and 99% level. Standard error in parentheses are clustered at the firm-level. + p<0.10, * p<0.05, ** p<0.01, *** p<0.001.

Text-based Measures of Financial Constraints We collect text-based measures of financial constraints from Hoberg & Maksimovic (2015) and Linn & Weagley (2024). These measures capture the extent to which firms face financial constraints and are likely to constrain investment based on the text of their annual reports. Appendix Table F21 reports estimates of OLS regressions of changes in the firm's financial constraints on changes in the BMI of a firm. The estimated coefficients of BMI are close to zero and not statistically significant across all measures. Importantly, Column (1) of Appendix Table F21 shows that changes in BMI do not correlate with firm statements about plans to delay investments.

Table F22: Changes in CDS Spreads and CAPM $\hat{\beta}$s of CDS Spreads

Dependent variable:	Δ CDS Spread (in σ units)				Δ CDS CAPM β (in σ units)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Δ BMI (in σ units)	-0.0221	-0.0244	-0.0189	-0.0283	0.0280	0.0189	0.0014	0.0305
	(0.0212)	(0.0209)	(0.0207)	(0.0210)	(0.0240)	(0.0242)	(0.0253)	(0.0260)
Momentum (Cum. Ret.)		-0.120***	-0.140***			-0.0618**	-0.0366	
(in σ units)		(0.0315)	(0.0332)			(0.0238)	(0.0259)	
Fixed Effects								
Firm FE	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓			✓	✓		
Year × Size Decile			✓				✓	
Year × Momentum Decile				✓				✓
Adj. R^2	0.260	0.269	0.303	0.315	0.103	0.106	0.179	0.155
Observations	2,798	2,798	2,798	2,798	2,299	2,299	2,299	2,299

Notes: This table reports coefficients estimates for regression specifications of the form: $\Delta\text{CDS Spreads}_{i,t} = \alpha_i + \alpha_t + \gamma\ \Delta\text{BMI}_{i,t} + \nu_{i,t}$. Coefficients are standardized to unit variances. CDS spreads for senior unsecured debt with tenor of 5 year and doc clause XR14 (no restructuring). CDS CAPM $\hat{\beta}$s are calculated on daily data from 2010 to 2019 using the weighted least squares estimator of Welch (2022) with exponentially decay of 3 months half life. Changes in CDS spreads and CDS CAPM $\hat{\beta}$s are trimmed at the 2% and 98% level. Standard error in parentheses are clustered at the firm-level. + p<0.10, * p<0.05, ** p<0.01, *** p<0.001.

Changes in CDS Spreads and CDS CAPM $\hat{\beta}$ We collect CDS spreads for senior unsecured debt with tenor of 5 year from 2010[60] to 2019. We calculate CDS CAPM $\hat{\beta}$s on daily data using the estimator of Welch (2022). We calculate changes in a firm's CDS spreads and firm's CAPM $\hat{\beta}$ of CDS spreads as the difference between the average of daily observations in the first and last quarter of a year. Appendix Table F22 reports estimates of OLS regressions of changes in CDS spreads and changes in the CDS CAPM $\hat{\beta}$ on changes in the BMI of a firm. We find no evidence that changes in the BMI predict changes in firm CDS spreads or CDS CAPM $\hat{\beta}$s. The estimated coefficients on BMI are insignificant and close to zero.

F.4 Changes in BMI and Measures of Corporate Governance

An increase in BMI and associated institutional ownership could impact investment through improved corporate governance (Appel et al., 2016, Aghion et al., 2013). However, increased passive ownership may also decrease monitoring incentives, as in the model of Bebchuk & Hirst (2019). We test whether measures of governance change with changes in BMI but find no evidence of such an effect.

We use governance and ESG scores from S&P, Sustainalytics, and Refinitiv and test whether changes in BMI correlate with changes in those scores. Appendix Table F23 reports estimates

[60] We focus on the period after ISDA's "Big Bang" reforms of April 2009 to maintain a consistent sample.

Table F23: Changes in measures of corporate governance

(in σ units)	(1) Δ S&P G-Score	(2) Δ Sus. G-Score	(3) Δ Ref. G-Score	(4) Δ Sus. ESG	(5) Δ S&P ESG	(6) Δ Ref. ESG
Δ BMI	-0.024	-0.020	0.008	-0.009	0.031	-0.003
	(0.057)	(0.024)	(0.017)	(0.026)	(0.057)	(0.017)
Fixed Effects						
Firm FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Adj. R^2	0.31	0.20	0.07	0.23	0.34	0.10
Observations	2,003	7,168	13,925	7,326	2,003	13,925

Notes: This table reports coefficients estimates for regression specifications of the form: $\Delta\text{Governance Score}_{i,t} = \alpha_i + \alpha_t + \gamma\,\Delta\text{BMI}_{i,t} + \nu_{i,t}$. Governance and ESG scores of Standard & Poor, Sustainalytics, and Refinitiv. Coefficients are standardized to unit variances. Changes in G-Scores, ESG Scores, and BMI are trimmed at the 1% and 99% level. Standard error in parentheses are clustered at the firm-level. + p<0.10, * p<0.05, ** p<0.01, *** p<0.001.

of OLS regressions of changes in governance and ESG scores on changes in the BMI of a firm. The estimated coefficients are close to zero and are not statistically significant. Our findings are consistent with Kacperczyk et al. (2021), who also find no evidence of changes in governance at benchmark inclusion.

Table F24: Marginal Effects of BMI on the Probability of an Activist Investor Campaign

Outcome y	ΔPr(y) when ΔBMI=10 p.p.	SE	p-value	No. Obs.	Mean y	# y=1
Activist Campaign (12 mos.)	-0.0017	0.0007	0.02	18,059	0.0156	282
Activist Campaign (24 mos.)	-0.0000	0.0008	0.95	18,059	0.0246	444
Activist Campaign (36 mos.)	-0.0004	0.0015	0.76	18,059	0.0328	592
Activist Campaign (48 mos.)	0.0005	0.0018	0.76	18,728	0.0408	765
Activist Campaign (60 mos.)	0.0003	0.0020	0.86	18,728	0.0479	898

Activist Investor Campaigns An alternative channel through which benchmarking could affect investment is by altering the incentives for activist investor campaigns. A BMI could increase the likelihood of an activist campaign through two mechanisms. First, higher BMI increases a stock's liquidity, which reduces the cost for an activist to accumulate a large stake. Second, a larger passive investor base, which correlates with BMI, may increase an activist's probability of success in a proxy contest (Appel et al., 2019, Kedia et al., 2021). However, countervailing economic forces also exist. An activist targeting a high-BMI firm must bear the higher factor risk associated with the increases in stock's CAPM $\hat{\beta}$. This factor risk increases the cost and uncertainty of an activist campaign.

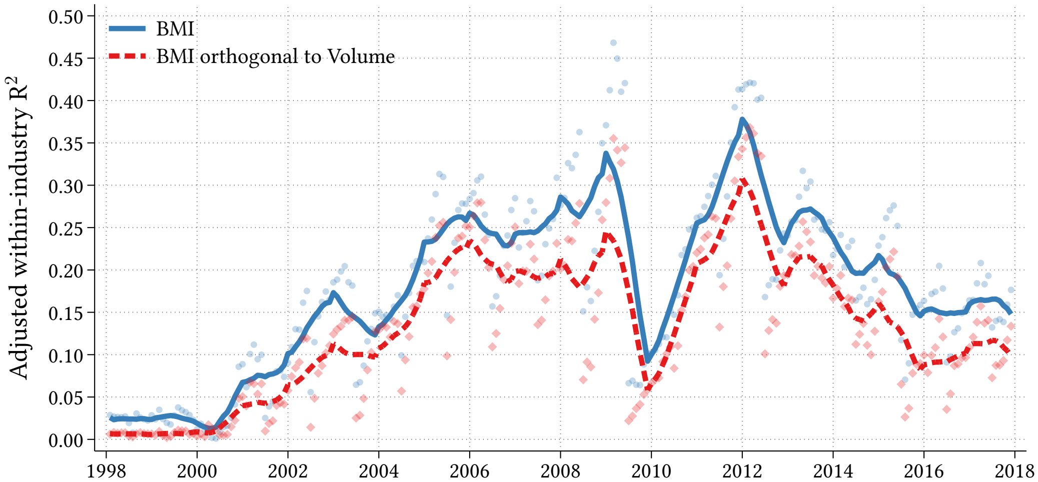
To test this channel, we use data on activist campaigns from FactSet's SharkWatch, restricting the sample to campaigns with the objective to "Maximize Shareholder Value." We estimate the following logit model:

$$\Pr\left[\text{Activist Campaign}_{i,t+h} = 1\right] = \Lambda\left(\alpha_t + \gamma\,\Delta\text{BMI}_{i,t} + X'_{i,t}\xi + \nu_{i,t+h}\right)$$

in which $\Lambda(\cdot)$ is the logistic function. The dependent variable is an indicator for an activist campaign initiated against firm i between month t and $t+h$. We test horizons $h \in \{12, 24, 36, 48, 60\}$ following the Russell reconstitution. The vector $X'_{i,t}$ contains the log market capitalization and banding controls.

Table F24 reports marginal results for a 10 p.p. increase in BMI. We find no evidence that an increase in BMI leads to a higher probability of an activist campaign over a one- to five-year horizon. The coefficient on ΔBMI is statistically indistinguishable from zero for all horizons of 24 months or longer. For the 12-month horizon, the coefficient is negative, pointing to a decrease in the probability of an activist campaign. These findings do not support the hypothesis that activism is a channel through which benchmarking affects firm investment.

Figure G19: Share of Within-industry Variation Explained by Projecting CAPM $\hat{\beta}$ onto BMI



Notes: This figure plots the time series of within-industry R^2 from cross-sectional regressions CAPM $\hat{\beta}_i = \alpha_{j,s} + \sum_{k=1}^{5} \varphi_k \text{BMI}_i^k + \epsilon_i$ in which $\alpha_{j,s}$ is an industry×size-quartile fixed effect (industries at 4-digit NAICS, size by market cap). The solid blue line shows a two-sided moving average of within-R^2. The dashed red line shows the same after orthogonalizing BMI and CAPM $\hat{\beta}$s with respect to log(Volume). We report the within-R^2 and exclude variation explained by industry×size fixed effects.

G Additional Results on Misallocation

A large literature highlights how resource misallocation, characterized by dispersion in firms' marginal products of inputs, negatively affects aggregate productivity and output (e.g., Bau & Matray, 2023). David et al. (2022) show that, in a production economy with aggregate risk, cross-sectional dispersion in the marginal product of capital (MPK) partly reflects variation in firms' CAPM βs. Thus, dispersion in MPK may represent not only resource misallocation but also risk-adjusted capital allocation. Firms set their expected MPK equal to their cost of capital: $\mathbb{E}[t]\, MPK_{i,t+1} = r_t^f + \delta + \beta_{i,t}\lambda$, where δ denotes the depreciation rate. The cross-sectional variance in expected MPK at time t is given by $\sigma^2(\mathbb{E}[t]\, MPK_{i,t+1}) = \sigma^2_{\beta_t}\lambda^2$, in which $\sigma^2_{\beta_t}$ is the cross-sectional variance in CAPM βs. The degree to which risk contributes to MPK dispersion thus depends positively on the cross-sectional variation in firms' risk exposures and the market price of risk.

We start by examining whether benchmarking generates excess dispersion in CAPM $\hat{\beta}$s. Figure G19 shows that benchmarking-induced variation in CAPM $\hat{\beta}$s is making up an increasing share of within-industry variation in CAPM $\hat{\beta}$s. In each month, we approximate the relationship between CAPM $\hat{\beta}$s and BMI by fitting a flexible 5th order polynomial as well as industry-by-size-quartile fixed effects. We then plot the within-industry variation explained by BMI (within

Table G25: Misallocation: Elasticity of MPK Dispersion with Respect to Dispersion in CAPM $\hat{\beta}$s

Dependent variable:	$\sigma(mpk)_{t+1}$				$\sigma(\mathbb{E}_t[mpk])_t$			
	RF		IV		RF		IV	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\sigma(\widehat{\text{CAPM }\beta})_t$	0.798**	0.492**			0.723**	0.505**		
	(0.231)	(0.147)			(0.222)	(0.159)		
$\sigma(\text{CAPM }\beta)_t$			0.615**	0.547**			0.548**	0.551**
			(0.195)	(0.181)			(0.179)	(0.192)
Fixed Effects								
Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Industry FE		✓		✓		✓		✓
Adj R^2	0.02	0.67			0.03	0.66		
FS F-stat.			129.3	90.2			137.9	73.2
Observations	3,469	3,468	3,461	3,460	3,466	3,465	3,460	3,459

Notes: This table reports coefficient estimates of regressions at the NAICS 4-digit industry-level of the form: $\sigma(mpk)_{j,t+1} = \alpha_t + \alpha_j + \sigma(\widehat{\text{CAPM }\hat{\beta}})_{j,t} + \varepsilon_{j,t+1}$ in which we instrument industry j's cross-sectional dispersion in CAPM $\hat{\beta}$s with the predicted cross-sectional dispersion due to benchmarking. mpk is the natural log of MPK, calculated as $mpk = \log(Sales) - \log(PPENT)$ and expected MPK assuming AR(1) productivity, $a_t = \log(Sales)_t - \theta \log(PPENT)_t$, as $\mathbb{E}[t]\, mpk_{t+1} = \rho a_t - (1-\theta)k_{t+1}$ where ρ=0.93 and θ=0.65 (see David et al., 2022). FS F-stat is Kleibergen-Paap F-stat of first stage. Standard errors clustered at industry- and year-level in parentheses. + p<0.10, * p<0.05, ** p<0.01, *** p<0.001.

R^2). Importantly, we exclude variation explained by industry-by-size-quartile fixed effects. Before 2000, benchmarking explains less than 5% of the average within-industry variation in CAPM $\hat{\beta}$s. In 2018, benchmarking explains approximately 15% of the average within-industry variation in CAPM $\hat{\beta}$s. This suggests that benchmarking affects allocative efficiency by creating within-industry dispersion in firm's perceived cost of capital.

Next, we test whether the benchmarking-induced excess dispersion in within-industry CAPM $\hat{\beta}$s affects the dispersion in industries' marginal products of capital (MPK). To address the endogeneity between MPK and CAPM βs, we implement a two-step procedure. In the first step, we predict a firm's CAPM $\hat{\beta}$ using its benchmarking intensity. Since the level of benchmarking intensity may not be exogenous, we instrument the intensity level in year t with changes in benchmarking intensity (ΔBMI) driven by Russell reconstitution between May and June over the past five years. This ensures that the variation in CAPM $\hat{\beta}$s we use is due to benchmarking. We then calculate the cross-sectional dispersion in CAPM $\hat{\beta}$s, $\sigma(\text{CAPM }\beta)_t$, the dispersion specifically created by benchmarking, $\sigma(\widehat{\text{CAPM }\hat{\beta}})_t$, and the natural logarithm of the marginal product of capital at the 4-digit NAICS industry level annually.[61]

In the second step, we estimate how dispersion in CAPM $\hat{\beta}$s affects dispersion in log (MPK)

[61]With Cobb-Douglas production, the log MPK is $mpk = \log(Sales) - \log(PPENT)$ (David et al., 2022).

at the industry-level using specifications of the form:

$$\sigma(mpk)_{j,t+1} = \alpha_t + \alpha_j + \gamma\, \widehat{\sigma(\text{CAPM}\,\hat{\beta})}_{j,t} + \varepsilon_{j,t+1} \tag{39}$$

in which we instrument industry j's cross-sectional dispersion in CAPM βs with the predicted cross-sectional dispersion created by benchmarking.

Table G25 shows that benchmarking-induced CAPM $\hat{\beta}$ changes affect dispersion in marginal products of capital. Our two-step approach shows that higher within-industry dispersion created by benchmarking increases within-industry dispersion in MPKs. Our results help explain the rise in within-industry productivity dispersion from 1997 to 2016 (Cunningham et al., 2023).[62] Figure G19 and Table G25 suggest that benchmarking-induced excess dispersion in CAPM $\hat{\beta}$ prevents the equalization of marginal products across producers within industries. This is important because non-fundamental changes in within-industry capital allocation have first order implications for aggregate and industry-level productivity growth (Hsieh & Klenow, 2009).

[62]In unreported results, we confirm that increases in $\sigma(\widehat{\text{CAPM}\,\beta})_t$ are correlated with rising TFP dispersion in the data of Cunningham et al. (2023).

H Semi-Elasticity of Investment by Sales in Compustat

Our analysis is similar to Zwick & Mahon (2017), who study the bonus depreciation stimulus policies from 2001 to 2004 and from 2008 to 2010. In both episodes, firms were allowed to use an accelerated schedule to deduct the cost of investment purchases from taxable income, thereby affecting the relative price of capital q_t. We depart by focusing on the cost of equity part of the user cost of capital, $C_t = q_t \left[(1-\mu_t)(1-\tau_t)r_t^d + \mu_t(r_t^f + \beta_{i,t}\lambda) + \delta\right]$, which benchmarking affects by changing CAPM $\hat{\beta}$s.

We estimate the investment semi-elasticity with respect to the user cost of capital (ϵ^C) for each of 10 sales deciles. Figure H20 plots our OLS estimates of the semi-elasticities by sales decile. The figure shows that smaller firms, as measured by sales, have more negative investment semi-elasticities than larger firms. The semi-elasticity estimates for the smallest sales decile is -9, while that for the largest sales decile is around -1. The difference between the smallest and largest sales decile is statistically significant at the 1% level. The estimates are robust to adding controls for cash flow, operating leverage (SGA/sales), and log MRPK (blue circles) and further adding industry by time fixed effects (green diamonds). The results are consistent with prior research showing that smaller firms' investment is more sensitive to changes in the user cost of capital than larger firms' (e.g., Zwick & Mahon, 2017).

To estimate the investment semi-elasticity with respect to the user cost of capital (ϵ^C) for each of 10 sales deciles, we use Compustat data from 1989 to 2019 in a three-step procedure.

1. We first estimate the elasticity of investment with respect to CAPM $\hat{\beta}$ (ε_j^β) by regressing the change in the log investment-to-capital ratio on log CAPM beta, including firm and year fixed effects and controls ($X_{i,j,t}$):

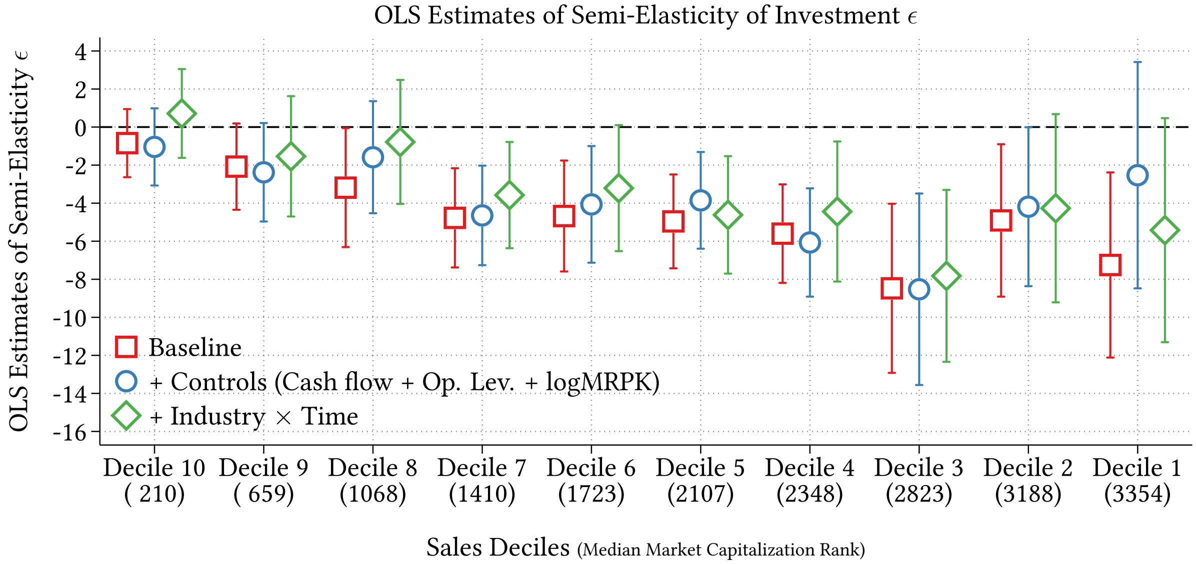
$$\Delta \log(I/K)_{i,j,t} = \alpha_i + \alpha_t + \varepsilon_j^\beta \log(\hat{\beta}_{i,j,t}) + X'_{i,j,t}\zeta + \varepsilon_{i,j,t} \tag{40}$$

2. We then convert the estimated elasticity (ε_j^β) to the target semi-elasticity (ϵ_j^C) using:

$$\epsilon_j^C = \frac{\partial \log(I/K)}{\partial C_j} = \underbrace{\frac{\partial \log(I/K)}{\partial \log \beta_j}}_{\text{Step 1: } \hat{\varepsilon}_j^\beta} \times \underbrace{\frac{1}{\bar{\beta}_j}}_{\text{Elasticity to Semi-Elasticity}} \times \underbrace{\left(\frac{\partial C_j}{\partial \beta_j}\right)^{-1}}_{\text{Rescaling to User Cost}}$$

3. The final term, the sensitivity of the user cost to β, is $(\partial C/\partial \beta)^{-1} = (q\mu\lambda)^{-1}$. We use the average equity share for each decile (μ_j) and assume an equity risk premium (λ) of 6% and

Figure H20: Semi-Elasticity of Investment by Sales Deciles



Notes: The figure plots estimates of the semi-elasticity of investment with respect to the user cost of capital, ϵ^C, by sales decile. Numbers in parentheses on the x-axis report the median May market-capitalization rank for each sales decile. Red squares show the baseline specification with firm and year fixed effects. Blue circles add controls for cash flow, operating leverage (SGA/sales), and log MRPK. Green diamonds further add industry by time fixed effects. 95% confidence intervals based on standard errors double-clustered by firm and year.

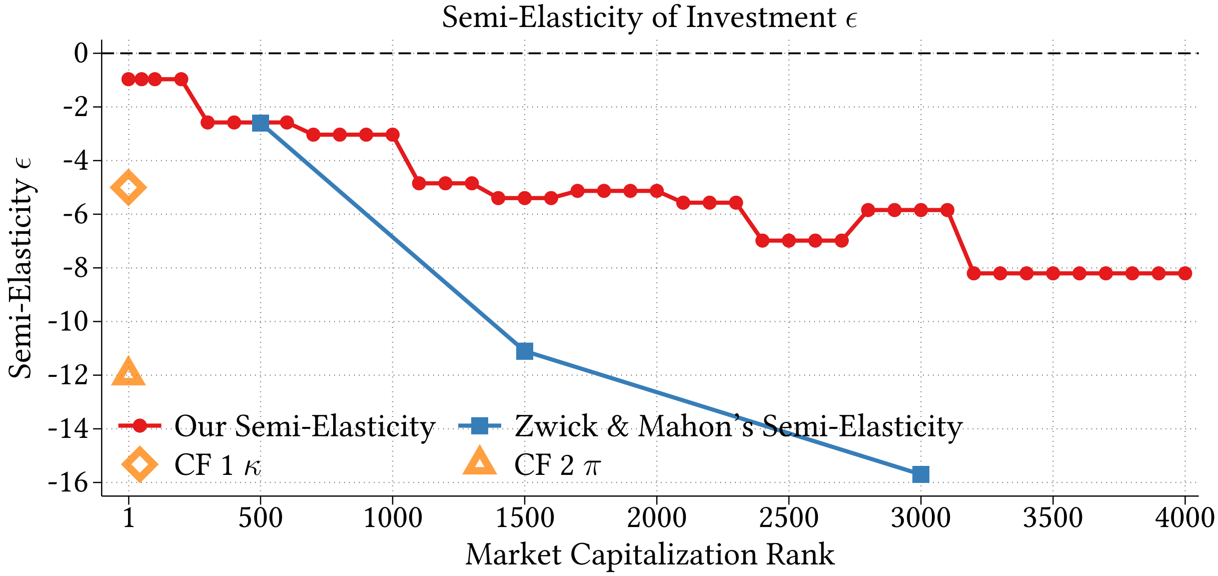
a relative price of capital (q) of 1.

Attenuation Bias in OLS Estimates Our estimates of the investment semi-elasticity with respect to the user cost of capital (ϵ^C) are likely biased towards zero for several reasons. First, our CAPM $\hat{\beta}$ are subject to classical measurement error, which attenuates the coefficient toward zero. Second, investment-opportunity shocks might confound our estimates. For instance, a positive productivity shock could raise both investment and $\hat{\beta}$ (via operating leverage), masking the true negative relationship. Third, an expectations channel may violate our identification strategy: if managers, similar to analysts raise growth expectations (Jylha & Ungeheuer, 2021), when β increases, investment may increase for reasons not running through the user cost, again biasing our coefficient toward zero.

Recognizing these biases, we compare our OLS estimates to the well-identified estimates from Zwick & Mahon (2017). Their tax-based identification is less susceptible to the confounders we face, and in a standard investment model, the elasticity with respect to the user cost is proportional to the elasticity with respect to the net-of-tax rate (Koby & Wolf, 2020).

Figure H21 plots our scaled estimates and estimates from Zwick & Mahon (2017) by mar-

Figure H21: Semi-Elasticity of Investment by Market Capitalization Rank



Notes: The figure plots estimates of the semi-elasticity of investment with respect to the user cost of capital, ϵ^C, by market-capitalization rank. We map our sales-decile estimates to ranks using the median market-cap rank within each decile. For comparison, we overlay estimates from Zwick & Mahon (2017), positioned at the median rank of their small- and large-firm groups. Orange markers (CF1 κ and CF2 π) show the semi-elasticities that the largest 50 firms would need to offset the observed decline in aggregate investment implied by the cross-sectional rise in CAPM $\widehat{\beta}$; the two markers use alternative weighting schemes.

ket capitalization rank, confirming our main result: smaller firms have more negative investment semi-elasticity than larger firms. Zwick & Mahon (2017) find an average investment semi-elasticity with respect to the user cost of approximately -11, which is twice the size of our unadjusted estimates.[63]

[63]The estimates from Zwick & Mahon (2017) for the Compustat sample are taken from their Appendix Table B.2. The estimates need to be rescaled by the investment tax rate to represent the semi-elasticity with respect to the user cost of capital, as described on their page 230 (see also Koby & Wolf, 2020, p.21f).

I Aggregation using a Heterogeneous Firm General Equilibrium Model

Set-up Our discrete-time model builds closely on Khan & Thomas (2008) and Winberry (2021).

Firms There is a fixed mass of firms $j \in [0,1]$ producing output $y_{j,t}$ with technology

$$y_{j,t} = z_t \varepsilon_{j,t} k_{j,t}^{\theta} l_{j,t}^{\nu},$$

in which z_t is an aggregate productivity shock, $\varepsilon_{j,t}$ is an idiosyncratic productivity shock, $k_{i,t}$ is the capital stock, and $l_{j,t}$ is labor input. The parameters θ and ν are the output elasticities of capital and labor, respectively. Throughout, we assume that $\theta + \nu < 1$.

The aggregate shock process is common across all firms while the idiosyncratic shock $\varepsilon_{j,t}$ is independent across firms. The two shocks follow AR(1) processes in logs:

$$\log z_{t+1} = \rho_z \log z_t + \sigma_z \epsilon_{z,t+1}, \quad \epsilon_{z,t+1} \sim N(0,1),$$
$$\log \varepsilon_{j,t+1} = \rho_\varepsilon \log \varepsilon_{j,t} + \sigma_\varepsilon \epsilon_{\varepsilon,j,t+1}, \quad \epsilon_{\varepsilon,j,t+1} \sim N(0,1).$$

Each period, a firm j observes these two shocks, uses its pre-existing capital, hires labor from a competitive labor market at wage w, and produces output. After production, the firm decides how much it should investment for the next period. Capital follows the usual law of motion $k_{j,t+1} = (1-\delta)k_{jt} + i_{jt}$, in which δ is the depreciation rate and i_{jt} is investment.

Firms face two types of capital adjustment costs. First, there is a fixed investment cost, $\xi_{j,t} \overset{iid}{\sim}$ uniform$[0, \bar{\xi}]$, paid in labor units if the firm invests a positive amount. Second, there is a standard convex investment adjustment cost. The adjustment cost function takes the form

$$\phi(k_{j,t}, i_{j,t}, \xi_{j,t}; \kappa) = \frac{\kappa}{2}\left(\frac{i_{jt}}{k_{jt}}\right)^2 k_{jt} + \xi_{jt} w(\boldsymbol{s}) \mathbb{1}\{i_{jt} > 0\}.$$

Households There is a representative household with GHH preferences over consumption C_t and labor supply L_t, which maximizes their expected discounted lifetime utility

$$\max_{C,N} E_0 \sum_{t=0}^{\infty} \rho^t \log\left(C_t - \chi \frac{L_t^{1+\eta}}{1+\eta}\right)$$
$$\text{subject to} \quad C_t = w_t L_t + \Pi_t$$

in which ρ is the discount factor, χ is the weight on disutility from labor, and η is the inverse of the Frisch elasticity of labor supply. We normalize the total time endowment to 1, so that $L_t \in [0,1]$. Markets are complete, the household owns all firms and rents labor to them in a competitive labor market at wage w_t.

Recursive firm problem The firms' individual state variables are its current draw of the idiosyncratic productivity shock, ε, its capital stock, k, and its investment fixed cost shock, ξ. The aggregate state is $\boldsymbol{s} = (z, \mu)$ where z is the aggregate productivity shock and μ is the distribution of firms over their individual states (ε, k, ξ). Note that that the firm's choice of labor is a purely static problem and we can thus separate it out to define the revenue function as

$$\pi(\varepsilon, k, \xi; \boldsymbol{s}) = \max_n \Big\{ z\varepsilon k^\theta l^\nu - w(\boldsymbol{s}) l \Big\}$$

The firm's value function takes the following form

$$v(\varepsilon, k, \xi; \boldsymbol{s}) = \pi(\varepsilon, k, \xi; \boldsymbol{s}) + \max_i \left\{ -q(\boldsymbol{s})i - \phi(k, i, \xi; \kappa) + \mathbb{E}\left[\Lambda(z'; \boldsymbol{s})\, v(\varepsilon', k', \xi'; \boldsymbol{s}') | \varepsilon, k, \xi, \boldsymbol{s}\right] \right\}$$

where $\Lambda(z'; \boldsymbol{s})$ is the stochastic discount factor and q is the adjusted relative price of investment. Markets are complete with respect to aggregate risk, so the stochastic discount factor used by firms is equal to the household's intertemporal marginal rate of substitution state by state.

Equilibrium Definition and Solution Method The aggregate state vector is $\boldsymbol{s} = (z, \mu)$, where z denotes the aggregate productivity shock and μ is the distribution of firms over their individual state vector (ε, k, ξ). A formal equilibrium definition is provided in Winberry (2021).

We solve the model using Winberry's (2018) method. The main difficulty is that $\boldsymbol{s}$ includes the infinite-dimensional distribution μ. To address this, the method approximates μ at each point with a flexible but finite-dimensional parametric family. The parameters of this family become endogenous aggregate state variables in the reduced model. Winberry (2021) notes that accurately capturing the distribution typically requires more than five parameters, which makes global methods impractical because of the curse of dimensionality. We therefore characterize the aggregate dynamics using a second-order perturbation.

I.1 Calibration

Following Winberry (2021), we parameterize the model in two steps. First, we calibrate a subset of parameters to match standard steady-state macroeconomic targets. Second, conditional on

Table I26: Micro investment moments and calibration

Panel A: Target moments

Moment	Data	Model
Investment moments		
Average investment rate (%)	14.9	13.0
Standard dev. of investment rates (%)	15.6	13.9
Spike rate (%)	20.7	22.0
Perceive cost of equity moments		
Share of employment by top firms w/ lower $\hat{\beta}$ (in %)	33.5	32.6
Weighted-average increase in cost of capital (in %)	1.38	1.39

Panel B: Fixed & calibrated parameters

Block	Parameter	Value
Household (fixed)		
Discount rate	ρ	0.99
Inverse Frisch elasticity	η	0.50
Firm (fixed)		
Labor share	ν	0.64
Capital share	θ	0.21
Capital depreciation	δ	0.03
Aggregate TFP AR(1)	ρ_z	0.97
	σ_z	0.008
Firm heterogeneity (calibrated)		
Upper bound on fixed cost	$\bar{\xi}$	0.55
Convex adjustment cost	κ	3.10
Idiosyncratic productivity AR(1)	ρ_ε	0.90
	σ_ε	0.05
Perc. cost of equity heterogeneity (calibrated)		
Shape of $\hat{\beta}$	α	2.5
Upper bound of $\hat{\beta}$	$\bar{\beta}$	0.20
Lower bound of $\hat{\beta}$	$\underline{\beta}$	-0.058
Benchmarking shock AR(1)	ρ_λ	0.95

Notes: This table summarizes our calibration strategy. Panel A reports micro investment moments from the data and the model. Panel B reports fixed and calibrated parameters. Micro investment moments from our annual firm-level Compustat panel, 1998–2018. Statistics drawn from distribution of investment rates pooled over firms and time. Spike rate is fraction of observations with investment rate greater than 20 percent.

these values, we calibrate the remaining parameters to match data moments. One model period equals one quarter.

Fixed Parameters Panel B of Table I26 summarizes our fixed parameters. We mostly follow Winberry (2021) and set the household discount factor to $\rho = 0.99$, the inverse of the Frisch elasticity to $\eta = 0.50$, the labor share to $\theta = 0.64$, the capital share to $\nu = 0.21$, and the depreciation rate to $\delta = 0.03$. We set the aggregate TFP process to $\rho_z = 0.97$ and $\sigma_z = 0.008$.

Calibrated Investment Parameters We calibrate the parameters governing the firm heterogeneity in panel B of Table I26 such that the model matches key micro investment moments in our Compustat panel shown in panel A of Table I26. We exogenously fix the persistence of the idiosyncratic productivity process to $\rho_\varepsilon = 0.90$.

Mapping our Empirical Findings to the Model We introduce shocks to firms' discount rates that depend on firm size to capture the empirical patterns we document. Rather than embedding a full asset pricing structure with subjective expectations, we model these shocks as wedges in the relative price of capital.[64] This preserves tractability while capturing the central mechanism in the data. Moreover, this is consistent with our empirical evidence that the change in $\hat{\beta}$ originates in the financial market and changes the *perceived* riskiness of equity while the fundamental risk-exposure is still determined by the firm's cash flows produced by $y_{i,t}$.

We model changes in CAPM $\hat{\beta}$ due to benchmarking as size-dependent, exogenous shocks to the relative price of investment:

$$\widehat{q}(\boldsymbol{s}) = 1 + \lambda \times \left[\beta_0 + \beta_1 \exp\left(-\alpha\, n(\varepsilon, k; \boldsymbol{s})\right)\right]$$

in which β_0, β_1, and α are constants which we calibrate to match the empirical distribution of changes in firms' CAPM $\hat{\beta}$s. Specifically, $\beta_0 = \underline{\beta} - \frac{\bar{\beta}}{e^a - 1}$ and $\beta_1 = \bar{\beta}\frac{e^a}{e^a - 1}$ where $\underline{\beta}$ is the average decrease in CAPM $\hat{\beta}$ experienced by the largest firms, $\bar{\beta}$ is average increase in CAPM $\hat{\beta}$ experienced by smaller firms, and α governs how quickly the change in CAPM $\hat{\beta}$ decreases with firm size. That is, the minority of large firms in the model experience a decrease in their discount rate, while the majority of smaller firms experience an increase. We assume that the benchmarking shock λ follows an AR(1) process

$$\lambda_{t+1} = \rho_\lambda \lambda_t + \epsilon_{\lambda,t+1}, \quad \epsilon_{\lambda,t+1} \sim N(0,1).$$

We set the quarterly autocorrelation of $\rho_\lambda = 0.95$ to match the persistent of CAPM $\hat{\beta}$s.

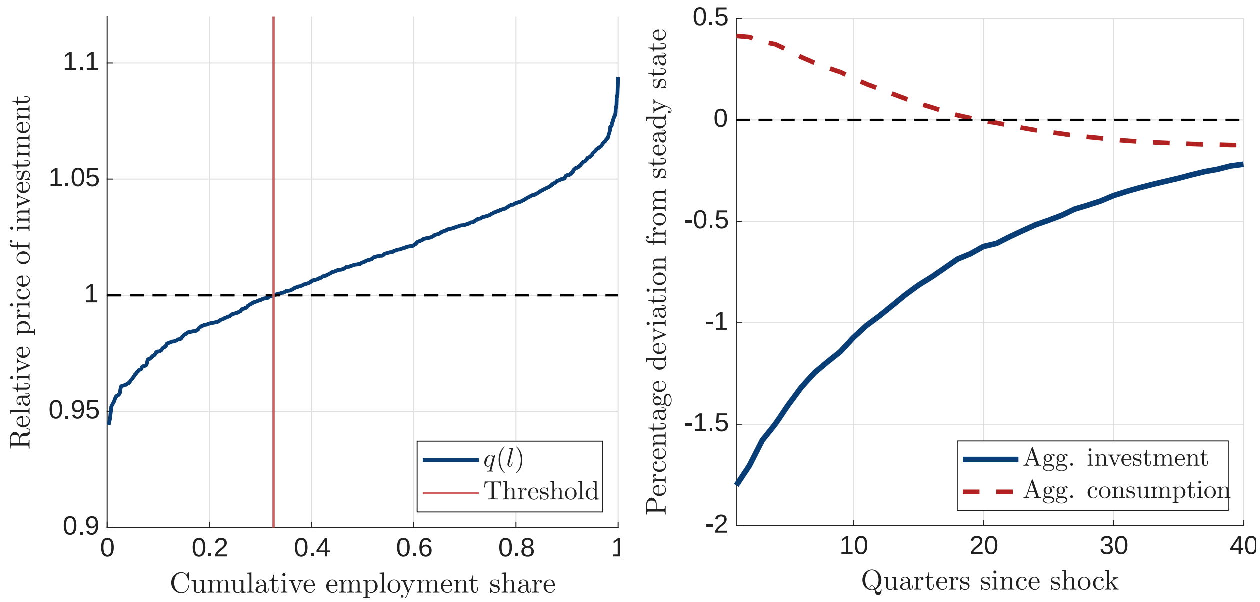
We calibrate α, $\bar{\beta}$, and $\underline{\beta}$ to match two key empirical moments and the distribution of changes in CAPM $\hat{\beta}$s documented in Section 3. Specifically, we target the average share of employment held by firms with a decrease in their CAPM $\hat{\beta}$ (33.5%) and the investment-share-weighted increase in the cost of capital (1.38%).[65]

Panel (a) in Figure I22 plots the calibrated shape of $\hat{q}(\boldsymbol{s})$ as a function of size-sorted cumulative employment share in a simulated panel of 1000 firms. The figure shows that the smallest firms experience an increase in their relative price of investment of around 10%, while the largest firms experience a decrease of around 5%.

[64] The relevant semi-elasticities between r and q are intimately linked as Proposition 4 in Koby & Wolf (2020) show.

[65] The investment-share-weighted increase in CAPM betas is 0.043 (see Section 8). The investment-share-weighted increase in the average WACC is around 0.21%, which corresponds to a 1.38% increase relative to the average hurdle rate of 15% in Gormsen & Huber (2025).

Figure I22: Distributions of Perc. Cost of Equity Shock and Impulse Responses of Investment



(a) Relative price of investment $\hat{q}(\boldsymbol{s})$ vs. size-sorted cumulative employment share in simulated panel

(b) Impulse Response of Aggregate Investment and Consumption after Shock to $\hat{q}(\boldsymbol{s})$

I.2 Results

Panel (b) of Figure I22 displays the impulse response to a one standard deviation shock to λ. On impact, aggregate investment contracts by 1.83%. This response operates almost entirely through the extensive margin, as the shock prevents formerly infra-marginal firms from undertaking planned investments.

The underlying mechanism is rooted in firm heterogeneity. In the model, the incentive to invest is strongest for firms with low initial capital relative to their optimal level. These are typically small, high-growth firms consistent with firm-level data. Because they are actively growing to reach their optimal scale, these small firms constitute the majority of infra-marginal investors in the economy.

The adverse shock λ to the relative price of capital lowers the net benefit of investing, pushing these formerly infra-marginal firms to be marginal and cancel their investment. Conversely, larger firms, who receive a subsidy, are less likely to investment since they are closer to their optimal scale, and their decisions are thus less affected. Therefore, the sharp drop in aggregate investment reflects the withdrawal of many small, marginal firms from investment.

J Data Appendix and Variables Descriptions

Variable	Description and Source
Welch (2022) *Simply Better Market Beta*	Estimated using WLS regressions with exponentially decaying weights of 4-month half-life on an expanding window after winsorizing daily returns at −2x and +4x the contemporaneous market return. See Welch (2022) for estimation details.
Rolling-window CAPM Beta (21 days)	Month-end estimates using 21 daily returns (WRDS Beta Suite)
Rolling-window CAPM Beta (252 days)	Month-end estimates using 252 daily returns (WRDS Beta Suite)
Rolling-window CAPM Beta (156 weeks)	Month-end estimates using 156 weekly returns (WRDS Beta Suite)
Rolling-window CAPM Beta (36 months)	Month-end estimates using 36 monthly returns (WRDS Beta Suite)
Cash Flow Beta	Estimated as $\text{ROE}_{i,t} = \alpha_i + \beta_i^{CF}\text{ROE}_{Mkt,t} + \varepsilon_{i,t}$ where ROE is the ratio of clean surplus accounting $X_t = BE_t - BE_{t-1} + D_t$ to beginning-of-the-period book equity (BE_{t-1}). D_t are gross dividends computed as the difference between CRSP returns and returns excluding dividends (Cohen et al., 2009). Estimated quarterly from 1975 to 2018 separately for each firm in Compustat using an expanding window of observations.
Consumption Beta (Kim et al., 2024)	Weighted average of firms' and industry peers' consumption βs $\beta_{i,t}^{C\star} = \frac{2}{3}\beta_{i,t}^{C} + \frac{1}{3}\beta_{-i,t}^{C}$, normalized by standard deviation ($\sigma_{\beta_{i,t}^{C\star}}$). See Kim et al. (2024) for details on estimation.
Equity Ratio $\frac{E}{E+D}$	Using quarterly Compustat variables $\frac{cshoq \times prccq}{atq - ceqq - txdbq + cshoq \times prccq}$
Benchmarking Intensity (BMI)	See definition in Eq. (1). Provided by Pavlova & Sikorskaya (2023).
Institutional Ownership (IOR)	Estimated using Thomson-Reuters 13F filings on WRDS using the code provided by Palacios, Moussawi, Glushkov (2009).
Net Equity Issuance	Equity Issuance − Buy Backs over Total Assets Provided by Jensen et al. (2023)
Bid-Ask Spread	Provided by Abdi & Ranaldo (2017)
Amihud Illiquidity	Provided by Jensen et al. (2023)
Momentum	Cumulative return over the past 12 months Provided by Jensen et al. (2023)
May Market Capitalization Rank	Firm's market capitalization rank in May of each year calculated using methodology of Ben-David et al. (2019). See Appendix F.1.
Banding Variables/Controls	Indicator variables for having rank-date market cap in the reconstitution bands, an indicator for being in the Russell 2000 in May before reconstitution, and the interaction of these indicators. See Appendix F.1.

Variable	Description and Source
Average Implied Cost of Capital (ICC)	Average of the residual income models of Gebhardt et al. (2001) and Claus & Thomas (2001), and the dividend discount models of Easton (2004) and Ohlson & Juettner-Nauroth (2005). Provided by Eskildsen et al. (2024)
Managers' Perceived Cost of Capital	Provided by Gormsen & Huber (2025) For details see https://www.costofcapital.org/
Managers' Hurdle Rate	Provided by Gormsen & Huber (2025) For details see https://www.costofcapital.org/
Net Flows into Passive Mutual Funds and ETFs	Excluding feeder funds and funds of funds. Provided by Morningstar Direct.
Net Flows into Active Mutual Funds and ETFs	Excluding feeder funds and funds of funds. Provided by Morningstar Direct.
Total Net Assets of Passive Mutual Funds and ETFs	Excluding feeder funds and funds of funds. Provided by Morningstar Direct.
Total Net Assets of Active Mutual Funds and ETFs	Excluding feeder funds and funds of funds. Provided by Morningstar Direct.
Investment Rate	Using annual Compustat variables $\frac{capx_t}{ppegt_{t-1}}$
Tobin's q^{tot}	Total Tobin's q provided by Peters & Taylor (2017).
Current Ratio	Using annual Compustat variables $\frac{act_t}{lct_t}$
Leverage	Using annual Compustat variables $\frac{lt_t}{at_{t-1}}$
Cash Flow	Using annual Compustat variables $\frac{ib_t+dp_t}{ppegt_{t-1}}$
Operating Leverage	Using annual Compustat variables $\frac{xsga_t}{sale_t}$
Firm Age	Years since first appearance in Compustat

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