The Real Cost of Benchmarking*

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Abstract

This paper provides causal evidence that asset price distortions caused by benchmarking affect corporate investment decisions. We document that the rise in benchmark-linked investing over the past two decades fundamentally changed the cross-section of CAPM $\widehat{\beta}$s. Exploiting exogenous variation from Russell index reconstitutions, we show inclusion in benchmark indices leads to higher CAPM $\widehat{\beta}$s, with larger effects observed among stocks facing greater benchmarking intensity. Firm managers interpret the resulting higher CAPM $\widehat{\beta}$ as an increase in their firm's cost of capital, leading them to reduce investment. Six years after inclusion, firms experience 7.1% and 8.4% declines in physical and intangible capital, respectively. Supporting evidence shows that benchmark-inclusion similarly increases the perceived cost of equity among stock analysts and regulators. We find consistent results at the industry level. Industries which experienced greater increases in CAPM $\widehat{\beta}$s due to benchmarking accumulated less capital over the past two decades. Moreover, benchmarking creates excess dispersion in the cost of capital within industries, causing inefficient capital allocation across firms. The rise in CAPM $\widehat{\beta}$s largely offset the decline in the risk-free rate over the past decades and can explain 57% of the "missing investment" puzzle.

JEL classification: D22, E22, E44, E71, G11, G14, G23, G31, G32, G40

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1 Introduction

Over the past 25 years the U.S. economy has been shaped by two trends: weak corporate investment relative to valuations and a rise in benchmark-linked investing. The growth of passive index funds and the evaluation of active funds against benchmarks means that a large share of capital today is allocated based on stocks' membership in benchmark indices, as opposed to fundamentals.[1] This inelastic demand distorts asset prices, leading to higher prices (Shleifer, 1986), increased volatility (Ben-David, Franzoni, and Moussawi, 2018), and greater co-movement (Barberis, Shleifer, and Wurgler, 2005) for stocks in benchmark indices. Whether these asset price distortions have contributed to weak corporate investment is not well understood.

This paper studies the causal effects of benchmarking-induced asset price distortions on corporate investment. We document a novel mechanism through which benchmarking influences corporate behavior. We use exogenous variation in stocks' benchmarking intensity to show that increased exposure to benchmark-linked capital flows raises stocks' CAPM β estimates (i.e., $\widehat{\beta}$). Firm managers interpret this increase in CAPM $\widehat{\beta}$ as a higher cost of capital and consequently reduce investment. Importantly, we show that these results are not driven by changing firm fundamentals. Instead, we argue that firm managers rely on textbook guidance to set discount rates using CAPM $\widehat{\beta}$s without accounting for distortions created by benchmarking. These distortions have a substantial impact on investment at the firm, industry, and aggregate level through their effect on the perceived cost of equity capital. Our study thus provides new insights into how the growing trend of benchmark-linked investing affects real economic outcomes.

We illustrate our proposed mechanism in a stylized model that introduces two frictions into a standard model of corporate investment. The first source of friction are benchmarking-induced asset price distortions that drive wedges into firm discount rates (Kashyap, Kovrijnykh, Li, and Pavlova, 2021). The inelastic demand of benchmarked funds for benchmark constituent stocks raises their price, but also increases their co-movement. These forces have opposing effects on the discount rate: the increased stock price lowers the implied discount rate and incentivizes investment, while greater co-movement discourages it. As such, the overall effect of benchmarking on discount rates and optimal investment is ambiguous. The second friction is a behavioral assumption that firm managers behave exactly as they are taught to in textbooks and MBA classrooms: they use the weighted average cost of capital 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 total U.S. stock market assets in 2023. Chinco and Sammon (2024) put the overall passive share at twice that number, accounting for institutions with internally managed index portfolios and quasi-indexing active managers (see also Cremers and Petajisto, 2009).

While the assumption that firm managers practice what textbooks teach[2] may seem innocuous, it is key to our mechanism. Managers who set discount rates using their stocks' CAPM $\widehat{\beta}$ will observe an increase in co-movement upon benchmark inclusion which discourages investment. However, they will overlook the price effect that incentivizes investment. This failure to internalize the distortionary effects of benchmarking leads managers to perceive an increase in their cost of capital. Consequently, benchmarking has an unambiguously negative impact on investment.

We test our model's predictions using the benchmarking-intensity measure (BMI) developed by Pavlova and Sikorskaya (2023). BMI measures the total inelastic demand that a stock attracts from benchmarked funds, expressed as a fraction of the stock's market capitalization. We merge the BMI measure with CAPM $\widehat{\beta}$s from Welch (2022b), accounting data from Compustat, data on managers' perceived cost of capital from Gormsen and Huber (2024), and market data from CRSP.

We begin by documenting new facts about the cross-section of CAPM $\widehat{\beta}$s. We show that over the past 25 years, stocks' CAPM $\widehat{\beta}$s and benchmarking intensity increased in lockstep. Firms representing over 40% of annual capital expenditures in Compustat experienced a significant increase in their CAPM $\widehat{\beta}$, with an average increase of 0.33. However, this increase in CAPM $\widehat{\beta}$s is not due to changes in firms' fundamental risk, as measured by cash flow βs, or changes in leverage. Instead, we find distortions in the cross-section of CAPM $\widehat{\beta}$s across market capitalization ranks used to construct benchmark indices. This suggests that the rise in benchmark-linked investing affected the measurement of CAPM βs over the past 25 years.

We establish a causal link between benchmarking and CAPM $\widehat{\beta}$ using a difference-in-differences design around Russell index reconstitutions. The Russell indices are widely used benchmarks for U.S. equity markets and reconstitute annually based on market capitalization ranks. Changes in Russell index membership around benchmark inclusion cutoffs lead to plausibly exogenous changes in benchmarking intensity (Pavlova and Sikorskaya, 2023). Our 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 stock's CAPM $\widehat{\beta}$ would have evolved similarly absent changes in benchmarking intensity. We restrict our sample to all stocks within 300 ranks around the Russell index cutoffs to ensure we capture only changes in benchmarking intensity due to index reconstitution. We control for stocks' momentum over the past 12 to 24 months before index reconstitution to account for the possibility that stocks' momentum affects CAPM $\widehat{\beta}$. We further include high-dimensional fixed effects that remove as much time-varying

[2]For example, corporate finance textbooks by Brealey, Myers, Allen, and Edmans (2023), Berk and DeMarzo (2023), and Ross, Westerfield, Jaffe, and Jordan (2016). A notable exception is Welch (2022a, Chapter 10) who suggests to always use a market β of 1 to calculate discount rates. Gollier (2021) estimates that the welfare loss from using a single discount rate is equivalent to a permanent reduction in consumption of up to 45% in a calibrated Lucas model.

unobserved heterogeneity as possible to ensure that our estimates are well-identified.

The difference-in-differences results show that an increase in the BMI of a stock by at least 5 percentage points (p.p.) due to index reconstitution increases its CAPM $\widehat{\beta}$ by 0.18. The treatment effects of benchmark inclusion on CAPM $\widehat{\beta}$ increase with benchmarking intensity: Stocks with a BMI increase of at least 10 p.p. (20 p.p.) subsequently have 0.23 (0.35) higher CAPM $\widehat{\beta}$s. Micro-cap stocks do not drive the effects. The effects are also present for stocks with market capitalization above the 20th percentile of the NYSE. The changes in CAPM $\widehat{\beta}$s are not due to changes in fundamentals or risk exposure. Instead, our results show that increased co-movement with the market is explained by institutional ownership and exposure to benchmark-linked capital flows. Specifically, we show that cross-sectional changes in CAPM $\widehat{\beta}$s correlate with net flows into passive mutual funds and ETFs but not with net flows into active mutual funds.

The increase in firms' CAPM implied cost of equity is substantial and persistent. Assuming an annual equity risk premium (ERP) of 6%, our baseline results imply an increase of 108 basis points (bps). The effect persist for years and only partly reverses: we find a 125 bps higher cost of equity after one year, 75 bps after four years, and 67 bps after seven years. Compared to other discount rate shocks these effects are fast, large, and persistent.[3] If managers rely on the CAPM to allocate capital, persistent changes in $\widehat{\beta}$s have long-lasting effects on investment behavior.

In contrast, the implied cost of capital (ICC) derived from stock price levels experiences only short-lived effects at benchmark inclusion.[4] We observe an initial decrease of 36 bps in the ICC, equivalent to a 5.24% price increase—close to the 5% price effect documented by Chang, Hong, and Liskovich (2015). However, this effect fades to 14 bps after one year and becomes insignificant thereafter. The short-lived impact implies that benchmarking effects on investment via price levels are limited. Berk and Van Binsbergen (2025) argue that short-term price shifts do not significantly influence a firm's long-term cost of capital. This conclusion is supported by studies documenting a substantial decline in benchmark inclusion price effects, from 7.4% in the 1990s to under 1% recently for the S&P 500 (Greenwood and Sammon, 2024), and similarly for Russell benchmarks (Chang et al., 2015). Our findings suggest benchmarking primarily impacts the cost of capital through persistent changes in CAPM $\widehat{\beta}$s rather than short-term stock price fluctuations.

Increases in a stock's benchmarking intensity predict a higher perceived cost of capital by the firm's managers as reported in the data collected by Gormsen and Huber (2023). We use changes in benchmarking intensity around index reconstitutions as an instrumental variable (IV)

[3]For example, Bauer and Rudebusch (2020) estimate that the natural rate declined by 100 bps between 2002 and 2020.

[4]Following Eskildsen, Ibert, Jensen, and Pedersen (2024), we calculate ICC by averaging four widely used accounting models: the residual income models from Gebhardt, Lee, and Swaminathan (2001) and Claus and Thomas (2001), and the dividend discount models from Easton (2004) and Ohlson and Juettner-Nauroth (2005).

to identify the causal effect of changes in CAPM $\widehat{\beta}$ on a firm's perceived cost of capital. Our IV estimates imply that managers use a perceived equity risk premium of around 3.4%, close to the average equity risk premium of 3.6% reported by Chief Financial Officers (CFO) from 2000 to 2017 in the CFO Outlook Survey by Graham and Harvey (2018). Moreover, the estimates show that managers' perceived cost of capital responds to benchmarking-induced increases in CAPM $\widehat{\beta}$: a 0.2 change in CAPM $\widehat{\beta}$ increase managers' perceived cost of capital by approx. 70 bps.

We provide corroborating evidence of the causal channel from benchmarking-induced changes in CAPM $\widehat{\beta}$ to 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 a stock's benchmarking intensity. Similarly, the requested and subsequently authorized cost of equity of regulated monopolies such as public utilities and railroads increases with benchmarking intensity.[5] We again identify the causal effect of CAPM $\widehat{\beta}$s on analysts', regulated firms', and regulators' perceived cost of equity using (changes in) benchmarking intensity as an instrumental variable. Across datasets, we find perceived equity risk premia between 4% and 8% annually. In other words, a 0.2 change in CAPM $\widehat{\beta}$ increase analysts', firms', and regulators' perceived cost of equity between 80 and 160 bps.

Our second set of results investigates how firms react to changes in their CAPM $\widehat{\beta}$ induced by changes in their stock's benchmarking intensity. For a firm manager who follows textbook guidance to set investment policies using the WACC implied by the CAPM, an increase in CAPM $\widehat{\beta}$ raises the user cost of capital and should lead to a decline in investment (Jorgenson, 1963).

We test whether changes in CAPM $\widehat{\beta}$ affect firm outcomes like capital expenditure, physical and intangible capital stocks, cash holdings, payouts, and employment. We use Jordà's (2005) local projections (LP) to estimate the effects of an increase in CAPM $\widehat{\beta}$ on capital allocation over horizons of up to 6 years using changes in BMI as IV. The instrument uses the plausibly exogenous variation in BMI from Russell index reconstitution to instrument for the endogenous relationship between CAPM β and investment. We ensure that our estimates are well-identified using three methods. First, we saturate our LP-IV estimator with high-dimensional fixed effects to remove as much time-varying unobserved heterogeneity as possible. Second, we confirm that our results are robust to inclusion of known predictors of capital accumulation (e.g., Tobin's Q or cash flow). Third, we conduct several tests to validate the exclusion restriction but find no evidence that changes in BMI correlate with changes in risk exposure, debt market access, or corporate governance: The CAPM $\widehat{\beta}$ of peer firms remains stable when a treated firm's BMI changes, and firm-level risk measures show no correlation with changes in BMI. BMI changes do not affect

[5] The CAPM is frequently used to set allowed returns on equity under rate-of-return regulation (Kontz, 2025).

measures of financial frictions and the cost of debt, including CDS spreads. Corporate governance scores do not change when BMI changes. These findings suggest that BMI changes are orthogonal to other factors that influence investment and support their use as valid instrument.

A benchmarking-induced increase in a firm's CAPM $\widehat{\beta}$ leads to a substantial and persistent reduction in investment. Specifically, a 20% rise in CAPM $\widehat{\beta}$ results in a cumulative decrease of 10.0% in capital expenditure over a six-year period. Rather than investing, treated firms initially accumulate cash and later increase shareholder payouts. The treatment effects align with firms gradually updating their discount rates in response to higher CAPM $\widehat{\beta}$s (Gormsen and Huber, 2023): the effects are negligible at short horizons, grow steadily over time, and become statistically significant after three years. Over six years, the average treated firm's physical capital stock falls by 7.1%, and its intangible capital stock by 8.4%. These responses imply a user cost of capital elasticity near unity, consistent with Cobb-Douglas production.

We find supporting evidence in the NBER-CES manufacturing data, where higher industry-level CAPM $\widehat{\beta}$s lowered capital accumulation by 12.5% from 2000 to 2016. The dataset spans over 100 industries, covering both public and private firms.[6] To estimate the impact of rising industry-level CAPM $\widehat{\beta}$s on capital accumulation, we use IV regressions in long-differences from 2000 to 2016. We instrument the value-weighted change in industry-level CAPM $\widehat{\beta}$s with the corresponding change in benchmarking intensity. The results are robust to controlling for industry-level pre-trends, exposure to the China shock, and the inclusion of sector fixed effects, which restrict identification to within-sector variation.

We further show that benchmarking distorts capital allocation by increasing within-industry dispersion in firms' perceived cost of capital. Building on David, Schmid, and Zeke (2022), who argue that dispersion in the marginal product of capital (MPK) partly reflects variation in firms' CAPM βs, we document that benchmarking-induced variation in $\widehat{\beta}$s has become an increasingly large component of within-industry dispersion over time. Using Russell Index reconstitutions as an instrument for exogenous changes in benchmarking intensity, we isolate the variation in CAPM $\widehat{\beta}$s attributable to benchmarking. We then show that this excess dispersion in perceived risk exposures leads to greater dispersion in the marginal product of capital across firms within an industry, a common measure of allocative inefficiency (e.g., Bau and Matray, 2023).

Lastly, we estimate a counterfactual weighted average cost of capital (WACC) for the average firm by removing benchmarking-induced distortions from its CAPM $\widehat{\beta}$. This exercise reveals an average wedge of 145 basis points between actual and counterfactual WACC since 2004. From 1975 to 2000, the equal-weighted average CAPM $\widehat{\beta}$ was relatively stable, but over the past 25

[6]Many private firms also use the CAPM, estimating their cost of equity from $\widehat{\beta}$s of comparable publicly traded firms.

years it rose by 0.41, 88% of which we attribute to a 14 percentage point increase in average benchmarking intensity. Adjusting for this rise, we find that the decline in the risk-free rate over the past two decades has been largely offset by higher CAPM $\widehat{\beta}$s.

We assess whether the wedge between actual and counterfactual WACC is sufficient to explain the puzzle of missing aggregate investment documented by Gutiérrez and Philippon (2017). Using 1990–2002 data, we estimate the historical relationship between aggregate investment and Tobin's Q, then predict post-2002 investment assuming this relationship remains constant. The cumulative shortfall since 2002 represents the "missing investment". We adjust Tobin's Q following Gormsen and Huber (2023) to account for the discrepancy between the market's discount rate and firms' perceived cost of capital.

The WACC wedge we document can explain 57% of the missing investment puzzle at the aggregate level. Without adjustment, the investment shortfall implied by Tobin's Q is approximately 25% of the capital stock by 2019. After accounting for the WACC wedge created by benchmarking, this shortfall reduces to about 11%. The remaining gap is likely related to other macro developments, such as rising market power (Barkai, 2020, Crouzet and Eberly, 2023) and mismeasurement of intangible capital (Peters and Taylor, 2017).

The paper is organized as follows: The remainder of this section discusses related literature. Section 2 documents several new facts about the cross-section of CAPM $\widehat{\beta}$s. Section 3 illustrates our proposed mechanism in a stylized model. Section 4 describes the data. Section 5 establishes a causal link between benchmarking, CAPM $\widehat{\beta}$s, and the perceived cost of equity capital. Section 6 documents that benchmarking-induced changes in CAPM $\widehat{\beta}$ affect real outcomes at the firm- and industry-level. Section 7 studies whether the CAPM $\widehat{\beta}$ distortions caused by benchmarking are large enough to explain the missing investment puzzle at the aggregate-level. Section 8 concludes.

Related literature This paper contributes to several strands of literature, including the effects of benchmark-linked investing on asset prices, corporate behavior, and capital (mis-)allocation.

The literature on benchmark-linked investing, starting with Shleifer (1986) and Harris and Gurel (1986), established that stocks appreciate when included in an index and that stock volatility (Ben-David et al., 2018) and co-movement with the index (e.g, Barberis et al., 2005, Boyer, 2011) increase after benchmark inclusion (see Wurgler, 2010, for a survey). We provide causal evidence that a stock's benchmarking intensity affects its CAPM $\widehat{\beta}$ and document that the CAPM $\widehat{\beta}$s increased in lockstep with benchmarking intensity over the past 25 years. We show that these increases in CAPM $\widehat{\beta}$s are not due to changes in firm fundamentals, leverage, or risk exposure as measured by cash flow βs. Rather, benchmark-linked capital flows drive a wedge between measured CAPM βs and cash flow βs that is unrelated to the risk exposure of firms' cash flows.[7]

Basak and Pavlova (2013) provide a theoretical framework showing that performance benchmarking of asset managers leads to asset class effects consistent with the observed benchmark inclusion effects.[8] Kashyap et al. (2021) derive optimal corporate investment policies in the presence of benchmarked funds, arguing that firm managers should internalize the inelastic demand for benchmark stocks and invest more to maximize firm value. We contribute to the discussion about the effects of benchmarking on real investment in two ways: empirically, we provide causal evidence that increases in benchmarking lead to a higher perceived cost of capital and lower investment. Conceptually, we introduce a behavioral argument that reconciles our findings with Kashyap et al. (2021). We argue that firm managers, relying on textbook guidance to estimate the cost of equity using the CAPM, fail to internalize benchmarking-induced asset price distortions. This results in an overestimation of the cost of capital and a sub-optimal decline in investment, ultimately destroying shareholder value.

We also contribute to the discussion about whether the rise of passive investing affects information production and price efficiency in the stock market.[9] Coles, Heath, and Ringgenberg (2022) extend the model of Grossman and Stiglitz (1980) to incorporate index investing. In their model, an exogenous increase in index investing leads to a drop in asset-specific information production but to no change in price informativeness. Whereas the model of Bond and Garcia (2022) predicts that, as passive investing becomes more popular, individual stock trading decreases, and aggregate price efficiency falls. Empirically, Koijen, Richmond, and Yogo (2024) estimate that the transition from active to passive management had a large impact on equity prices but a small impact on price informativeness, as measured by cross-sectional regressions of future profitability on current market-to-book ratios. We provide evidence that increased exposure to benchmarked-linked capital flows affect the covariance of stock returns with the market and thus the discount rates used by firm managers, stock analysts, and regulators. The fact that cash flow βs remain stable while CAPM $\widehat{\beta}$ increase and firm managers respond by reducing investment implies that revelatory price efficiency decreased (Bond, Edmans, and Goldstein, 2012). Consistent with our results, Sammon (2024) shows that passive ownership negatively affects the degree to which stock prices anticipate earnings announcements. Brogaard, Ringgenberg, and Sovich (2019) pro-

[7]Relatedly, Kim (2025) studies *discretionary* risk-taking by *active* mutual fund managers which create correlated demand shocks that can amplify a stock's market risk. In contrast, we focus on benchmark-linked capital *flows* as a source of correlated demand shocks, similar in spirit to the work of Greenwood and Thesmar (2011). Appendix B documents that flows into passive mutual funds and ETFs predict cross-sectional changes in CAPM $\widehat{\beta}$.

[8]See also Cuoco and Kaniel, 2011, Buffa, Vayanos, and Woolley, 2022, and Buffa and Hodor, 2023.

[9]Our findings also relate to corporate governance and passive investing (Appel, Gormley, and Keim, 2016, Bebchuk, Cohen, and Hirst, 2017, Heath, Macciocchi, Michaely, and Ringgenberg, 2021, Lewellen and Lewellen, 2022).

vide evidence from commodity futures markets that index investing impacts the real economy partly because it impedes the ability of agents to extract signals from market prices.

Additionally, our paper contributes to the literature on how firm managers set discount rates. Despite the CAPM's failure to explain the cross-section of expected stock returns (Fama and French, 2004),[10] it reigns supreme in practice: Welch (2008) reports that about 75% of finance professors recommend using the CAPM and the Duke CFO survey (Graham, 2022) finds that the CAPM is the leading method to determine discount rates. Further evidence from earnings calls (Gormsen and Huber, 2024), M&A transactions (Dessaint, Olivier, Otto, and Thesmar, 2020), mutual funds (Berk and Van Binsbergen, 2016, Barber, Huang, and Odean, 2016), experiments with professional investors (Bloomfield and Michaely, 2004, Merkle and Sextroh, 2021), and share repurchases (Cho and Salarkia, 2022) shows that the CAPM is widely used in practice. We add by documenting that benchmarking-induced CAPM distortions have first-order effects on the discount rates that managers, analysts, and regulators use. We argue that these distortions have become large enough over the past 25 years to affect the economy as a whole.

Despite the widespread use of the CAPM in practice, the effects of variation in CAPM $\widehat{\beta}$s on investment are not widely studied. The literature primarily focuses on how the cost of debt (Gilchrist and Zakrajšek, 2007, Philippon, 2009) or tax policy (Zwick and Mahon, 2017, Mark, Garrett, Ohrn, Roberts, and Suárez Serrato, 2021, Matray, 2023) affect investment. Notable exceptions are Krüger, Landier, and Thesmar (2015) and Frank and Shen (2016). Krüger et al. (2015) document investment distortions caused by the use of a single discount rate within firms. Using OLS regressions, Frank and Shen (2016) find that higher contemporaneous CAPM $\widehat{\beta}$s are associated with higher investment. In contrast, we use an IV approach to address the endogenous relationship between CAPM βs and investment (Berk et al., 1999, Zhang, 2005, Kuehn and Schmid, 2014) and forecasts the effects of CAPM distortions up to six years into the future. Consistent with theoretical predictions, we find that exogenous increases in CAPM $\widehat{\beta}$s lead to lower investment.

Finally, we contribute to a nascent literature that uses subjective expectation about required rates of return to revisit classic puzzles in asset pricing and corporate finance (Adam and Nagel, 2023). Gormsen and Huber (2023) document a widening gap between firms' discount rates and their perceived cost of capital, while Gormsen and Huber (2024) show that firms' perceived costs can diverge significantly from market-implied ones. Gormsen, Huber, and Oh (2024) show that when climate concerns surged after 2016, green firms perceived their cost of capital to be 1 p.p. lower. Jensen (2024) finds that the CAPM explains subjective risk and return expectations

[10] Berk, Green, and Naik (1999) show that stock returns need not satisfy the CAPM even when expected returns on all individual projects do, since a firm's stock also embeds real options to undertake new and abandon old projects.

well but fails to explain realized returns because risk correlates with mispricing. We contribute by showing that across six datasets, subjective expected returns closely follow CAPM predictions: they are well explained by subjective βs and the market risk premium. However, we also find that these expectations are distorted by benchmarking-induced variation in CAPM $\widehat{\beta}$s. Contrary to the irrelevance result of Modigliani and Miller (1958), subjective expectations depend on capital (ownership) structure, not just on the risk of underlying assets.

2 New Facts About CAPM β Estimates and Benchmarking

This section documents new facts about CAPM $\widehat{\beta}$s in the cross-section of U.S. stocks. Over the past 25 years, CAPM $\widehat{\beta}$s and benchmarking intensity have increased in lockstep. Firms accounting for over 40% of annual capital expenditures in Compustat experienced an increase in CAPM $\widehat{\beta}$. Importantly, this increase is not driven by changes in fundamental risk—measured by cash flow βs—or by shifts in leverage. Instead, we find systematic distortions in CAPM $\widehat{\beta}$s across market capitalization ranks used in benchmark construction. This suggests that benchmarking affects the measurement of CAPM βs—a hypothesis we test using causal inference methods in Section 5.

We use monthly estimates of benchmarking intensity (BMI) from Pavlova and Sikorskaya (2023) from 1998 to 2018. BMI measures the amount of capital that inelastically demands the equity of a publicly traded firm. The BMI for stock i in month t is defined as

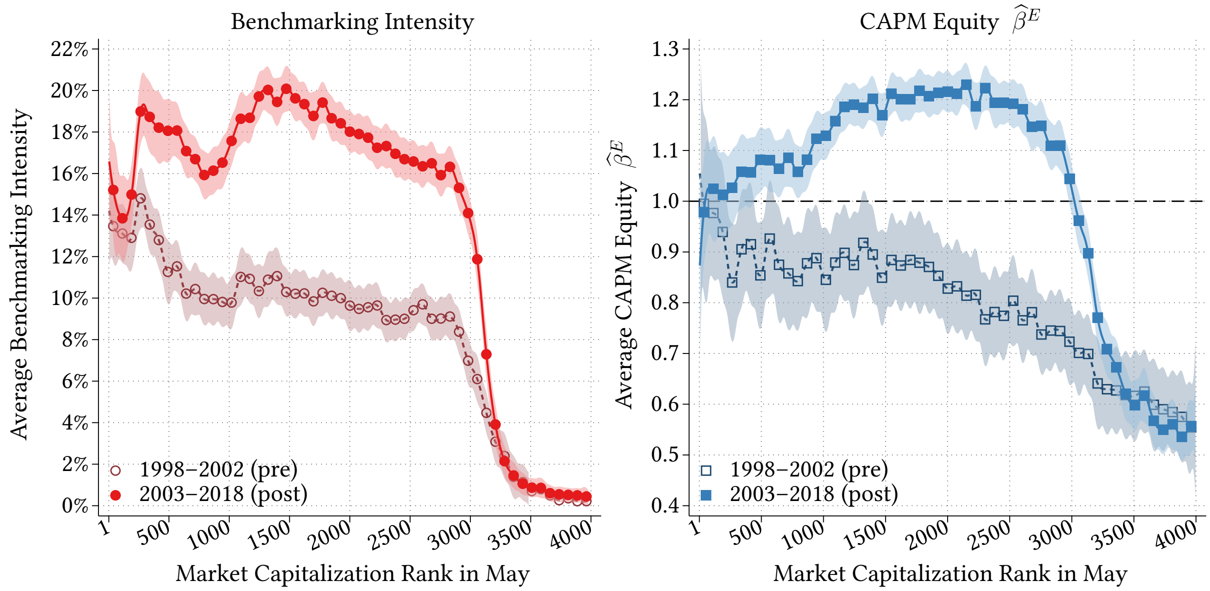
$$\mathrm{BMI}_{i,t} = \sum_{j=1}^{J} \frac{\lambda_{j,t} \times \omega_{i,j,t}}{\text{Market Capitalization}_{i,t}} \tag{1}$$

in which $\lambda_{j,t}$ are the assets under management (AUM) of mutual funds and ETFs benchmarked to index j and $\omega_{i,j,t}$ is stock i's weight in index j. We combine the BMI measure with estimates of stocks' CAPM βs. We use the estimator proposed by Welch (2022b) to calculate the market risk exposure of all common U.S. stocks with respect to the CRSP value-weighted index.[11] We split our sample into two periods: a pre-period from 1998 to 2002 and a post-period from 2003 to 2018.

We compare the distribution of conditional means of stocks' BMI and CAPM $\widehat{\beta}$ across market capitalization ranks. We fix a stock's market capitalization rank at the end of May and plot the stock's BMI and CAPM $\widehat{\beta}$s from June to May of the following year against that rank. This procedure mimics the construction of the Russell benchmark stock indices which are based on

[11] The estimator first winsorizes daily stock returns at -2x and +4x the contemporaneous market return. It then estimates β using WLS regression with exponentially decaying weights of 4-month half-life on an expanding window. Welch (2022b) shows that this estimator outperforms other estimators in predicting future CAPM $\widehat{\beta}$s out of sample.

Figure 1: Benchmarking Intensity and CAPM Equity $\widehat{\beta}^E$ vs. Market Capitalization Rank in May



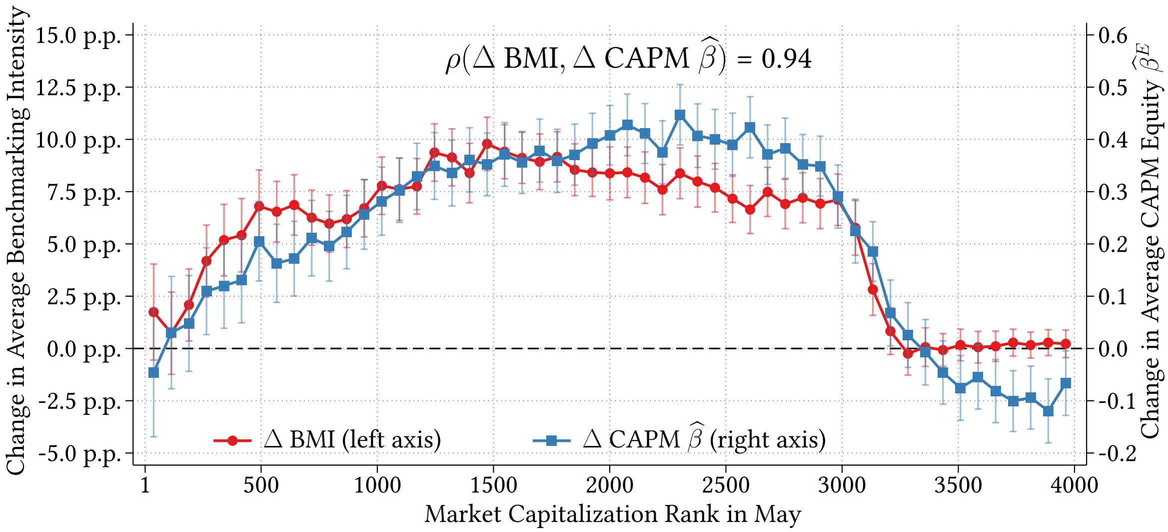
Notes: This figure shows binned scatter plots of monthly BMI and CAPM equity $\widehat{\beta}^E$ against May market capitalization ranks. Each bin reflects the equal-weighted average of 100 ranks. Conditional means are identified from cross-sectional variation by absorbing year-month fixed effects. Outlined bins use data from 1998–2002; filled bins from 2003–2018. Shaded areas show 95% confidence bands with standard errors clustered by stock and year-month.

end of May market capitalization ranks and reconstitute every year in June. For example, the Russell 3000, which comprises the largest 3000 stocks by market capitalization at the end of May. Pavlova and Sikorskaya (2023) estimate that 72.6% of the average stock's BMI is contributed by funds benchmarked to Russell indices. Beyond this, market capitalization ranks in May hold no inherent economic significance.

To analyze the raw data, we group stocks into bins of approximately 100 consecutive ranks. For each bin, we calculate the equal-weighted mean of BMI and CAPM $\widehat{\beta}$. We use monthly data and absorb year-month fixed effects to identify the conditional means across market capitalization ranks using only the cross-sectional variation within each month. We then plot pooled estimates of the conditional means across market capitalization ranks for the pre- and post-periods using the non-parametric binscatter methods developed by Cattaneo, Crump, Farrell, and Feng (2024).

Fact 1: Stocks' benchmarking intensity correlates with CAPM $\widehat{\beta}$. Both stocks' benchmarking intensity and $\widehat{\beta}$s have increased markedly since 2003. Figure 1 shows binned scatter plots of stocks' monthly BMI (left panel) and CAPM $\widehat{\beta}$ (right panel) against market capitalization ranks. Benchmarking intensity rose across the entire market capitalization spectrum, while $\widehat{\beta}$s increased for nearly all ranks. Among Russell 2000 stocks (ranks 1000–3000), average BMI nearly doubled—from 9.7% pre-2003 to 17.8% post-2003—while their $\widehat{\beta}$s rose by 46%, from 0.81 to 1.18.

Figure 2: Differences in Benchmarking Intensity and CAPM Equity $\widehat{\beta}^E$ Between Pre and Post



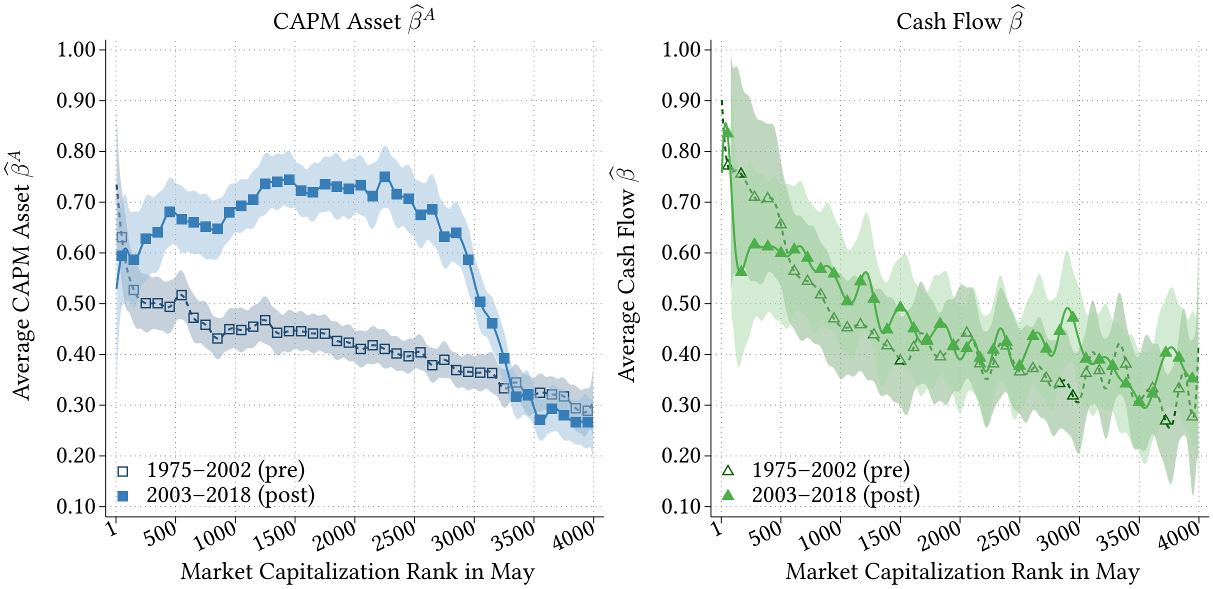
Notes: This figure plots changes in average BMI (left axis) and CAPM equity $\widehat{\beta}^E$ (right axis) between the pre- (1998–2002) and post- (2003–2018) periods against May market capitalization ranks. Each bin shows the change in conditional means from Figure 1. $\rho(\Delta\text{BMI}, \Delta\text{CAPM } \beta)$ reports the correlation between changes in BMI and CAPM $\widehat{\beta}$s. Error bars indicate pointwise 95% confidence intervals with standard errors clustered by stock and year-month.

Changes in the average benchmarking intensity and CAPM $\widehat{\beta}$ line up surprisingly well across market capitalization ranks. Figure 2 plots the difference in conditional means of BMI and $\widehat{\beta}$s between the pre- and post-periods. Differences in BMI and CAPM $\widehat{\beta}$s across market capitalization ranks are highly correlated (ρ=0.94). This strong correlation suggests that changes in benchmarking intensity could be a key driver of changes in firms' perceived risk exposure.

The distributions of BMI and CAPM $\widehat{\beta}$ in Figure 1 change visibly at Russell index cutoffs. Average BMI and $\widehat{\beta}$s decline sharply around the cutoff for the Russell 3000. Similarly, both measures rise around rank 1000, the threshold between the Russell 1000 and 2000 indices. Appendix Figure A1, which plots average BMI and $\widehat{\beta}$s separately for both indices, shows discrete jumps around the threshold: Russell 2000 stocks have, on average, 5 p.p. higher BMI and 0.09 higher $\widehat{\beta}$ than Russell 1000 stocks. The figure also shows corresponding changes in firm managers' perceived cost of capital and hurdle rates (Gormsen and Huber, 2024) around the threshold. These discontinuities suggest that market risk exposure and the perceived cost of equity depend on the institutional design of benchmark indices. In Section 5, we exploit plausibly exogenous variation in BMI due to index reconstitutions to identify the causal effect of benchmarking on CAPM $\widehat{\beta}$ and the perceived cost of equity capital.[12]

[12] Appendix Figure A2 shows robustness to estimating CAPM $\widehat{\beta}$s using daily, weekly, or monthly rolling windows.

Figure 3: CAPM Asset $\widehat{\beta}^A$ and Cash Flow β vs. Market Capitalization Rank in May



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

Fact 2: The increases in CAPM $\widehat{\beta}$s are not driven by changes in firms' capital structure. A potential concern is that changes in firms' capital structure, rather than benchmarking, could have caused the observed upward shift in equity $\widehat{\beta}$s. While it seems unlikely that systematic changes in leverage would align with arbitrary market capitalization rank bins, we verify that changes in $\widehat{\beta}$s are not due to systematic changes in leverage.

CAPM asset $\widehat{\beta}$s exhibit similar patterns as equity $\widehat{\beta}$s. The left panel of Figure 3 shows binned scatter plots of stocks' (unlevered) CAPM asset $\widehat{\beta}$s against market capitalization ranks for the periods pre and post-2003. The average asset $\widehat{\beta}$ of Russell 2000 stocks increased by 0.29. We find no evidence that changes in firms' leverage are driving the observed changes in the cross-section of stock's CAPM $\widehat{\beta}$s. The figure also extends the pre-period back to 1975 to ensure our facts are not driven by market dislocations during the Dot-Com boom. We find no evidence that either changes in capital structure or the Dot-Com boom account for the observed patterns.

Fact 3: CAPM $\widehat{\beta}$s increased while fundamental risk exposure stayed constant. The increases in CAPM $\widehat{\beta}$ are unrelated to changes in firms' fundamental risk as measured by cash flow βs. Figure 3 allows us to compare cash flow βs estimated from accounting data to CAPM asset βs estimated from stock market returns.[13] Cash flow βs remain stable across market capitalization ranks in both periods, while unlevered CAPM $\widehat{\beta}$s show a significant increase post 2003. This is particularly pronounced for Russell 2000 stocks, for which CAPM asset $\widehat{\beta}$s rose by an average of 0.29, while cash flow βs stayed constant. This suggests that the observed increase in CAPM $\widehat{\beta}$s reflects distortions rather than changes in firms' underlying cash flow risk.

3 A Stylized Model that Highlights the Mechanism

With these facts in hand, we present a stylized model that illustrates how distortions in CAPM $\widehat{\beta}$s through their effect on discount rates affect corporate investment decisions. Every standard corporate finance textbook instructs firm managers to implement investment policies that maximize firm value. The canonical guidance is to maximize net present value (NPV).[14] Firm managers need two key components to calculate NPV: the expected cash flows and the discount rate to convert future cash flows to present value. Most finance textbooks recommend using the weighted average cost of capital (WACC) as discount rate and to estimate the CAPM β to determine the cost of equity. The following stylized model highlights how the presence of benchmarked funds distorts firms' discount rates and thus affects capital allocation decisions.

Textbook investment policy Firm value $V_{i,t}$ is determined by the net present value of its expected future cash flows $\{CF_{i,t+h}\}_{h=1}^{\infty}$ discounted at the firm-specific discount rate $\{R_{i,t\to t+h}\}_{h=1}^{\infty}$:

$$V_{i,t} = \mathbb{E}_t \left[\sum_{h=1}^{\infty} \frac{CF_{i,t+h}}{R_{i,t\to t+h}} \right]. \tag{2}$$

The discount rate $R_{i,t\to t+h}$ equals the firm's weighted average cost of capital, determined by exposure to aggregate risk of the cash flows generated by the firm's assets, β_i^A, and the yield curve of risk-free rates $\{R_{t+h}^f\}_{h=1}^{\infty}$.

$$R_{i,t\to t+h} = \prod_{j=1}^{h} \left(R_{t+j}^f + \beta_i^A ERP_{t+j} \right) \tag{3}$$

[13] We follow Cohen, Polk, and Vuolteenaho (2009) and estimate cash flow βs as $\text{ROE}_{i,t} = \alpha_i + \beta_i^{CF}\, \text{ROE}_{Mkt,t} + \varepsilon_{i,t}$. ROE denotes the ratio of clean-surplus earnings ($X_t = BE_t - BE_{t-1} + D_t$) to beginning-of-the-period book equity (BE_{t-1}). D_t are gross dividends computed from the difference between CRSP returns and returns excluding dividends. We extend our analysis to the period from 1975 to 2018 since accounting information is only available quarterly and compute β_i^{CF} separately for each firm in Compustat using an expanding window of observations.

[14] Graham, Harvey, and Puri (2015) show that CEOs and CFOs prioritize NPV in capital allocation decisions.

Assuming for simplicity that firm leverage remains constant over time and 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 the equity risk premium (ERP_t):

$$\beta_i^A = \frac{\beta_i^E}{1 + (1-\tau)\frac{D_i}{E_i}} \tag{4}$$

As such, it can be directly inferred from the empirical CAPM β of the firm's equity $\widehat{\beta}_i^E = \frac{\widehat{\text{Cov}}(r_i, r_m)}{\widehat{\text{Var}}(r_m)}$. A firm manager considering a firm-typical project with cost $C_{i,t}$ and future cash flows $\{y_{i,t+h}\}_{h=1}^{\infty}$ should invest in the project if it has positive NPV and thus increases firm value, that is if

$$\mathbb{E}_t\left[\sum_{h=1}^{\infty} \frac{y_{i,t+h}}{\widehat{R}_{i,t+h}}\right] = \mathbb{E}_t\left[\sum_{h=1}^{\infty} \frac{y_{it+h}}{\prod_{j=1}^{h}\left(R_{t+j}^f + \frac{\widehat{\beta}_i^E}{1+(1-\tau)\frac{D_i}{E_i}} ERP_{t+j}\right)}\right] > C_{i,t}, \tag{5}$$

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

The presence of benchmarked funds distorts asset prices. Kashyap et al. (2021) show that benchmarked funds' inelastic demand for benchmark constituents increases their price and thereby lowers their implied discount rate. However, benchmark membership also induces excess co-movement between constituents that is unrelated to the aggregate risk exposure of the firm's cash flows (Vijh, 1994, Barberis et al., 2005, Boyer, 2011).[15] The excess co-movement of benchmark stocks increases $\widehat{\beta}_i^E$ and thus the discount rate proportional to the equity risk premium.

We illustrate the two opposing effects 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 $\Delta_I(BMI_{i,t})$. At the same time, β^E increases to $\widehat{\beta}_{i,t}^E = \beta_i^E + \Delta_\beta(BMI_{i,t})$. Both $\Delta_I(BMI_{i,t})$ and $\Delta_\beta(BMI_{i,t})$ monotonically increase in $BMI_{i,t}$ and satisfy $\Delta_I(0) = \Delta_\beta(0) = 0$.

The discount rate, adjusted for benchmarking distortions, that maximizes firm value is

$$\widetilde{R}_{i,t\to t+h} = \prod_{j=1}^{h}\left(R_{t+j}^f + \frac{\beta_i^E + \Delta_\beta(BMI_{i,t})}{1+(1-\tau)\frac{D_i}{E_i}} ERP_{t+j} - \Delta_I(BMI_{i,t})\right). \tag{6}$$

CAPM investment policy with benchmarking distortions Whether the benchmarking distortions to the discount rate in Eq. (6) cause firm managers to invest more or less is ambiguous.

[15]See also Appendix D of Kashyap et al. (2021) for further details.

The price effect of benchmark inclusion, $\Delta_I(BMI_{i,t})$ (in blue) incentivizes investment, whereas the increase in CAPM $\widehat{\beta}$, Δ_β (in red), discourages investment. Empirically, positive price effects at inclusion (see e.g., Chang et al., 2015) suggest that $\Delta_I(BMI_{i,t})$ may dominate in the short-run.

What if firm managers do not internalize the inelastic demand of benchmarked funds for index constituent stocks 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. Firm managers, with subjective expectations $\mathbb{E}_t^\star[\cdot]$, observe an increase in their stock's CAPM β from β_i^E to $\widehat{\beta}_i^E = \beta_i^E + \Delta_\beta(BMI_{i,t})$ and infer an increase in the firm's cost of capital. Firm managers now invest only in projects that satisfy

$$\mathbb{E}_t^\star\left[\sum_{h=1}^{\infty}\frac{y_{i,t+h}}{\widetilde{R}_{i,t+h}}\right] = \mathbb{E}_t^\star\left[\sum_{h=1}^{\infty}\frac{y_{i,t+h}}{\prod_{j=1}^{h}\left(R_{t+j}^f + \frac{\beta_i^E + \Delta_\beta(BMI_{i,t})}{1+(1-\tau)\frac{D_i}{E_i}}ERP_{t+j}\right)}\right] > C_{i,t}. \tag{7}$$

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

Testable hypothesis Our proposed mechanism rests on the behavioral assumption that firm managers do not internalize the total effect of benchmarking-induced discount rate distortions. Instead, managers follow textbook guidance to form a weighted average cost of capital using their firm's empirical CAPM $\widehat{\beta}$s. Benchmarking-induced co-movement distorts the CAPM $\widehat{\beta}$s 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 $\widehat{\beta}^E$,

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

(iii) and leads to a decline in investment.

4 Data and Sample

We use five main sources in our empirical analysis: (1) the measure of benchmarking intensity developed by Pavlova and Sikorskaya (2023), (2) estimates of firm CAPM $\widehat{\beta}$s from Welch (2022b), (3) firm-level data from S&P's Compustat North America Fundamentals, (4) data on firm managers' (Gormsen and Huber, 2024), stock analysts', and regulators' perceived cost of capital, and (5) additional firm-level variables from various sources.

Benchmarking intensity We use monthly estimates of benchmarking intensity from Pavlova and Sikorskaya (2023) which cover 1998 to 2018. Similar to Pavlova and Sikorskaya (2023), we use changes in BMI between the rank day of Russell indices in May and the reconstitution day in June as an instrumental variable for changes in institutional ownership.[16] Changes in BMI satisfy the relevance condition because they predict how benchmarked investors rebalance their portfolios after a Russell index reconstitution. The exclusion restriction requires that index membership is exogenous. The literature on benchmark inclusion effects argues that after controlling for factors that determine benchmark inclusion, most importantly the ranking variable (market value) that Russell uses for index assignment at the end of May, the index membership is exogenous.

Estimates of CAPM βs We use end-of-month estimates of the winsorized and exponentially weighted CAPM $\widehat{\beta}$s from Welch (2022b), calculated using daily data against the CRSP value-weighted index. The β estimator first winsorizes a firm's daily stock return at −2 and +4 times the contemporaneous market return, and then estimates an exponentially weighting least squares regression of the stock's (winsorized) excess return on the market excess return. The half-life of the exponential decay is 90 trading days. Welch (2022b) shows that this estimator outperforms other β estimators like Bloomberg's β or the Vasicek (1973) β in predicting future market βs out of sample. We focus on common equities that trade on either the NYSE, AMEX, or NASDAQ, and exclude ADRs, REITs, and ETFs. Appendix Table A1 reports descriptive statistics for the matched BMI-CAPM data covering 1998 to 2019.

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 sales (in 2017 dollars). Firms must have at least five years of consecutive data. We winsorize the data at the 2.5% and 97.5% level.

Data on perceived cost of equity capital We source data on firm managers' perceived cost of capital from Gormsen and Huber (2024), who hand-collect these from earnings calls. We additional obtain data on the perceived cost of equity capital from Morningstar Direct, data on the perceived riskiness of stocks from Value Line, data on subjective expected returns from I/B/E/S (for details see Appendix C) and data on perceived cost of equity for public utilities and railroads (for details see Appendix C.2) .

[16] For the average stock, approximately 72.6% of BMI is contributed by funds which are benchmarked to Russell indices while 10.7% come from S&P 400/500 and 8.4% from CRSP indices. The remainders consists of other index providers such as Dow Jones, FTSE, and Wilshire (Pavlova and Sikorskaya, 2023).

Additional firm data We obtain stock returns and market data from the Center for Research in Security Prices (CRSP). We use measures of firm-level intangible capital from Peters and Taylor (2017). We collect Executive compensation peer group information from Institutional Shareholder Services (ISS). We use firm-level risk measures from Hassan, Hollander, Van Lent, and Tahoun (2019) and data on financial frictions from Hoberg and Maksimovic (2015) and Linn and Weagley (2021). We obtain Governance scores from Sustainalytics, Refinitiv, and S&P and estimates of stocks' implied cost of capital (ICC) from Eskildsen et al. (2024).

5 Changes in Stocks' CAPM βs Caused by Benchmarking

We estimate the causal effect of changes in a firm's benchmarking intensity on its CAPM equity $\widehat{\beta}$ using a difference-in-differences design. We compare the evolution of CAPM $\widehat{\beta}$s of (treated) stocks that experience BMI changes around Russell index reconstitution dates to (control) stocks that do not. The results show that changes in a stock's BMI around index reconstitutions causally change its CAPM $\widehat{\beta}$. This effect is symmetric and monotonically increasing in treatment intensity. A stock whose BMI increases (decreases) by at least 5 p.p. experiences an increase (decrease) in CAPM $\widehat{\beta}$ by 0.18 (-0.23) relative to the control group. The change in CAPM $\widehat{\beta}$ persist for at least 7 years and only partly reverses over time.

Managers' perceived cost of capital responds to benchmarking-induced increases in CAPM $\widehat{\beta}$s. Using data from Gormsen and Huber (2024), we find that increases in BMI predict increases in managers' perceived cost of capital. We use changes in BMI as an IV to identify the causal effect of changes in CAPM $\widehat{\beta}$s on a firm's perceived cost of capital. The IV estimates imply that a 0.2 change in CAPM $\widehat{\beta}$ increases managers' perceived cost of capital by approximately 70 bps.

We provide additional evidence from five alternative datasets which show that benchmarking-induced increases in a stocks' CAPM βs increase the perceived cost of equity capital. Independent analysts from Morningstar, Value Line, and I/B/E/S report higher perceived equity costs following an exogenous increase in a stock's benchmarking intensity. Similarly, regulated monopolies, including utilities and railroads, request higher cost of equity which regulators authorize. Across datasets, CAPM-implied perceived equity risk premia range from 4% to 8% annually.

The effects of increases in benchmarking on CAPM $\widehat{\beta}$s are large and economically significant. An increase of 0.2 in CAPM β translates to a 120 bps rise in the cost of equity capital, assuming a 6% equity risk premium. The bias can have substantial implications for NPV calculations. For instance, a firm investing in a project that generates $100 in perpetuity would value it at $1,000 with a 10% discount rate. However, increasing the discount rate to 11.2% reduces the project's value to \$893. Overestimating the WACC by just 1.2% leads to more than 10% undervaluation. We analyze the effects of these distortions on firm- and industry-level investment in Section 6.

5.1 Difference-in-differences Strategy

We analyze the effect of an increase in BMI on a firm's CAPM $\widehat{\beta}$ by estimating a series of difference-in-differences specifications of the form:

$$\text{CAPM } \widehat{\beta}_{i,t} = \delta \text{ Treated}_i \times \text{Post}_{t>\text{May}} + \theta_i + \theta_{t,s} + \zeta X_{i,t} + \varepsilon_{i,t} \tag{8}$$

in which Treated_i is an indicator variable for whether firm i's BMI changed by more than ± 5 p.p.. The coefficient of interest, δ, summarizes the treatment effect on a firm's CAPM $\widehat{\beta}$. We restrict our sample to all stocks stocks within 300 ranks around the Russell index cutoffs to ensure we capture only changes in BMI due to Russell index reconstitution.[17]

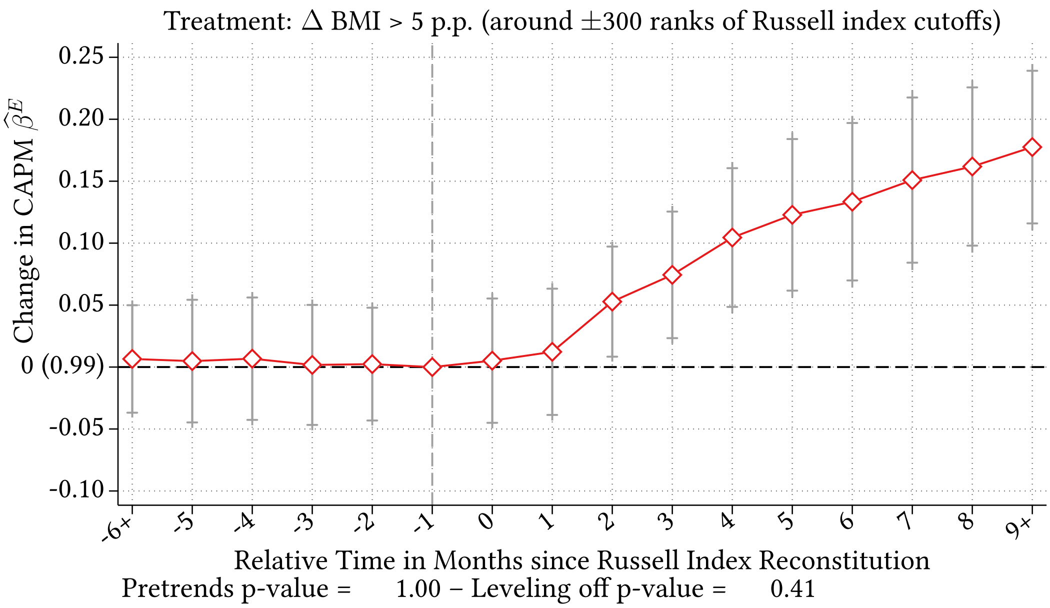
The inclusion of firm fixed effects, θ_i, removes time-invariant heterogeneity across firms and accounts for possible ex-ante differences between treated and control firms. Size-by-month or liquidity-by-month fixed effects, $\theta_{s,t}$, restrict the identifying variation to comparisons within the same size or liquidity decile each period, controlling for time-varying unobserved heterogeneity correlated with a firm's CAPM $\widehat{\beta}$. We exclude stocks with market values below the fifth percentile of the NYSE to ensure that micro-cap stocks do not drive the results.[18] We additionally include stock-level controls, $X_{i,t}$, to improve precision. These are the stock's monthly excess return, log of trading volume, as well as the cumulative excess return over the past 12 and 24 months.

The Russell indices reconstitute each year, and identification in (8) thus exhibits staggered treatment timing with potentially misleading estimates if the treatment effect is heterogeneous between cohorts or over time (De Chaisemartin and d'Haultfoeuille, 2023). We follow the suggestion of Baker, Larcker, and Wang (2022) to stack the yearly cohorts and include cohort by firm and cohort by time fixed effects but suppress cohort subscripts for brevity.[19]

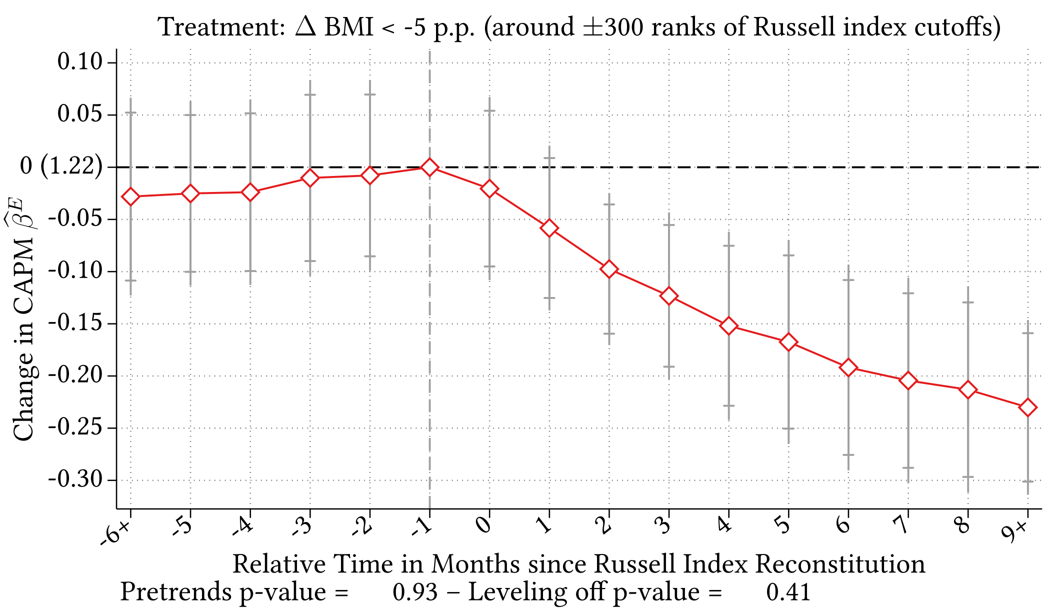
Identifying assumptions and threats to identification. Our identification strategy relies on the following assumption: conditional on the set of fixed effects and control variables, firms that experience changes in BMI are not differentially exposed to unobservable shocks that correlate with BMI. The identification assumption does not require random assignment of benchmark inclusion, nor does it require that firms have similar characteristics in levels. Rather, we rely on

[17] Our findings are robust to changing the bandwidth to 100, 250, 500 ranks or not imposing restrictions.
[18] We obtain similar results when using the 10th or 20th percentile of the NYSE as a cutoff (see Appendix Table A2).
[19] See, e.g., Gormley and Matsa (2011), Cengiz, Dube, Lindner, and Zipperer (2019) and Deshpande and Li (2019) for similar implementations of stacked difference-in-differences designs.

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



(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 of Eq. (8). Change in CAPM $\widehat{\beta}^E$ 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 (99%) and sup-t confidence bands based on double-clustered standard errors. Values in parentheses on the Y-axis show the average CAPM $\widehat{\beta}^E$ before treatment.

Table 1: Causal Effects of Changes in Benchmarking Intensity on CAPM $\widehat{\beta}$s

Treatment Group:	Δ BMI > 5 p.p.				Δ BMI < -5 p.p.			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treated × Post 9 Months	0.177***	0.178***	0.179***	0.180***	-0.232***	-0.232***	-0.226***	-0.230***
	(0.024)	(0.024)	(0.023)	(0.023)	(0.022)	(0.025)	(0.021)	(0.023)
Momentum Controls	✓	✓	✓	✓	✓	✓	✓	✓
Fixed Effects								
Firm × Cohort	✓	✓	✓	✓	✓	✓	✓	✓
Time × Cohort	✓				✓			
Rank Decile × Time × Cohort		✓				✓		
Volume Decile × Time × Cohort			✓				✓	
Shrs. Out. Decile × Time × Cohort				✓				✓
Observations	127,285	127,242	127,158	127,175	128,427	128,387	128,284	128,292

Notes: This table reports $\hat{\delta}$ for specifications of the form: CAPM $\widehat{\beta}_{i,t} = \delta$ Treated$_i$ × Post$_{t>\text{May}} + \theta_i + \theta_{t,s} + \varepsilon_{i,t}$. Treated×Post is average of post-treatment coefficients after 9 months (to account for the expanding-window estimation of CAPM $\widehat{\beta}$). Control group are firms with $|\Delta\text{BMI}| < 1$ p.p.. Estimation sample is restricted to stocks within 300 ranks around Russell index cutoffs. Standard errors in parentheses are double-clustered at stock and year-month level. + p<0.10, * p<0.05, ** p<0.01, *** p<0.001.

the parallel trends assumption that CAPM $\widehat{\beta}$s for treated and control firms would have trended similarly absent an increase in BMI. We provide supporting evidence of parallel pre-treatment trends in Figures 4a and 4b and additionally perform a placebo test in Figure A4. As expected, this placebo test finds no treatment effect.

Results Figures 4a and 4b show the event study coefficients of our difference-in-differences estimation for treatments defined as an increase or decrease in BMI of 5 p.p., respectively. We normalize the dynamic treatment effect to zero in May and estimate dynamic treatment effects for the period from 9 months before to 12 months after benchmark inclusion.

Several facts are worth noting. First, the CAPM $\widehat{\beta}$s of treated and control firms evolve in close parallel before index reconstitution, supporting the identification assumption and causal interpretation of treatment effects. The p-values for the Wald-style pre-trend test suggested by Freyaldenhoven, Hansen, Pérez, and Shapiro (2021) are 1.00 and 0.93, respectively. Second, after index reconstitution, CAPM $\widehat{\beta}$s begin to diverge for both increases and decreases in BMI. The smooth event-time trend in Figure 4 is largely mechanical as older information receives exponentially smaller weights.[20] The treatment effect of a BMI increase on a firm's CAPM $\widehat{\beta}$ is likely immediate, but our measurement captures it only once older information is sufficiently down-weighted. Third, treatment effects for BMI increases and decreases of at least 5 p.p. have similar magnitudes but opposite signs, suggesting that treatment effects are linear in BMI.

Table 1 reports the average estimated post-shock coefficient. We report the average treatment effect nine months after treatment to ensure that the majority of the data used to estimate

[20]The β estimator uses an expanding-window with exponential weights of 4.5 months half-life.

CAPM $\widehat{\beta}$s reflects the post-treatment period. By this point, post-treatment data accounts for approximately three-quarters of the weighting in the estimation. The coefficient estimate for the interaction Treated$_i$ $\times$ Post$_{t>\text{May}}$ is positive for increases in BMI and negative for decreases in BMI, with treatment effects always statistically significant at the 0.1% level. Columns (1) and (5) present results with firm and year-month fixed effects, while subsequent columns add more granular fixed effects by year-month, market capitalization rank, volume, or shares outstanding. These fixed effects control for potential size or liquidity differences between treated and control firms. The estimated effects of BMI changes remain stable across different fixed effects. Column (2) shows that a BMI increase of at least 5 p.p. raises a firm's CAPM $\widehat{\beta}$ by 0.18, while Column (6) shows that a decrease in BMI by at least 5 p.p. lowers a firm's CAPM $\widehat{\beta}$ by -0.23.

The estimates of the average treatment effect in Table 1 mask substantial heterogeneity. Appendix Figure A3 plots the event-time coefficients for three different treatment intensities. Treatment levels are defined in increasing order of treatment intensity as changes in BMI by 5 p.p. to 10 p.p., 10 p.p. to 20 p.p., and greater than 20 p.p.. The estimated treatment effect is 0.15 for the lowest treatment intensity, 0.24 for the medium treatment intensity, and 0.35 for the highest treatment intensity after 12 months. The treatment effects are statistically significant at the 0.1% level for all treatment intensities. For firms in the highest treatment intensity group, the treatment effect is 0.35, equivalent to a 210 bps increase in the cost of equity capital.

What causes the increases in CAPM $\widehat{\beta}$? The difference-in-differences results above show that exogenous increases in benchmarking intensity due to index reconstitution raise stocks' CAPM $\widehat{\beta}$s. While the proximate cause of this effect is the rise in benchmarking intensity, we posit that the fundamental driver is likely the inelastic demand by passive index funds. Recall that BMI captures the total inelastic demand a stock attracts from benchmarked active and passive mutual funds and ETFs. Since passive funds have by definition inelastic demand for benchmark stocks, changes in *passive flows* likely exert a strong influence on returns and CAPM $\widehat{\beta}$s. Kim (2025) proposes a complementary mechanism wherein *discretionary* risk-taking by *active* managers increases a stock's market risk.

Appendix B.1 examines the link between flows into passive mutual fund and cross-sectional increases in CAPM $\widehat{\beta}$. Using Morningstar Direct data, we analyze the effect of net flows into active and passive mutual funds on CAPM $\widehat{\beta}$. Our panel regression show that net flows into passive fund significantly increase $\widehat{\beta}$, particularly for stocks ranked below 1000 in market capitalization, where passive ownership is more concentrated (Pavlova and Sikorskaya, 2023). A two-standard-deviation net inflow into passive funds raises the $\widehat{\beta}$ of the smallest stocks by 0.06, while active fund flows have negligible and often statistically insignificant effects. The relationship between passive flows and CAPM $\widehat{\beta}$ appears to have changed over time. Before 2010, benchmarking intensity (BMI) served as a key channel through which passive investing affected $\widehat{\beta}$s, while after 2010, the effect operates more directly through observed passive flows. This suggests that BMI is a reasonable proxy for passive flows in earlier periods when official data on passive ownership is less comprehensive.

In Appendix B.2, we use simulations to show that the emergence of a passive flow factor can explain the evolution of CAPM $\widehat{\beta}$s from 1998 to 2018. We propose a simple two-factor model. In this model, a stock's CAPM $\widehat{\beta}$ depends on a fundamental factor and a flow factor. The fundamental factor summarizes key macro-financial variables. Its loadings are fixed to the distribution of $\widehat{\beta}$ observed in 1990, before passive investing became widespread. The flow factor captures net flows into passive mutual funds and ETFs. Stocks' benchmarking intensity proxies their exposure to this flow factor. Our simulations show that a passive flow factor successfully captures the cross-sectional and time-series patterns of CAPM $\widehat{\beta}$s. When calibrated with passive flows, the model closely matches the empirical distribution of $\widehat{\beta}$s. Flows into active funds fail to replicate the empirical patterns.

This evidence suggests that the fundamental cause which increases CAPM $\widehat{\beta}$s is the shift toward passive index investing. Since 1998, cumulative net flows into passive funds have exceeded those into active funds by more than \$10 trillion (see Appendix Figure B10).[21] We show through both panel regressions and a simulation exercise that these passive flows can explain the time series and cross-sectional evolution of CAPM $\widehat{\beta}$s.

Alternative CAPM β estimators To verify that our results are not driven by the choice of β estimator, we estimate a series of OLS regressions for a set of alternative estimators. Appendix Table A3 shows OLS regressions results using different estimators for the unknown CAPM β. We compare the usual OLS estimator with alternative estimators proposed by Blume (1975), Dimson (1979), and Welch (2022b). We also report estimates of the $\widehat{\beta}$ with the ten largest stocks by market capitalization, and correlation with the market and idiosyncratic volatility. We find that *all* CAPM $\widehat{\beta}$ estimators show a statistically significant association with changes in BMI. Changes in $\widehat{\beta}$ occur due to changes in market correlation, not because of increases in idiosyncratic volatility. This aligns with Antón and Polk (2014), who show that mutual funds' common ownership increases return correlation of equities.

[21]In 2024 passive funds surpassed active funds in total net assets for the first time. While official data from 2021 indicate that index funds held 16% of the U.S. stock market, Chinco and Sammon (2024) estimate that the true passive ownership share is nearly twice as high when accounting for institutions managing index portfolios internally and active managers engaging in quasi-indexing.

5.2 Persistence of Effects and Changes in Stock's Implied Cost of Capital

We assume that managers use the CAPM to set discount rates and do not account for the distorting effects of benchmarking on stock prices. Alternatively, managers might infer the discount rate from stock prices and expected cash flows, as in Kashyap et al. (2021). We test whether BMI changes at index reconstitution influence the implied cost of capital (ICC) that managers could infer from stock prices. The ICC, based on current stock prices, captures any price distortion from benchmarking. Following Eskildsen et al. (2024),[22] we calculate the ICC by averaging four popular models from the accounting literature: the residual income models from Gebhardt et al. (2001) and Claus and Thomas (2001), and the dividend discount models from Easton (2004) and Ohlson and Juettner-Nauroth (2005). The ICC only captures the implied cost of equity, we thus compare it to the cost of equity implied by the CAPM.

We examine whether benchmarking distortions persist over long horizons. Our difference-in-differences analysis shows that BMI distortions in CAPM $\widehat{\beta}$s persist for at least 12 months. If these distortions in the cost of equity fade after a year, long-term effects on investment are unlikely. We extend our analysis to test for effects on the ICC and CAPM $\widehat{\beta}$s over a seven-year horizon using the following specifications:

$$\text{Avg. ICC}_{i,t+h} = \theta_0^h + \theta_1^h \Delta\text{BMI}_{i,t} + \xi^h X_{i,t} + \varepsilon_{i,t+h}, \quad h = 0, \ldots, 7, \tag{9}$$

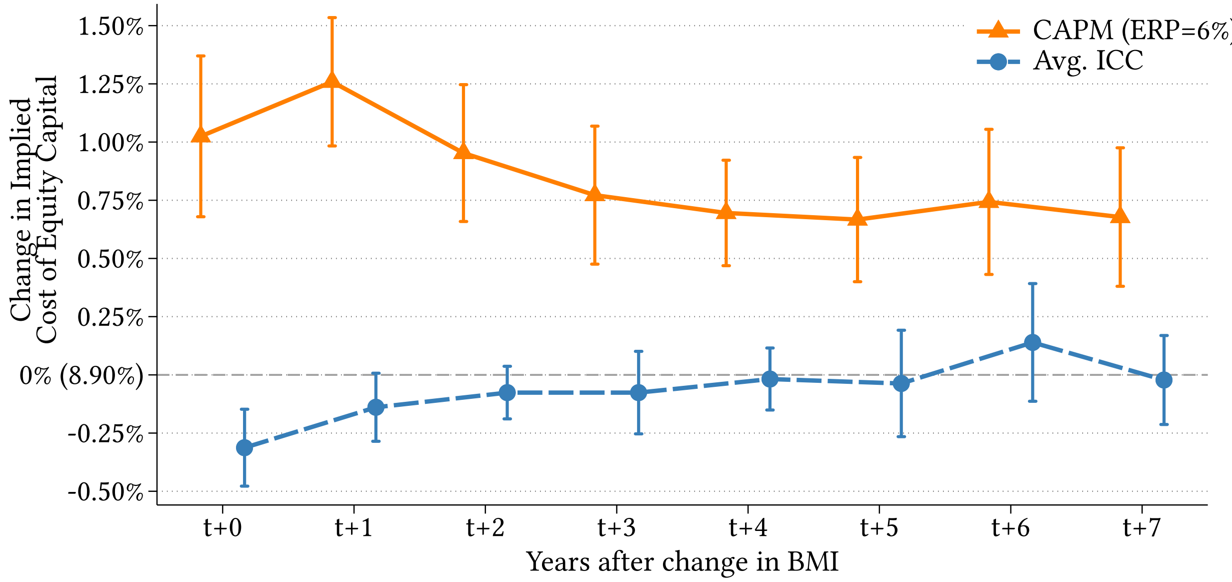
$$\text{CAPM } \widehat{\beta}_{i,t+h} \times 6\% = \gamma_0^h + \gamma_1^h \Delta\text{BMI}_{i,t} + \zeta^h X_{i,t} + \nu_{i,t+h}, \quad h = 0, \ldots, 7. \tag{10}$$

for firm i in year $t{+}h$. The coefficients of interest, γ_1^h and θ_1^h, summarize the long-term effects of an BMI increase on a firm's CAPM $\widehat{\beta}$ or ICC after h years, respectively. The vector $X_{i,t}$ contains year-by-industry fixed effects and the lagged level of BMI. 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. We focus on stocks in the 300 ranks around the Russell index cutoffs.

Results Figure 5 shows estimates for γ_1^h and θ_1^h of Eq. (10) and (10), respectively. The distortionary effects of BMI increases on CAPM $\widehat{\beta}$s persist for at least 7 years. At each forecast horizon, we find statistically significant positive effects of BMI increases on CAPM $\widehat{\beta}$s. These effects gradually diminish over time but remain economically significant. One year after the initial BMI increase, the cost of equity capital is 125 bps higher. Four years later, it remains 71 bps higher, and even seven years later, it is still 67 bps higher. This prolonged impact suggests that

[22]Using these measures, Eskildsen et al. (2024) estimate a negative annual green equity premium. Similarly, Kontz (2023) estimates a positive green convenience yield in auto asset-backed securities.

Figure 5: Persistence of BMI Shock on the Cost of Equity Capital Over Long Horizons



Notes: This figure shows the persistence of BMI shocks on estimates of firms' cost of equity for ICC and CAPM using regression of the form: CAPM $\widehat{\beta}_{i,t+h} = \gamma_0^h + \gamma_1^h \Delta\text{BMI}_{i,t} + \varepsilon_{i,t+h}$. Estimation sample is restricted to stocks within 300 ranks around Russell index cutoffs. Estimates are scaled to a 10 p.p. BMI increase. 99% confidence intervals based on standard errors clustered at stock and year. Value in parentheses on the Y-axis is the median ICC over the sample.

benchmarking has a long-term effect on firms' perceived cost of capital, potentially leading to sustained changes in investment behavior.

In contrast, changes in BMI have only short-lived effects on the implied cost of capital. The estimates for the year of benchmark inclusion show that the ICC decreases by approximately 36 bps. We perform a back-of-the-envelope calculation to estimate the implied stock return at benchmark inclusion using Gordon's growth model.[23] The 36 bps decrease in the ICC at benchmark inclusion implies a 5.24% increase in the stock price, close to the 5% documented by Chang et al. (2015). However, the effect on the ICC fades to 14 bps after one year and becomes statistically insignificant thereafter.

The small and short-lived impact on the ICC makes it unlikely that increased benchmarking affects investment through a price-level channel. A firm's cost of capital is a long-term rate, unaffected by short-term price effects (Berk and Van Binsbergen, 2025). Only permanent price changes affect the cost of capital, while much of the demand-driven price effect appears temporary (see also Harris and Gurel, 1986). Moreover, the temporary price effect of benchmark

[23] We assume the expected dividend, D_1, and expected dividend growth rate, g, remain constant when BMI changes, but r changes by $\hat{\theta}_1^0 \times \Delta\text{BMI}$. The implied stock return is given by: $\frac{P^{Post}}{P^{Pre}} - 1 = \frac{-\hat{\theta}_1^0 \times \Delta\text{ BMI}}{r + \hat{\theta}_1^0 \times \Delta\text{ BMI} - g} = \frac{0.36\%}{8.9\% - 0.36\% - 1.6\%} \approx 5.24\%$. We set r to the pre-benchmark inclusion average of the ICC ($\approx$8.9%), g to the long-run average of real dividend growth ($\approx$1.6%), and ΔBMI to 10 p.p (as in Figure 5).

inclusion seems to have all but disappeared: Greenwood and Sammon (2024) show that the price effect of joining the S&P 500 has fallen from an average of 7.4% in the 1990s to less than 1% over the past decade. Chang et al. (2015) similarly document that the price impact of inclusion in the Russell benchmarks has decreased over time.

5.3 Changes in CAPM β and Manager's Perceived Cost of Capital

We document that changes in the CAPM $\widehat{\beta}$ affect the perceived cost of capital of firm managers, using firm's self-reported data collected from earnings calls by Gormsen and Huber (2023). We estimate the pass-through of changes in a firm's CAPM $\widehat{\beta}$ on the perceived cost of capital using a series of instrumental variable (IV) regressions of the following form:

$$\Delta \text{ CAPM } \beta_{i,t} = \delta_i + \delta_{j,t} + \theta \Delta \text{ BMI}_{i,t} + \epsilon_{i,t} \tag{11}$$

$$\Delta \text{ Perceived Cost of Capital}_{i,t} = \alpha_i + \alpha_{j,t} + \gamma \sum_{s=0}^{p} \frac{p+1-s}{p+1} \Delta \text{ CAPM } \widehat{\beta}_{i,t-s} + \varepsilon_{i,t} \text{ ; } p = 4 \tag{12}$$

in which the coefficient of interest is the cumulative effect, $\lambda = \gamma(1+\frac{p}{2})$, which provides us with an estimate of the pass-through of changes in a firm's CAPM $\widehat{\beta}$ to its perceived cost of capital. Including firm fixed effects α_i ensures we remove time-invariant heterogeneity across firms, and, in particular, accounts for possible ex-ante differences in pass-through rates between treated and control firms. Size-by-year or industry-by-year fixed effects, $\alpha_{j,t}$, further restrict the identifying variation to comparing firms within the same size decile, liquidity decile, or industry each period.

We use a (restricted) distributed lag model in Eq. (12) for both economic and econometric reasons. Managers typically estimate CAPM $\widehat{\beta}$ using OLS regressions using two to five years windows. Rolling-window estimators gradually incorporate changes in CAPM $\widehat{\beta}$ into managers' perceived cost of capital as new data becomes available. Gormsen and Huber (2023) show that this perceived cost of capital affects managers' required returns on new investments and investment decisions, with a transmission lag of several years.[24] We restrict the shape of the lag weights in Eq. (12) to be linearly declining with horizon $t-q$ to economize on parameters. Restricting the shape of the lag weights also allows us to report a interpretable first stage F-statistic which is important for the validity of the IV estimates. Appendix Table A5 shows that one obtains similar results using an unrestricted distributed lag model. We further restrict the sample to be within 400 ranks around Russell index cutoffs to ensure that the treatment effect is related to changes in

[24] Additionally, the data supports a distributed lag model over a contemporaneous effect model, with Bayesian information criterion (BIC) values favoring fourth-order lags (see Appendix Table A4).

Table 2: Effect of Δ CAPM $\widehat{\beta}$ on Managers' Perceived Cost of Capital (Gormsen and Huber, 2024)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Dependent variable: Δ Perceived Cost of Capital (in p.p.)								
Δ BMI (in p.p.)	0.007^{+}	0.009*	0.011*						
	(0.003)	(0.003)	(0.004)						
Δ CAPM β^{A}				1.044***	0.998***	0.833***	2.424^{+}	3.588*	3.270*
				(0.182)	(0.163)	(0.141)	(1.328)	(1.409)	(1.444)
Fixed Effects									
Firm FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓			✓			✓		
Size Quartile $\times$ Year FE		✓			✓			✓	
Industry $\times$ Year FE			✓			✓			✓
FS F-stat.							38.7	29.9	54.6
Adj. R^2	0.14	0.16	0.34	0.15	0.16	0.34			
Observations	10,130	10,130	9,329	10,130	10,130	9,329	10,130	10,130	9,329

Notes: This table reports the cumulative effect $\lambda = \gamma(1 + \frac{p}{2})$ from specifications of the following restricted distributed lag model: $\Delta\text{Perc. Cost of Capital}_{i,t} = \alpha_i + \alpha_{j,t} + \gamma \sum_{s=0}^{p} \frac{p+1-s}{p+1} \Delta \text{ CAPM } \widehat{\beta}_{i,t-s} + \varepsilon_{i,t}$ in which $p = 4$ for reduced form, OLS, and IV regression in which the instrument is ΔBMI for stock i in year t. IV estimated via LIML. Estimation sample is restricted to stocks within 400 ranks around Russell index cutoffs. Standard errors in parentheses are clustered at firm-level. + p<0.10, * p<0.05, ** p<0.01, *** p<0.001.

BMI due to Russell index reconstitution. This results in an average of 622 stocks per year in the estimation sample. Smaller windows around the Russell index cutoffs (e.g., +/- 300 ranks) yield similar albeit somewhat noisier results (available upon request).

A firm's perceived cost of capital and its stock's CAPM β are jointly determined by its exposure to aggregate risk in equilibrium. To address endogeneity and measurement error, we use an instrumental variable approach, with BMI change as a natural instrument. BMI changes induce CAPM $\widehat{\beta}$ changes orthogonal to aggregate risk as shown by the difference-in-differences results. The exclusion restriction requires that BMI increases affect a firm's perceived cost of capital only through changes in its CAPM β. This could be violated if BMI impacts perceived cost through other channels, like reducing credit spreads due to reputational effects. However, in Appendix D, we find no evidence that BMI changes correlate with risk, financial constraints, or governance changes, supporting the validity of the exclusion restriction.

Table 2 reports coefficient estimates of Eq. (12) for reduced form (RF), OLS, and IV specifications. Columns (1) to (3) report RF, columns (4) to (6) OLS, and columns (7) to (9) IV estimates. The coefficients are positive, stable across specifications, and statistically significant. Columns (1) to (3) of Table 2 show that increases in BMI predict increases in managers' perceived cost of capital. OLS estimates show a downward bias relative to IV estimates, likely due to classical measurement error. Two mechanisms introduce measurement error. First, we do not observe how firms estimate their CAPM $\widehat{\beta}$ when calculating their perceived cost of capital. We use the CAPM $\widehat{\beta}$s of Welch (2022b) due to their superior performance in predicting future CAPM $\widehat{\beta}$s out of sample. In practice, firms often simply estimate CAPM $\widehat{\beta}$s using equally-weighted observations on a rolling window of two to five years (Berk and DeMarzo, 2023). Second, any empirical CAPM $\widehat{\beta}$ is an *estimate* of the true CAPM β and thus subject to measurement error.

The IV estimates in Column 8 and 9 of Table 2 imply that managers use a perceived equity risk premium between 3.2% to 3.6%, very close to the average equity risk premium of 3.6% reported by CFOs in the survey by Graham and Harvey (2018) from 2000 to 2017.

5.4 Other Perceived Cost of Equity Measures

We corroborate our findings on the pass-through of benchmarking-induced changes in the CAPM $\widehat{\beta}$ to perceived cost of capital using several alternative measures. 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 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.[25] Appendix C provides further details on the data and supplementary results.

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

$$\Delta \text{ Perceived Cost of Equity}_{i,t} = \alpha_t + \lambda \, \widehat{\Delta \text{ CAPM } \beta}_{i,t} + \varepsilon_{i,t} \tag{13}$$

in which we instrument changes in CAPM $\widehat{\beta}$ with changes in BMI due to the Russell index reconstitution between May and June. The year fixed effect, α_t, identifies λ using cross-sectional variation. We again restrict the estimation sample to +/- 400 ranks around Russell index cutoffs. Note that a stock's CAPM $\widehat{\beta}$ does not directly enter (13). The analysts' perceived equity risk premium is given by $\widehat{\lambda} = \widehat{\pi}/\widehat{\tau}$ in which $\widehat{\pi}$ is the reduced form coefficient of BMI on authorized cost

[25] Note that the subjective return expectations contain both perceived cost of equity capital as well as potentially perceived mispricing (Jensen, 2024).

Table 3: Effect of Δ BMI and Δ CAPM $\widehat{\beta}$ on Stock Analysts' Perceived Cost of Equity Capital

	Δ Morningstar Cost of Equity (in p.p.)				Value Line Safety Rank $\times$ 1.5 p.p.				Δ I/B/E/S Expected Return (in p.p.)			
	RF		IV		RF		IV		RF		IV	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Δ BMI (in p.p.)	0.046***	0.037**			0.032***	0.033***			0.078*	0.075*		
	(0.013)	(0.013)			(0.009)	(0.010)			(0.039)	(0.036)		
$\widehat{\Delta \text{ CAPM } \beta}$			5.548**	5.432*			4.663**	4.405*			7.914*	7.664*
			(1.999)	(2.467)			(1.804)	(1.709)			(3.695)	(3.609)
Mom. (Cum. Ret.)		-0.298***		-0.193**		0.015		-0.359*		0.410***		0.388***
		(0.035)		(0.072)		(0.031)		(0.166)		(0.044)		(0.056)
Mkt. Cap. Rank		-0.019***		-0.021**		0.034***		0.036***		-0.036		-0.039
		(0.004)		(0.007)		(0.004)		(0.005)		(0.029)		(0.032)
Fixed Effects												
Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Adj. R^2	0.08	0.10			0.02	0.08			0.21	0.23		
FS F-stat.			16.9	10.4			11.0	10.6			100.6	111.8
Observations	4,026	3,932	4,026	3,932	2,524	2,504	2,363	2,361	7,731	7,671	6,769	6,718

Notes: This table report estimates for specifications of the form: Δ Perceived Cost of Equity$_{i,t} = \alpha_t + \lambda\, \widehat{\Delta \text{ CAPM } \beta}_{i,t} + \varepsilon_{i,t}$ 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. Value Line's safety rank is converted to a required return on equity by multiplying it by 1.5 (p.p.) (Eskildsen et al., 2024). 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. Even columns control for momentum (cumulative return over the past 12 months) and market capitalization rank (dividend by 100) at the end of May. IV estimated via LIML. Standard errors in parentheses are clustered at the stock-level. + p<0.10, * p<0.05, ** p<0.01, *** p<0.001.

of equity and and $\widehat{\tau}$ is the first stage coefficient of BMI on CAPM $\widehat{\beta}$.[26]

Table 3 shows that exogenous increases in a stock's BMI increase analysts' perceived risk and return expectations. The IV specifications of (13) imply perceived equity risk premia between 4.4% and 7.9% across the three datasets. Marketing material by Morningstar (2022, page 4f) suggests that their analysts use a perceived equity risk premium of 4.5%. Our point estimates are 1 p.p. higher but not statistically different from 4.5%. The perceived equity risk premium implied by the I/B/E/S analysts' expected returns is somewhat higher the those implied by Value Line and Morningstar. This is likely due to the unconditional upward bias in analysts' target prices documented by Brav and Lehavy (2003). Results in even columns confirm that the results continue to hold after accounting for momentum (cumulative returns over past 12 months) and the stock's market capitalization rank in May. Similar to Greenwood and Shleifer (2014) and Nagel and Xu (2022), we find that past returns exert a positive influence on subjective expected excess returns.

[26] Appendix Figure C14 plots the CAPM security market line using stock analysts' subjective expected returns using the CAPM $\widehat{\beta}$ directly. The slope implies a 6.3% annual equity risk premium with an adj. R^2 of 0.22. Similarly, Value Line's CAPM $\widehat{\beta}$s explain more than 20% of the variation in Value Line's safety ranks.

5.5 Additional Evidence from Regulated Monopolies

This subsection provides further evidence that increased benchmarking affects the perceived cost of equity. Specifically, we test whether regulated monopolies perceive a higher cost of equity when their CAPM $\widehat{\beta}$ increases due to benchmarking. Regulated monopolies like public utilities and railroads in the U.S. are subject to rate-of-return regulation which allows firms to pass on changes in their cost of capital to consumers. 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 capital. Appendix C.2 describes the regulatory rate-setting process and data sources, drawing on Kontz (2025), which analyzes how the growth of passive investing impacts regulated monopolies' cost of equity and consumer energy prices.

Public utilities We collect data on the perceived cost of equity (CoE) authorized by U.S. state's public utility commissions. We test whether the authorized CoE is affected by benchmarking using IV specifications of the following form:

$$\text{Authorized CoE}_{i,t} - r_t^f = \alpha_i + \lambda \, \widehat{\text{CAPM } \beta}_{i,t} + \varphi \left(\text{DCF Implied CoE } - r^f \right) + \varepsilon_{i,t}, \tag{14}$$

in which we control for the DCF implied cost of equity and estimate the regulator's perceived equity risk premium, λ, using the utility's benchmarking intensity as an instrument. 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 4 reports coefficient estimates of Eq. (14). Columns 1 and 2 show that a higher benchmarking intensity predicts a higher authorized cost of equity. A 10 p.p. higher benchmarking 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 $\widehat{\beta}$ 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.

Regulatory practice often permits or mandates that a public utility's cost of equity, in addition to the CAPM, also be estimated using a discounted cash flow (DCF) method. The even-numbered columns in Table 4 show that our results remain robust when accounting for the DCF-implied risk premium. While the DCF risk premium explains a substantial share of the variation in authorized risk premia, its inclusion has only a negligible effect on the BMI coefficient. This suggests that

Table 4: Regulated Monopolies' Cost of Equity Capital 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 $\times$ 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 capital for public utilities and railroads are from Regulatory Research Associates and from the Surface Transportation Board, respectively. CAPM $\widehat{\beta}$ are based on weekly return data as usual in regulatory proceedings. Standard errors in parentheses are clustered at utility-level for public utilities and Newey-West with 5 lags for railroads. + p<0.10, * p<0.05, ** p<0.01, *** p<0.001.

omitted variable bias is unlikely to be a concern (Oster, 2017).

Appendix Table C11 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 $\widehat{\beta}$s while not affecting the cost of capital through other channels.

Railroads We obtain 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 capital, 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 $\widehat{\beta}$, 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 4 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.

6 Effects of CAPM β Distortions on Capital Accumulation

Our second set of results estimates how firms react to changes in their CAPM β induced by changes in BMI. For a firm manager who follows textbook guidance to set investment policies using the CAPM, an increase in CAPM $\widehat{\beta}$ raises the user cost of capital and should lead to a decline in investment. We therefore test whether changes in CAPM $\widehat{\beta}$ affect firm outcomes like capital expenditure, physical and intangible capital stocks, cash holdings, payouts, and employment.

The firm-level results show that firms react to BMI-induced changes in their CAPM $\widehat{\beta}$ by reducing investment. Specifically, capital expenditure declines by 10.0% over six years, and physical and intangible capital stocks are 7.1% and 8.4% lower, respectively. Firms initially accumulate cash and then increase payouts to shareholders. The findings are robust to the inclusion of other known predictors of investment like firm size, cash flow, and Tobin's Q.

We find supporting evidence at the industry-level: industries with higher CAPM βs due to higher benchmarking intensity have lower capital accumulation from 2000 to 2016. The results are robust to the inclusion of industry pre-trends and sectoral fixed effects. Furthermore, we show that dispersion in within-industry marginal products of capital are increasingly explained by benchmarking-induced dispersion in within-industry CAPM $\widehat{\beta}$s. This suggests that the CAPM $\widehat{\beta}$s distortions caused by benchmarking affect allocative efficiency.

The capital accumulation results at firm- and industry-level are consistent with the predictions of our augmented neoclassical investment model, in which firms adjust investment in response to changes in their *perceived* cost of capital implied by the CAPM.

6.1 Effects of Increased Benchmarking at the Firm-level

We use an instrumental variable (IV) local projections (LP) strategy to forecast the effects of a change in CAPM $\widehat{\beta}$ on capital allocation over horizons of up to 6 years.[27] We instrument changes in CAPM $\widehat{\beta}$ with plausibly exogenous changes in benchmarking intensity caused by Russell index reconstitutions to identify the causal effects of benchmarking distortions on investment.

To analyze the effect of BMI-induced changes in a firm's CAPM $\widehat{\beta}$ on real outcomes, we

[27] Similarly, researchers often use LP-IVs to study the effects of monetary policy on investment or asset prices (e.g., in Jordà, Schularick, and Taylor, 2020, Kroen, Liu, Mian, and Sufi, 2021, and Bauer and Swanson, 2023).

estimate a series of local projection instrumental variable regressions of the following form:

$$\Delta\text{CAPM}\ \beta_{i,t} = \delta_i + \delta_{j,t} + \theta\Delta\text{BMI}_{i,t} + \zeta X_{i,t} + \epsilon_{i,t} \tag{15}$$

$$\log\left(Y_{i,t+h}\right) - \log\left(Y_{i,t-1}\right) = \alpha_i^h + \alpha_{j,t}^h + \gamma^h \Delta\widehat{\text{CAPM}}\ \beta_{i,t} + \xi^h X_{i,t} + \varepsilon_{i,t+h} \tag{16}$$

for firm i in industry j in calendar year $t+h$. The coefficients of interests, γ^h, provide cumulative local average treatment effects in % after $h = 0, 1, \ldots, 6$ years.

We remove time-invariant heterogeneity across firms by including firm-fixed effects α_i and δ_i in both first and second stage. We additionally include (3-digit SIC) industry-by-year-by-total-asset quintile fixed effects $\alpha_{j,t}$ and $\delta_{j,t}$ to control for time-varying unobserved heterogeneity across industries, such as differences in industry-level business cycles, which may be correlated with firm outcomes. The use of industry-by-year-by-total-asset fixed effects forces the parameters of interest, γ^h, to be identified solely from comparing similar sized firms within the same industry. The vector $X_{i,t}$ includes a set of time-varying firm-level control variables, such as log of market equity (size) at the end of May and cumulative 1-year excess returns (momentum). We additionally include up to three lags of the outcome and shock variables.

We cluster standard errors at the firm-level, which allows for a completely unrestricted specification of the residual covariance matrix in the time-series dimension. This effectively addresses the issue of serial correlation in residuals arising in a local projection framework.

Identifying assumptions and threats to identification The instrumental variable exclusion restriction in a local projection setting differs slightly 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 be uncorrelated with past and future shocks, at least after including control variables. The exclusion restriction requires that assignment of index membership is exogenous and that changes in BMI only affect firm outcomes through changes in CAPM $\widehat{\beta}$.

However, concerns may arise that other factors, such as risk exposure, access to debt markets, or governance, could change alongside CAPM $\widehat{\beta}$s when BMI changes, potentially violating the exclusion restriction. In Appendix D, 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 D14 shows that changes in BMI do not correlate with firm statements about delaying investments. Failure of the exclusion restriction would introduce bias in the estimated treatment effects. The size and sign of the bias depend on the size and sign of the failure and the strength of the instrument.[28] The literature on benchmark inclusion effects generally finds positive but modest direct effects of inclusion on real outcomes (e.g., Kacperczyk, Sundaresan, and Wang, 2021). We thus, if anything, might expect an upward bias in our estimates.

To ensure that our estimates are well-identified, we follow three steps. First, we include up to three lags of outcomes and shock in our regressions. Second, we saturate our LP-IV estimator with high-dimensional fixed effects to remove as much time-varying unobserved heterogeneity as possible. Third, we verify that including a set of known predictors of capital accumulation (e.g., Tobin's Q or cash flow) does not change our results in a robustness test.

Results Figure 6 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 an equity cost shock, while cash holdings increase. Eventually, firms increase dividends and stock repurchases. Employment also decreases, suggesting that firms reduce labor input in response to an increase in their perceived cost of capital.[29]

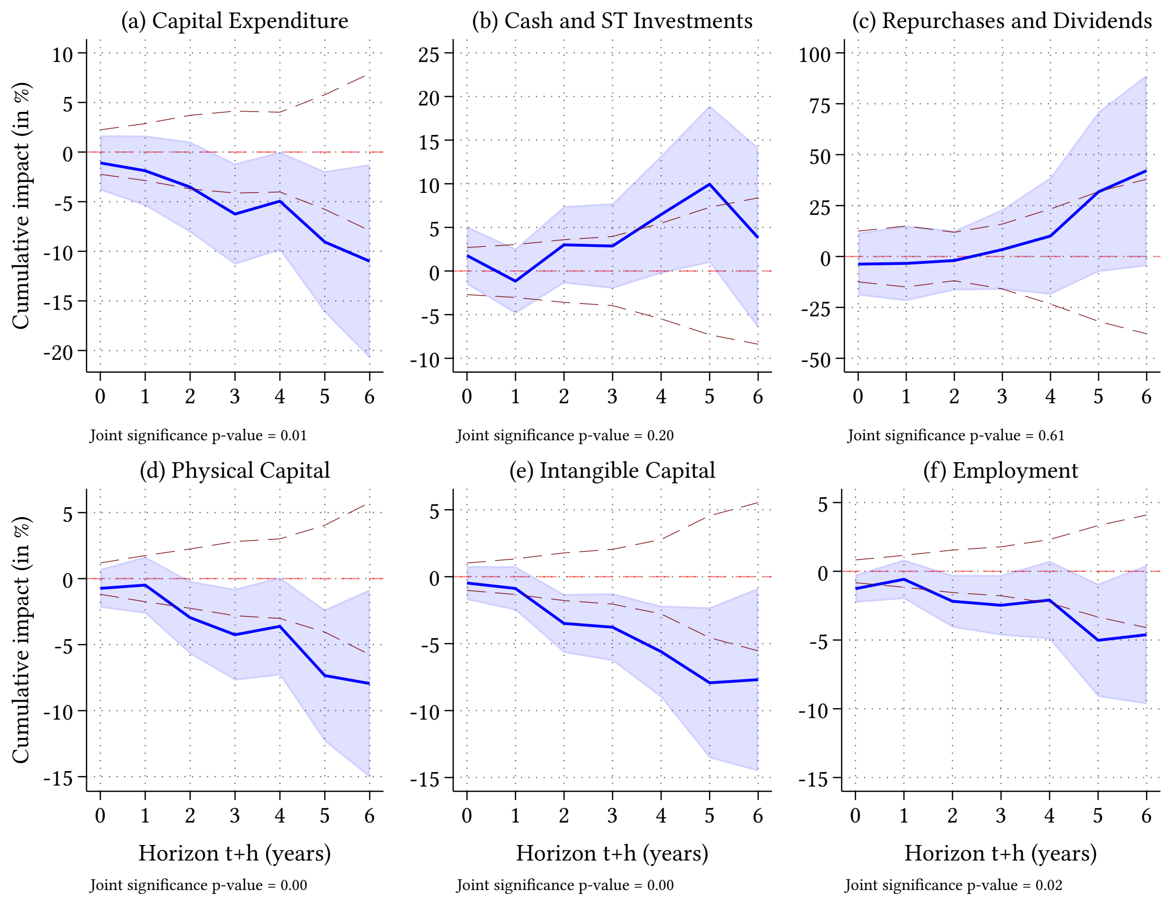
Second, firm respond gradually to an increase in CAPM $\widehat{\beta}$, with effects starting from zero in the treatment year and growing over time. The cumulative impact becomes statistically and economically significant after about three years, aligning with industry practices of using a two to five year rolling window to estimate CAPM $\widehat{\beta}$s. This gradual adjustment reflects how managers' estimated cost of capital incorporates older data points. Third, benchmarking-induced asset price distortions cause persistent effects on capital expenditure and capital stocks that remain significant for at least six years after the shock.

Benchmarking-induced increases in CAPM $\widehat{\beta}$s lead to large and persistent declines in investment. We scale the shock to the average treatment effect for a BMI increase of at least 5 p.p., which corresponds to a change in the CAPM $\widehat{\beta}$ of 20%. We find that firms reduce their capital expenditure by approximately 10.0% over six years in response to a shock to their CAPM $\widehat{\beta}$ of 20%. The resulting decrease in physical capital stocks is 7.1% and in intangible capital stocks is 8.4% after six years. Point estimates after six years imply a user cost of capital elasticity of physical and intangible capital larger but close to the theoretical elasticity of 1 implied by Cobb-Douglas production.

[28] Consider the example given by Jordà et al. (2020): let y be the outcome, Δr the intervention, and z the instrument. The IV setup consists of the first and second stage given by $\Delta r = zb + \eta$ and $y = \widehat{\Delta r}\beta + z\phi + \nu$ in which $\mathbb{E}\left[\Delta r \nu\right] \neq 0$ but $\mathbb{E}\left[z\nu\right] \neq 0$. The exclusion restriction assumes that $\phi = 0$. If $\phi \neq 0$, we have $\widehat{\beta}_{IV} \xrightarrow{p} \beta + \phi/b$. The bias induced by failure of the exclusion restriction depends on both the size of the failure, ϕ, and the strength of the instrument, b. Weaker instruments tend to worsen the bias (see also Conley, Hansen, and Rossi, 2012).

[29] This could either be due to labor and capital being complements in firm's production function or due to labor market frictions that prevent employment from freely adjusting in response to shocks. Borovička and Borovičková (2018) argue that fluctuations in discount rates and labor market frictions markets play an important role for employment.

Figure 6: LP-IV: Impulse Response of Outcome Variables to CAPM $\widehat{\beta}$ shock



Notes: This figure shows LP-IV coefficient estimates for $100\times$ cumulative log-changes of outcome variables. Intervention is a ≈0.16 shock to CAPM β^E estimated with change in BMI as an instrumental variable. 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).

Robustness checks We perform several robustness checks on the main results. First, we add known predictors of investment, such as cash flow, Tobin's Q, and the debt-to-equity ratio, to the LP-IV regressions. Second, we incorporate different levels of fixed effects, replacing firm size by industry by year fixed effects with sales by industry by year fixed effects. Appendix Figure A5 shows coefficient estimates of these robustness checks alongside the original estimate. The figure shows that adding firm-level controls does not change the estimates, supporting our identification strategy. Altering the level of fixed effects only marginally affects point estimates, with all changes well within one standard error of the original estimates.

Investment Rates Appendix Figure A6 shows the impact of a 20% increase in CAPM $\widehat{\beta}$ on investment rates.[30] The investment rate declines over time in response to the shock. Starting from a near-zero, gradually becoming more negative, reaching the lowest point after four to five years. The shock to the CAPM $\widehat{\beta}$ leads to a significant drop of -2.56 p.p. after four years. In standard deviation units, investments drops by 0.19. This compares in terms of economic magnitudes to Alfaro et al. (2024) who find that uncertainty shocks lead to a 0.18 sd drop in investment rates.

6.2 Misallocation due to Benchmarking Distortions

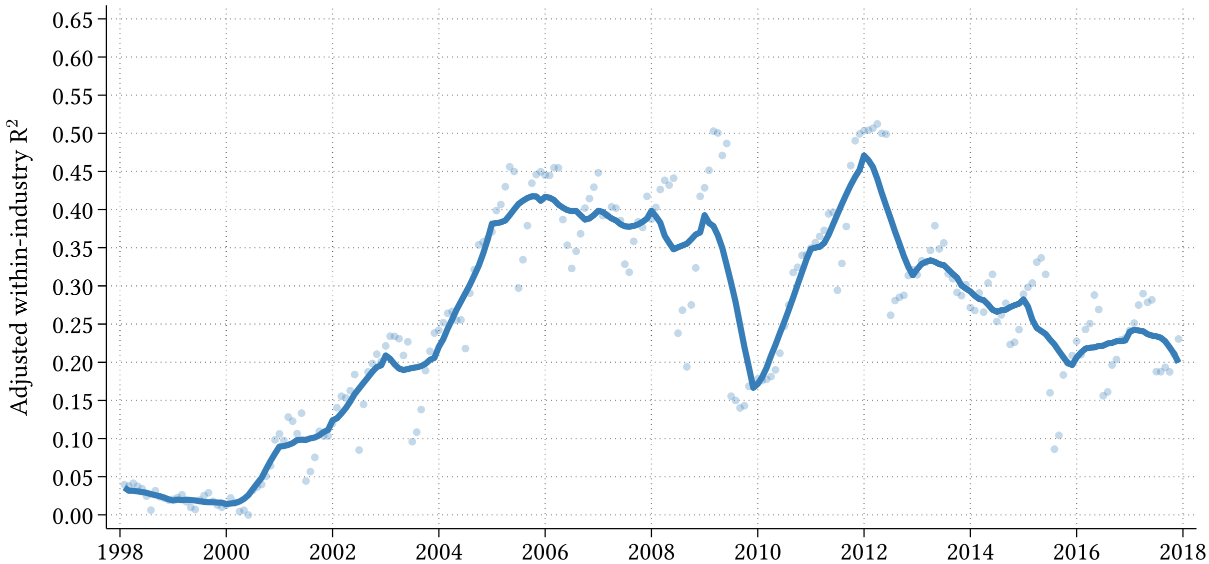
A substantial literature highlights how resource misallocation—characterized by dispersion in firms' marginal products of inputs—negatively affects aggregate productivity and output (e.g., Bau and Matray, 2023). David et al. (2022) show that, in a production economy with aggregate risk, cross-sectional 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: $\mathbb{E}_t\left[MPK_{i,t+1}\right] = r_t^f + \delta + \beta_{i,t}\lambda_t$, where δ denotes the depreciation rate. Consequently, the cross-sectional variance in expected MPK at time t is given by $\sigma^2(\mathbb{E}_t\left[MPK\right]_{i,t+1}) = \sigma^2_{\beta_t}\lambda_t^2$, 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 $\widehat{\beta}$s. Figure 7 shows that benchmarking-induced variation in CAPM $\widehat{\beta}$s is making up an increasing share of within-industry variation in CAPM $\widehat{\beta}$s. In each month, we approximate the relationship between CAPM $\widehat{\beta}$s and BMI by fitting a flexible 5th order polynomial as well as industry-fixed effects. We then plot the adjusted within-industry variation explained by BMI (within R^2). Importantly, we exclude variation explained by industry fixed effects. Before 2000, benchmarking explains less than 5% of the average within-industry variation in CAPM $\widehat{\beta}$s. In 2018, benchmarking explains approximately 20% of the average within-industry variation in CAPM $\widehat{\beta}$s. This suggests that benchmarking-induced CAPM $\widehat{\beta}$ distortions have an impact on 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 $\widehat{\beta}$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

[30] Defined as $\frac{\text{CAPX}_t}{\frac{1}{2}(\text{PPENT}_{t-1}+\text{PPENT}_t)}$ (see e.g, Belo, Lin, and Bazdresch, 2014 and Alfaro, Bloom, and Lin, 2024).

Figure 7: Percentage of Within-industry Variation Explained by Projecting CAPM $\widehat{\beta}$ onto BMI



Notes: This figure show the time-series of within-industry R^2s of the following cross-sectional regressions: CAPM $\widehat{\beta}_i = \alpha_j + \sum_{k=1}^{5} \varphi_k \mathrm{BMI}_i^k + \epsilon_i$ in which α_j is an industry fixed effect. We report the within-industry R^2 and exclude variation explained by industry fixed effects. Solid blue line is a two-sided moving average.

predict a firm's CAPM $\widehat{\beta}$ 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 Index reconstitutions between May and June over the past five years. This ensures that the variation in CAPM $\widehat{\beta}$s we utilize is solely attributable to benchmarking. We then calculate the cross-sectional dispersion in CAPM $\widehat{\beta}$s, $\sigma(\text{CAPM } \beta)_t$, the dispersion specifically caused by benchmarking, $\sigma(\widehat{\text{CAPM } \beta})_t$, and the natural logarithm of the marginal product of capital at the 4-digit NAICS industry level annually.[31]

In the second step, we estimate how dispersion in CAPM βs affects dispersion in $\log(\text{MPK})$ at the industry-level using specifications of the form:

$$\sigma(mpk)_{j,t+1} = \alpha_t + \alpha_j + \sigma(\widetilde{\text{CAPM } \beta})_{j,t} + \varepsilon_{j,t+1} \tag{17}$$

in which industry j's cross-sectional dispersion in CAPM βs is instrumented with the predicted cross-sectional dispersion caused by benchmarking.

Table 5 shows that benchmarking-induced CAPM $\widehat{\beta}$ distortions affect dispersion in marginal products of capital. Our two-step approach shows that higher within-industry dispersion caused by benchmarking increases within-industry dispersion in MPKs. The results we document help

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

Table 5: Misallocation: Elasticity of Dispersion in MPKs with Respect to Dispersion in CAPM $\widehat{\beta}$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: $\sigma(mpk)_{j,t+1} = \alpha_t + \alpha_j + \sigma(\widehat{\text{CAPM }\beta})_{j,t} + \varepsilon_{j,t+1}$ in which industry j's cross-sectional dispersion in CAPM βs is instrumented with the predicted cross-sectional dispersion caused by benchmarking. mpk is the 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.

explain the rise in within-industry productivity dispersion from 1997 to 2016 (Cunningham et al., 2023).[32] Figure 7 and Table 5 suggest that benchmarking-induced excess dispersion in CAPM $\widehat{\beta}$ prevents the equalization of marginal products across producers within industries. This is important because distortions of within-industry capital allocation have first order implications for aggregate and industry-level productivity growth (Hsieh and Klenow, 2009).

6.3 Effects of Increased Benchmarking at the Industry-level

We use the NBER-CES Manufacturing Industry Database to estimate the effect of increases in industries' average CAPM $\widehat{\beta}$ on capital accumulation over long horizons. Our results show that higher CAPM $\widehat{\beta}$s led to 12.5% lower capital accumulation from 2000 to 2016 at the industry level.

Long-term effects of CAPM $\widehat{\beta}$ distortions on capital accumulation We use the NBER CES Manufacturing Industry database to study the long-term effects of increasing CAPM $\widehat{\beta}$s due to increased benchmarking on capital accumulation at the industry-level. We estimate the long-

[32]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).

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

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable: log (Real Capital Stock in 2016/Real Capital Stock in 2000)						
Δ CAPM $\widehat{\beta}^A$ (2000-2016)	-0.414$^+$	-0.437*	-0.509*	-0.429*	-0.500$^+$	-0.490$^+$
	(0.243)	(0.214)	(0.218)	(0.176)	(0.276)	(0.232)
Real Capital Stock/Value Added (2000)		0.0705		-0.108		-0.0986
		(0.095)		(0.068)		(0.069)
log (Employment) (2000)		0.0290		0.0743		0.0717$^+$
		(0.037)		(0.044)		(0.039)
log (TFP) (2000)		0.427$^+$		-0.203		-0.211
		(0.221)		(0.156)		(0.154)
Pretrend Real Capital Stock (1990-1999)					-0.0771	-0.185
					(0.110)	(0.122)
Pretrend Employment (1990-1999)					0.296$^+$	0.276$^+$
					(0.147)	(0.143)
Pretrend Wages (1990-1999)					-0.0543	0.0938
					(0.446)	(0.588)
Constant	0.151$^+$	-0.0542				
	(0.082)	(0.254)				
Fixed Effects						
Subsector FE			✓	✓	✓	✓
FS F-stat.	7.54	12.93	22.31	19.54	21.42	21.85
Observations	111	111	107	107	107	107

Notes: This table reports coefficient estimates of regressions at the NAICS 5-digit industry-level of the form: $\Delta \log(\text{Real Capital Stock})_i = \alpha_j + \gamma \Delta \text{CAPM } \widehat{\beta}_i^A + \zeta X_i + \varepsilon_i$ in which changes in unlevered CAPM $\widehat{\beta}^A$ are instrumented with changes in BMI from 2000 to 2016. BMI and CAPM $\widehat{\beta}$ are market-value weighted averages at the NAICS 5-digit industry level of Compustat firms. Pretrends measure log changes in variables from 1990 to 1999. Regressions are weighted by industry value added in 2000. Sub-sector fixed effects are at the NAICS 3-digit level. FS F-stat is Kleibergen-Paap F-stat of first stage. All variables are winsorized at the 2.5% and 97.5% level. Standard errors clustered at subsector-level in parentheses. + p<0.10, * p<0.05, ** p<0.01, *** p<0.001.

term effects of increasing CAPM $\widehat{\beta}$s due to higher benchmarking at the NAICS-5 digit industry-level. We weigh each industry observation by its value-added in the year 2000 to obtain results comparable to the aggregate economy.

We estimate a series of IV regressions in long-differences from 2000 to 2016 of the form:

$$\Delta_{00}^{16} \text{CAPM } \widehat{\beta}_i^A = \delta_j + \theta \Delta_{00}^{16} \text{BMI}_i + \zeta X_i^{`00} + \epsilon_i \tag{18}$$

$$\log\left(\text{Real Capital Stock}_i^{`16} / \text{Real Capital Stock}_i^{`00}\right) = \alpha_j + \gamma \Delta_{00}^{16} \widehat{\text{CAPM } \widehat{\beta}_i^A} + \zeta X_i^{`00} + \varepsilon_i \tag{19}$$

in which α_j are NAICS 3-digit subsector fixed effects. The vector of control variables $X_i^{'00}$ includes industry-level characteristics in 2000, such as the log of employment and TFP. The controls account for initial differences in industry characteristics that may affect capital accumulation. We calculate the change in CAPM $\widehat{\beta}^A$ for industry i from 2000 to 2016 as the difference between the market equity-weighted average CAPM $\widehat{\beta}^A$ of firms in that industry in 2016 and 2000. Similarly, we calculate the change in industry BMI from 2000 to 2016 as the difference between the market equity-weighted average BMI of firms in the same industry in 2016 and 2000.

A potential concern with our industry-level analysis is that the effects of increasing benchmarking on capital accumulation may be confounded by other secular changes in the economy or that industries were already on different growth paths in 2000. We address these concern by including controls for pre-trends in capital accumulation, employment, and wages from 1990 to 1999. Additionally, we include NAICS 3-digit sub-sector[33] fixed effects in the regressions. Using sub-sector fixed effects, we identify the effects of changes in CAPM $\widehat{\beta}$ on capital accumulation using variation across industries within the same sub-sectors.

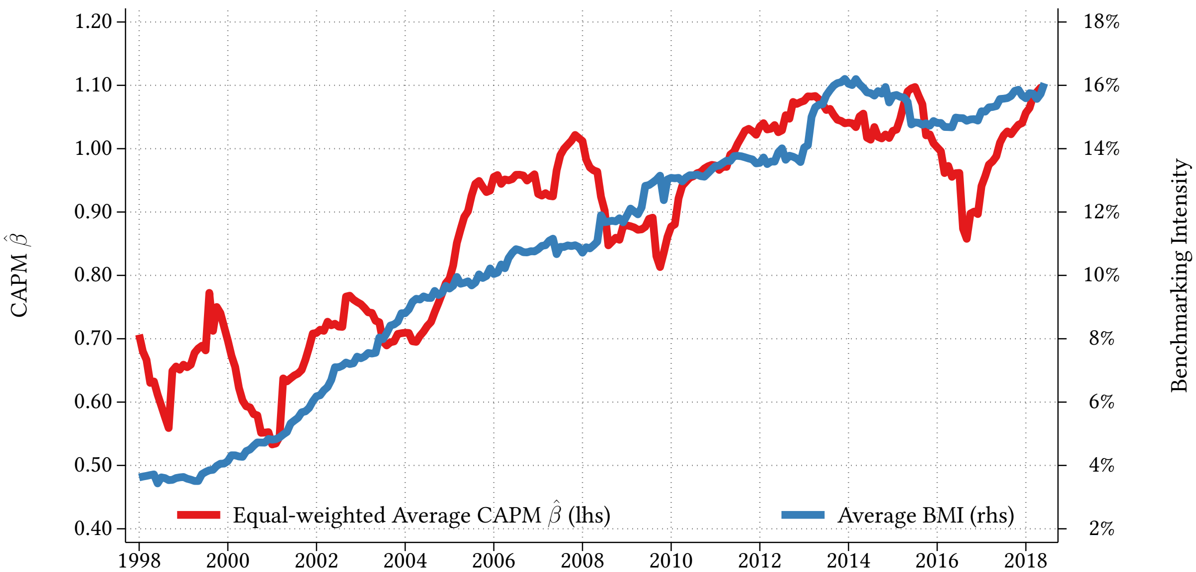
Results Table 6 reports coefficient estimates of Eq. (19). Several things are worth noting. First, across all specifications, we find that increases in CAPM $\widehat{\beta}$s have a statistically significant negative effect on long-term capital accumulation at the industry-level. Second, the estimated coefficients are economically meaningful. The coefficient of Column (4) implies that the 0.29 increase in average CAPM asset $\widehat{\beta}^A$ for Russell 2000 companies (see Figure 3) is associated with a 12.5% ($\approx$0.29$\times$0.43$\times$100%) lower aggregate capital stock over the 17-year period. These magnitudes imply a user cost of capital elasticity close to the value of 1 implied by Cobb-Douglas production. 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 $\widehat{\beta}$ even at the industry-level, with first-stage F-stats averaging 17.6 across columns.

7 Effects of Increased Benchmarking in Aggregate

We argue that increased benchmarking has contributed to the missing investment puzzle documented by (Gutiérrez and Philippon, 2017). Our difference-in-differences results show that exogenous BMI increases due to benchmark inclusion raise the CAPM $\widehat{\beta}$s of firms. Extending this to the broader cross-section of firms, we estimate that the equal-weighted average of CAPM $\widehat{\beta}$s

[33] For example, the NAICS 3-digit sub-sector "311 - Food Manufacturing" contains 12 NAICS 5-digit industries.

Figure 8: Equal-weighted Average Cross-Sectional CAPM $\widehat{\beta}^E$ and BMI Over the past 25 years



increased by 0.41 over the past 25 years after being relatively stable for 30 years.[34] We attribute almost 90% of this increase to the large increase in benchmarking intensity since 1998. We construct a counterfactual WACC which shows that the increase in benchmarking raised the average firm's WACC by 145 bps, on average. The counterfactual shows that the increase in the perceived equity risk largely offset the decline in risk-free rates over the past 25 years. The wedge is large enough to explain approximately 57% of the missing investment puzzle.[35]

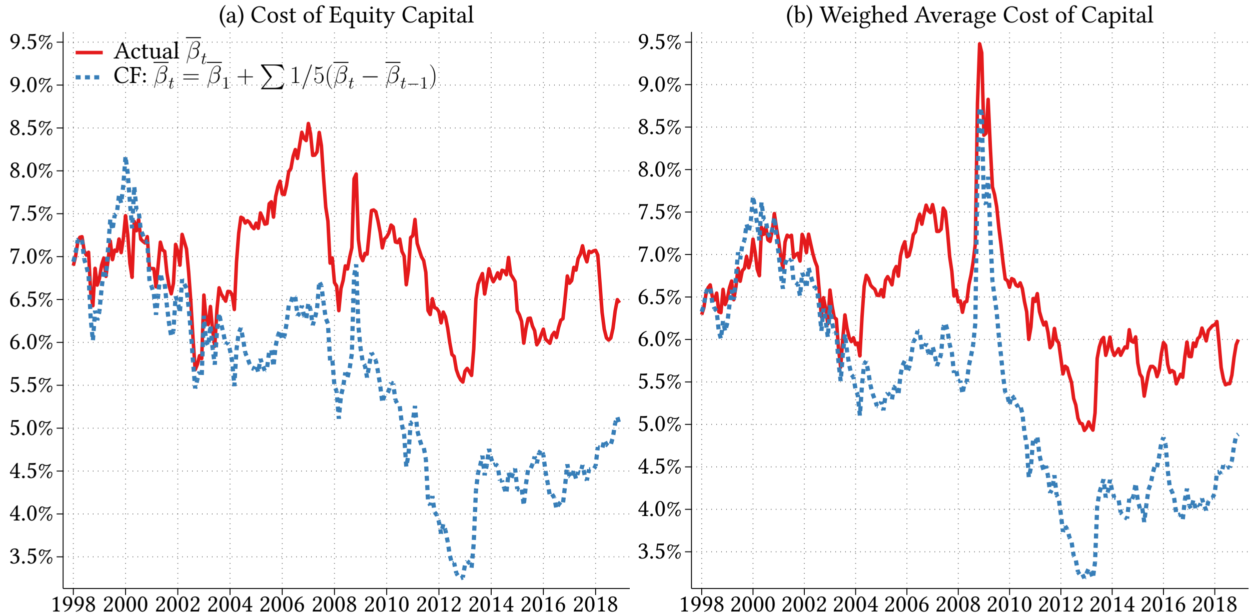
Increase in equal-weighted average CAPM $\widehat{\beta}$ over the past 25 years Figure 8 shows the evolution of average CAPM $\widehat{\beta}$ and average BMI from 1998 to 2018. A casual inspection of the graphs suggests that both time-series are related. The average BMI increased from 4% in 1998 to 16% in 2018, while the average CAPM $\widehat{\beta}$ increased from 0.63 to 1.09.

We estimate how an increase in the average cross-sectional BMI affects the average CAPM $\widehat{\beta}$. To address the potential of a "spurious regression", we follow the advice of Hansen (p. 588, 2023) and include a lag of the outcome variable. We additionally report results of Dynamic OLS (DOLS) (Stock and Watson, 1993) specifications. Appendix Table A6 reports results of these time-series regressions. The results imply that a 1 p.p. increase in average BMI increases the average CAPM

[34] Appendix Figure A7 plots the time series of equal-weighted average CAPM $\widehat{\beta}$ from 1975 to 2020. We start in 1975 to focus on the period after NASDAQ's addition to the CRSP sample. The equal-weighted average CAPM $\widehat{\beta}$ had a mean of 0.67 from 1975 to 2000 but increased in the 2000s, settling at new mean of around 1.02 post 2010.

[35] Farhi and Gourio (2018) estimate a macro-finance model and similarly find that higher perceived risk starting in the late 1990s explains weak investment. However, their model is silent on the mechanism which increases perceived risk. We offer a novel explanation for increases in perceived risk: benchmarking-induced distortions in CAPM $\widehat{\beta}$s.

Figure 9: Actual and Counterfactual Estimates of Cost of Equity Capital and WACC



Notes: This figure shows monthly estimates of the cross-sectional averages of cost of equity capital and WACC. Red solid line shows cost of capital estimates using the actual measured CAPM $\widehat{\beta}_t$. Blue dashed lines shows counterfactual in which CAPM $\widehat{\beta}_t$ is adjusted for BMI increases (see Eq. 22).

$\widehat{\beta}$ by 0.03 in the long-run. The rise in the average stocks's benchmarking intensity from 1998 to 2018 explains approximately 88% (=14p.p.×0.029/(1.09-0.63)) of the increase in average CAPM.[36]

Counterfactual weighted average cost of capital over the past 25 years We next document that the benchmarking-induced CAPM $\widehat{\beta}$ distortions are large enough to affect firm's weighted average cost of capital (WACC) over the past 25 years. We calculate a counterfactual WACC that adjusts the CAPM $\widehat{\beta}$ for the BMI increase and holds all other factors constant. The wedge between the actual and counterfactual WACC is on average 145 bps and is, by construction, due to the increase in CAPM $\widehat{\beta}$.

We calculate the average cross-sectional WACC in the Compustat sample as follows:

$$\overline{\text{WACC}}_t = \overline{\omega}_t \times \overline{r}_t^E + (1 - \overline{\omega}_t) \times \overline{r}_t^D \times (1 - \overline{\tau}_t) \tag{20}$$

in which $\overline{\omega}_t = \overline{E}_t / (\overline{E}_t + \overline{D}_t)$ represents the fraction of firm value financed by equity (on average 0.76 over the sample) and $\overline{\tau}_t$ is the average cross-sectional tax rate (on average 0.26). The expected

[36]We cannot statistically reject that 100% of the increase in average CAPM $\widehat{\beta}$ is driven by the increase in BMI.

return on equity is given by the CAPM

$$\overline{r}_t^E = r_t^f + \overline{\widehat{\beta}}_t \times \left(\mathbb{E}_t\left[r^{Mkt}\right] - r_t^f\right), \tag{21}$$

in which we set the real risk-free rate, r_t^f, to the constant maturity yield on 10-year Treasury Inflation-Protected Securities (TIPS). We assume a constant 6% ERP[37] and use the yield on the ICE-BofA High-Yield Bond Index to estimate the average expected return on debt, $\overline{r}_t^D$.[38]

We calculate a counterfactual WACC motivated by our findings that increases in BMI cause CAPM $\widehat{\beta}$s to rise and that at least 80% of the aggregate increase in CAPM $\widehat{\beta}$s was driven by increases in the BMI (see Figure 8). We adjust the average CAPM $\overline{\widehat{\beta}}_t$ in Eq. (21) as:

$$\overline{\widehat{\beta}}_t^{CF\ 2} = \overline{\widehat{\beta}}_{1998/1} + \frac{1}{5} \times \sum_{i=1998/2}^{t} \left(\overline{\widehat{\beta}}_i - \overline{\widehat{\beta}}_{i-1}\right) \quad \forall\, t \geq 1998/1. \tag{22}$$

This adjustment guarantees that the counterfactual CAPM $\overline{\widehat{\beta}}_t^{CF\ 2}$ is perfectly correlated with the actual CAPM $\overline{\widehat{\beta}}_t$, but the increase in CAPM $\widehat{\beta}$ is exactly 20% at the end of the sample.

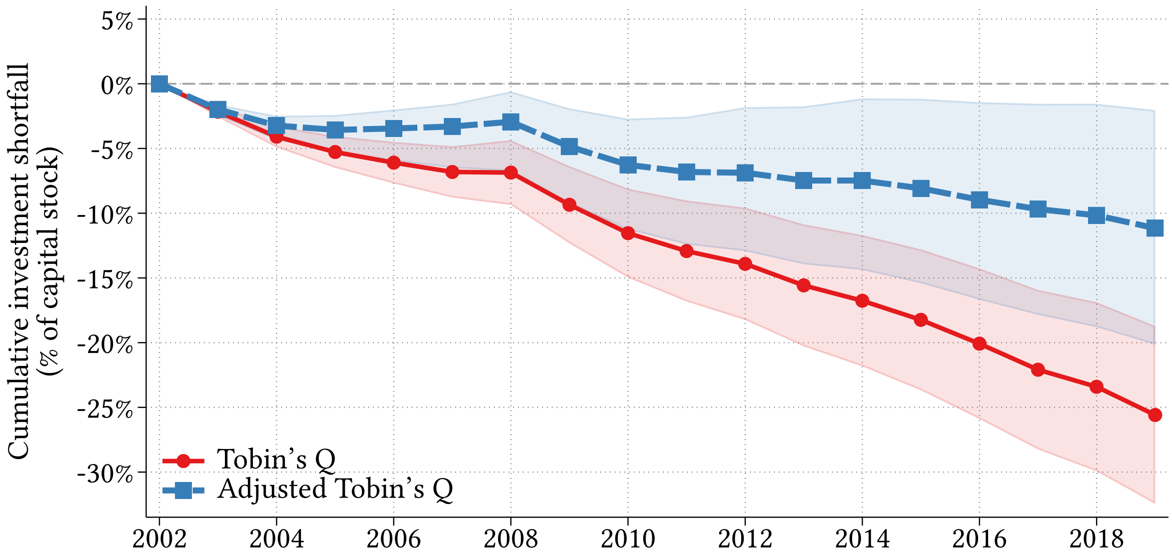
Figure 9 shows estimates of the actual and counterfactual cost of equity capital and WACC from 1998 to 2018. The actual cost of equity capital remained relatively stable over the time-period. The cost of equity for the average firm in 2018 is approximately 60 bps lower than in 1998. In the counterfactual scenarios, however, the cost of equity declines substantially. The secular decline in the risk-free rate over the past 25 years drives the decline in the cost of equity (Bauer and Rudebusch, 2020). The counterfactual uncovers that the decline in the risk-free rate was largely offset by an increase in equity risk premium for the average firm. The actual WACC decreased slightly over the sample period, while the counterfactuals decreased substantially. The actual WACC decreased by approximately 60 bps over the sample period. The counterfactual WACC declines by over 160 bps from 1998 to 2018.

Missing investment in the aggregate We assess whether the wedge between actual and counterfactual WACC, is large enough to account for the missing investment puzzle. We adopt the methods of Gutiérrez and Philippon (2017) and Gormsen and Huber (2023). Using data from 1990–2002, 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

[37]Results using a time-varying ERP show that the cost of equity and WACC have increase over the past 25 years. The weighted average cost of capital would have declined had the CAPM $\widehat{\beta}$ not increased (Appendix Figure A9).

[38]The ICE-BofA yield closely tracks other common proxies for the average cost of debt. For instance, Gormsen and Huber (2024) use interest expenses over total debt in Compustat. Appendix Figure A8 shows both time-series.

Figure 10: Adjusted Tobin's Q and the Cumulative Investment Shortfall



Notes: This figure 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 and Huber (2023), 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 firm managers' perceived cost of capital (see Eq. (23)). 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. Confidence intervals (95%) are derived using Newey-West standard errors with 5 lags.

"missing investment" is the cumulative shortfall since 2002, reflecting the divergence between Tobin's Q and observed investment. Gormsen and Huber (2023) 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:

$$\text{Adjusted Tobin's Q} = \text{Tobin's Q} \times \frac{1}{1 + \Delta\text{WACC} \times \text{Dur}} \tag{23}$$

in which ΔWACC is the wedge between actual and counterfactual WACC documented in Figure 9 and Dur is cash flow duration. 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. The influence of wedges thus grows with the duration of cash flows. We set the duration to 28 years which is the midpoint of the stock market duration estimates of Gormsen and Huber (2023) and Greenwald, Leombroni, Lustig, and Van Nieuwerburgh (2021).[39]

[39] We obtain quantitatively and qualitatively similar results using a time-varying measures of cash flow duration.

Figure 10 shows that the WACC wedge we document can explain 57% 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 11% of the capital stock. The wedge between actual and counterfactual WACC is thus large enough to account for more than half of the missing investment puzzle. The remaining gap is likely related to other macro developments, such as rising market power (Barkai, 2020, Crouzet and Eberly, 2023) and mismeasurement of intangible capital (Peters and Taylor, 2017).

A potential concern with the aggregate results is our reliance on the equal-weighted average CAPM $\widehat{\beta}$ to calculate changes in the perceived WACC. One might argue that the market value-weighted average CAPM $\widehat{\beta}$ is the one relevant for the aggregate economy but, by definition, must always equals 1. However, its relevance for aggregate investment is less clear than one might think. Lee, Shin, and Stulz (2021) document that high market valuations for large firms are a proxy for rents rather than for investment opportunities. Jiang, Vayanos, and Zheng (2024) find that flows into passive funds disproportionately raise the stock prices of the stock market's largest firms, and especially those large firms which the market already overvalues. Further, the Roll (1977) critique applies: the *stock* market's value-weighted CAPM $\widehat{\beta}$ is only meaningful if stock market values perfectly proxy aggregate investment opportunities.

We nevertheless explore other weighting schemes to calculate the weighted average CAPM $\widehat{\beta}$ of Compustat firms. Appendix Table A7 compares the cross-sectional weighted average CAPM $\widehat{\beta}$ of Compustat firms across two periods: 1975–2003 and 2004–2017, using seven different weighting schemes—market value, equal weight, PPENT, capital expenditures, total assets, sales, and value added. For all schemes except market value (by definition), the average CAPM $\widehat{\beta}$ increased after 2004, with changes ranging from 0.13 (value added) to 0.27 (equal weight). The increases are statistically significant at the 0.1% level for all schemes except market value.

8 Conclusion

This paper studies the causal effects of benchmarking-induced asset price distortions on corporate investment. We find that increases in benchmarking intensity cause CAPM $\widehat{\beta}$ to rise. Over the past 25 years, increased benchmarking has caused the equal-weighted average CAPM $\widehat{\beta}$ to rise by 0.41. In other words, benchmarking caused the average firm's perceived cost of equity to increase by more than 200 bps, largely offsetting the decline in the risk-free rate over the same period. Firms reduce investment in response to benchmarking-induced increases in CAPM $\widehat{\beta}$.

We argue that this behavior results from managers' reliance on textbook guidance to estimate the cost of capital using the CAPM, without internalizing the asset price distortions caused by benchmarking. Consistent with this mechanism, corporate managers, stock analysts, and regulators report higher perceived costs of equity capital after CAPM $\widehat{\beta}$s increases due to benchmarking.

An influential literature shows that U.S. investment has been low relative to valuations over the past two decades. Our findings suggest that increases in average CAPM $\widehat{\beta}$ can explain up to 57% of the cumulative investment shortfall since the early 2000s. The benchmarking of asset managers and the rise in passive investing therefore have significant and economically meaningful implications for aggregate investment. Our study highlights the important role of benchmarking in shaping asset prices and corporate investment decisions. The findings underscore the need for managers, policy makers, and investors to consider the unintended consequences of the growth in benchmark-linked investing and its impact on the real economy.

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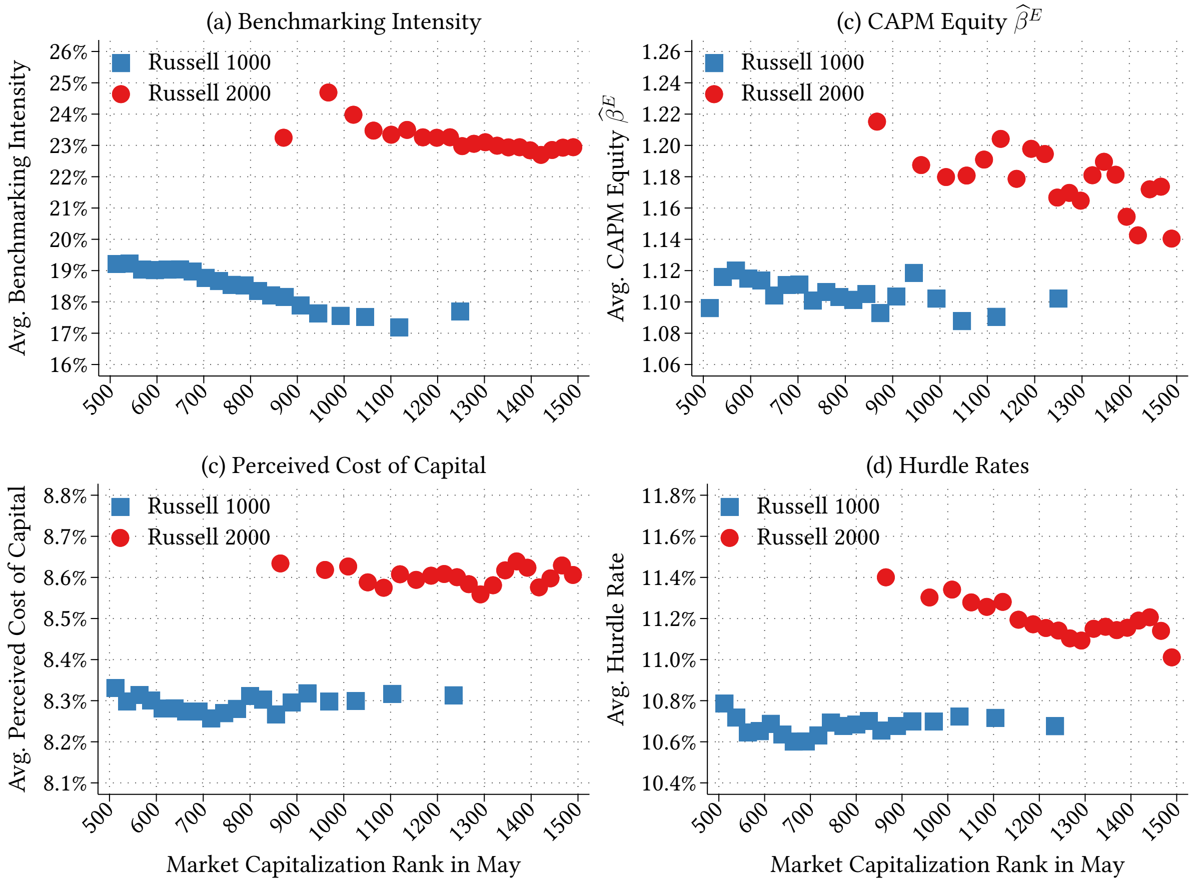
A Appendix

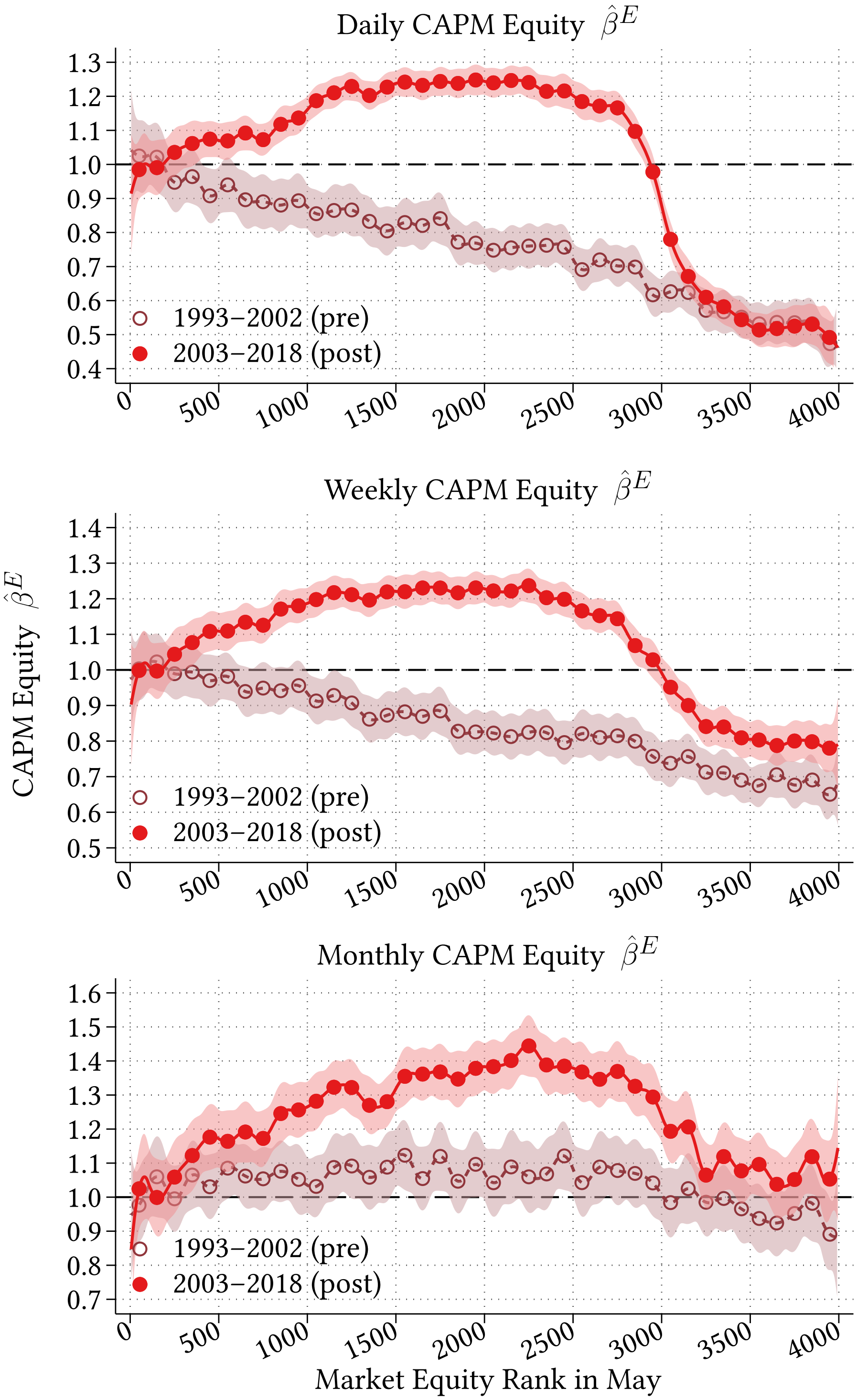
A.1 Appendix Figures

Figure A1: Discontinuities in Average Benchmarking Intensity, CAPM $\widehat{\beta}$s, Perceived Cost of Capital, and Hurdle Rates Around Russell 1000/2000 Cutoffs from 2007 to 2018



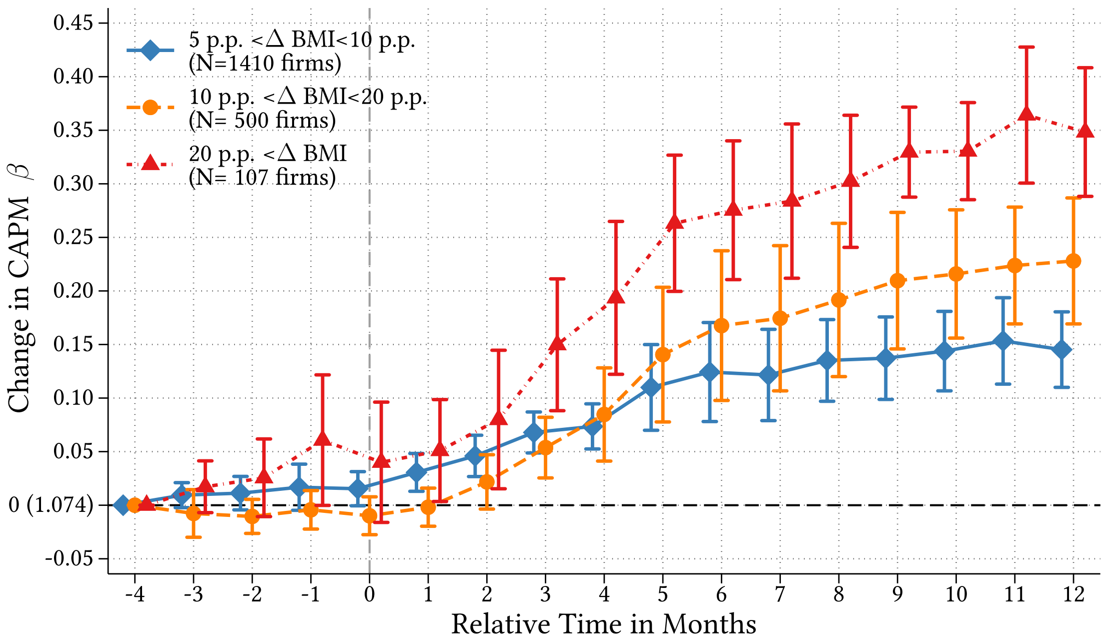
Notes: This figure shows binned scatter plots of (a) benchmarking intensity (Pavlova and Sikorskaya, 2023), (b) CAPM equity $\widehat{\beta}$s, (c) firm managers' perceived cost of capital (Gormsen and Huber, 2024), and (d) firm managers' hurdle rates (Gormsen and Huber, 2023) against May market capitalization ranks. We separately plot the conditional means for Russell 1000 (blue squares) and Russell 2000 (red dots) stocks. Conditional means are identified absorbing year-month and stock fixed effects. Sample period from 2007 to 2018 (after Russell introduced its banding-policy).

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

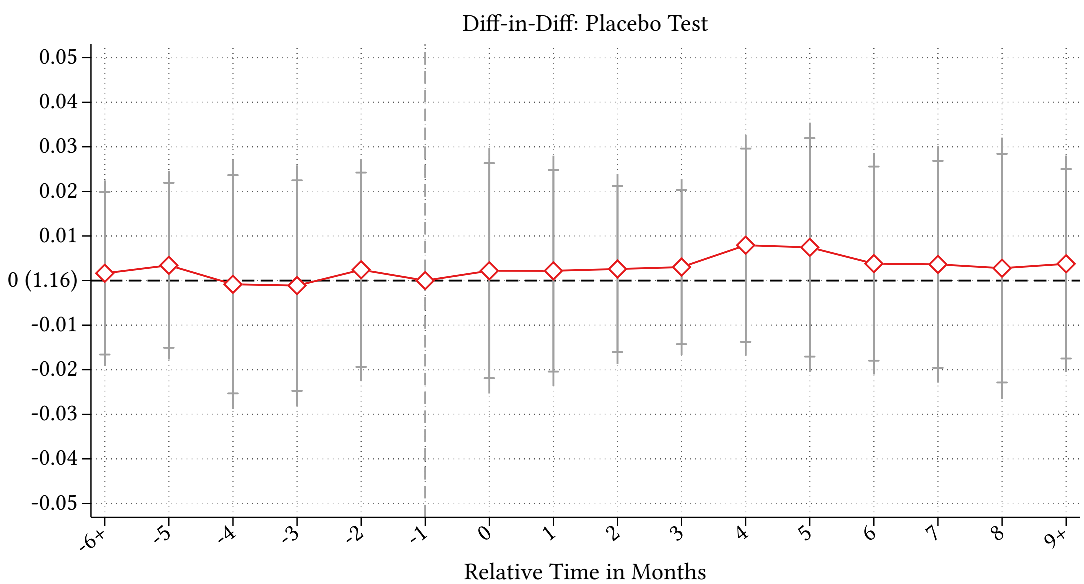


Notes: This figure shows binned scatter plots of rolling-window CAPM $\widehat{\beta}$s against May market capitalization ranks for different estimation frequencies. Daily rolling window estimates use 252 trading days, weekly rolling window estimates use 156 weeks of data, and monthly rolling window estimates use 36 months of data. Shaded areas are 90% confidence bands based on standard errors clustered at the stock and year-month level.

Figure A3: Difference-in-differences Event Study for Different Treatment Intensities

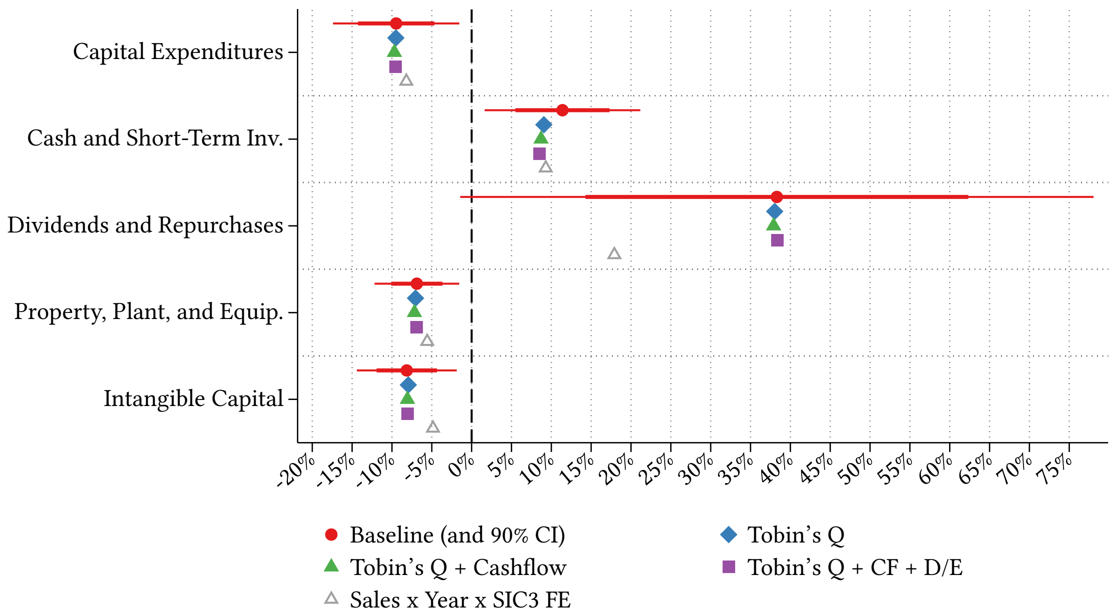


Notes: This figure shows Difference-in-differences event study coefficients for different treatment intensities.



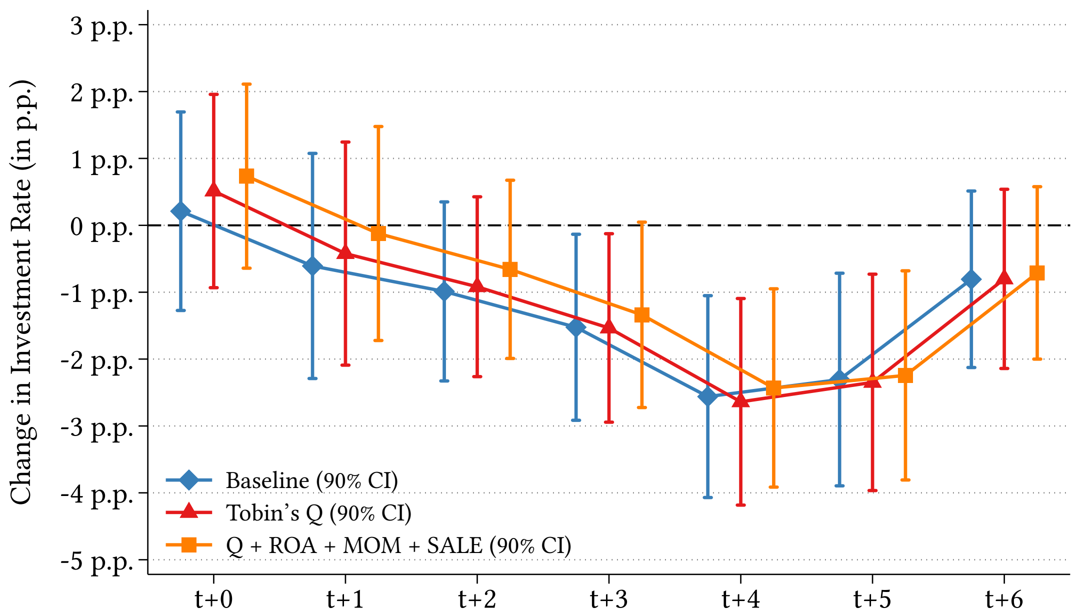
Notes: This figure shows difference-in-differences event study coefficients of Eq. (8). Treatment group: $\Delta\text{BMI} \in (0 \text{ p.p.}, 1 \text{ p.p.}]$. Control group: $\Delta\text{BMI} \in [-1 \text{ p.p.}, 0 \text{ p.p.}]$

Figure A5: LP-IV Robustness to various Alternative Specifications



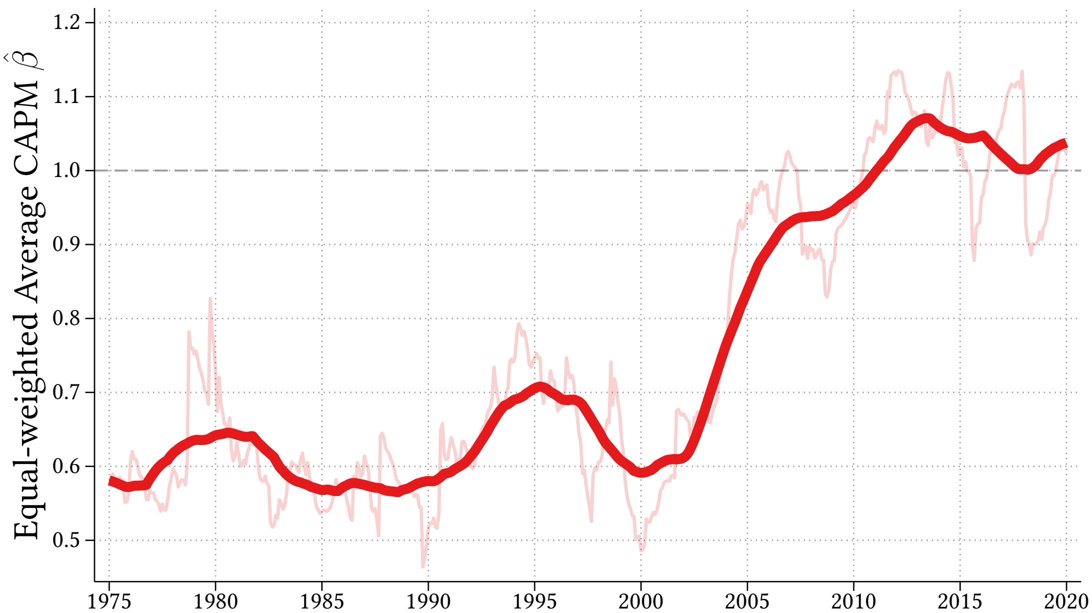
Notes: This figure shows estimates of LP-IV coefficient h=5 from Eq. (16) for baseline and alternative specifications.

Figure A6: Impact of changes in CAPM $\widehat{\beta}$ on investment rate



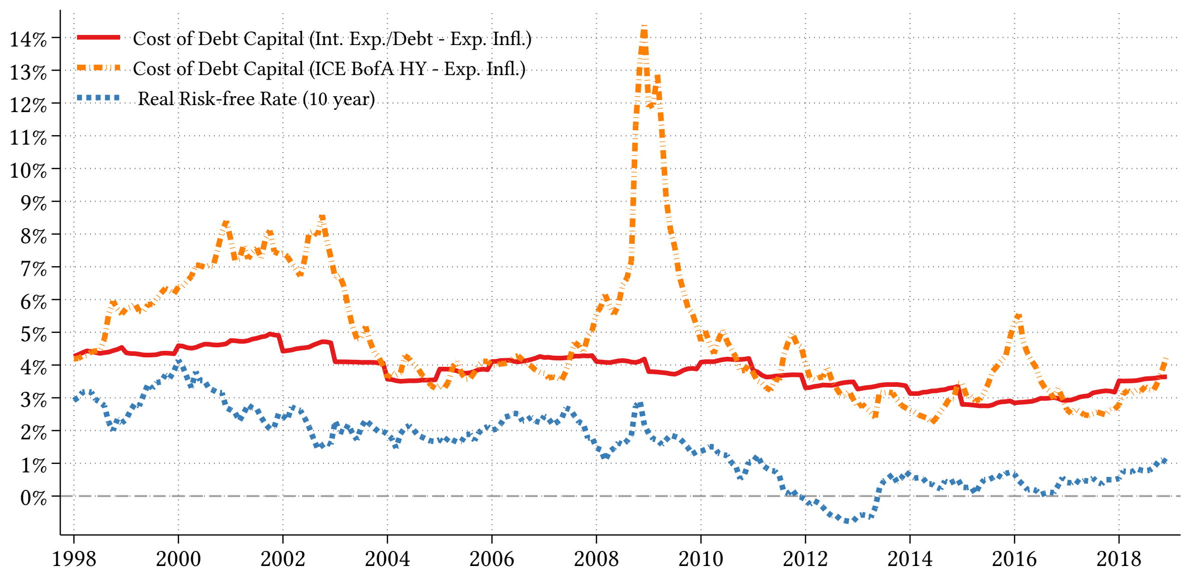
Notes: This figure shows estimates for γ^h of Investment Rate$_{i,t+h} = \alpha_i + \alpha_{j,t} + \gamma^h \widehat{\text{CAPM}}\ \beta_{i,t} + X'_{i,t}\xi + \varepsilon_{i,t+h}$, estimated using changes in BMI as an IV for changes in CAPM $\widehat{\beta}$. Estimates are scaled to a 0.16 change in CAPM $\widehat{\beta}$. Investment rate is defined as $\frac{\text{CAPX}_t}{\frac{1}{2}(\text{PPENT}_{t-1}+\text{PPENT}_t)}$ (see e.g, Alfaro et al., 2024 or Belo et al., 2014). Median and standard deviation of investment rate are 19.9% and 13.5%, respectively.

Figure A7: Time Series of Equal-weighted Average CAPM $\widehat{\beta}$ since 1975



Notes: This figure shows the monthly cross-sectional equal-weighted average CAPM $\widehat{\beta}$ of Welch (2022b) since 1975. We focus on the period after the NASDAQ's addition to the CRSP sample. Time-series are smoothed using a two-sided moving-average filter with 24 month window on either side.

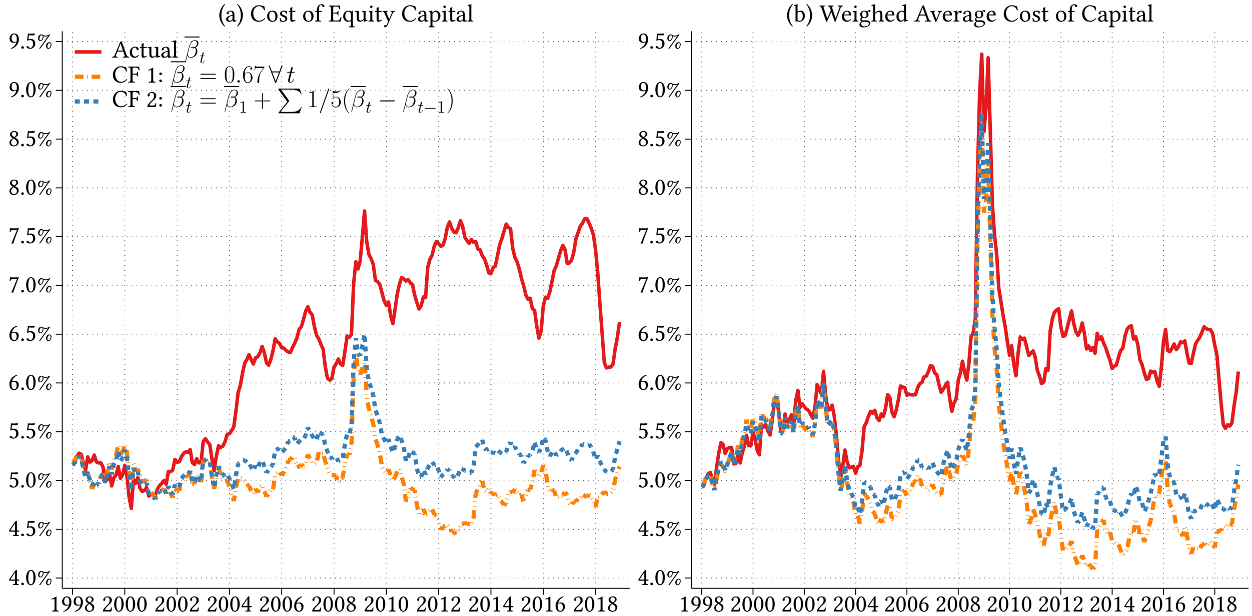
Figure A8: Average Cost of Debt Capital and Real Risk-free Rate over the past 25 years



Notes: This figure shows monthly estimates of the average firm's cost of debt. The solid blue line proxies for cost of debt using interest expenses over total debt in Compustat. The dashed red line proxies for cost of debt using the yield on the ICE-BofA HY index. Dashed blued line proxies for risk-free rate using the yield on 10-year TIPS from 2004 to 2018 and before 2004 nominal Treasurys adjusted for 10-year inflation expectations from the SPF.

Figure A9: Average Cost of Equity Capital and WACC over the past 25 years (Using Time-varying Equity Risk Premium Implied by S&P 500 Dividend Yield)

(a) Cost of Equity Capital (b) Weighed Average Cost of Capital



Notes: This figure shows monthly estimates of the cross-sectional averages of cost of equity capital and WACC using a time-varying ERP. We estimate $\mathbb{E}_t \left[r^{Mkt}\right] - r_t^f$ by calculating the time-varying expected return on the market (proxied by the S&P 500) using Gordon's growth model: $\mathbb{E}_t \left[r^{Mkt}\right] = D_{t+1}/P_t + \overline{g}$. We assume the average expected real dividend growth, $\overline{g}$, to be constant at 4.88%. We use the average expected dividend growth rate of the S&P 500 (7.31%) from 1994 to 2011 (Golez, 2014) and subtract expected annual inflation over the next 10 years (SPF). Red solid line shows cost of capital estimates using the actual CAPM β_t. Blue and orange dashed lines show counterfactuals in which CAPM β_t is adjusted for BMI increase (see Eq. 22) or set constant at its pre-2000 average, respectively.

A.2 Appendix Tables

Table A1: Summary Statistics of Matched BMI-CAPM Sample

	Mean	SD	Min	P5	P10	Median	P90	P95	Max	N
CAPM β (Welch, 2022)	0.88	0.48	-0.71	0.14	0.25	0.88	1.51	1.69	2.67	1,231,865
Δ CAPM β	0.02	0.27	-1.67	-0.41	-0.29	0.02	0.34	0.46	1.88	59,510
BMI in May	0.15	0.09	0.00	0.00	0.00	0.17	0.26	0.28	0.34	61,099
BMI in June	0.16	0.09	0.00	0.00	0.00	0.17	0.26	0.27	0.36	61,099
Δ BMI	0.00	0.04	-0.41	-0.04	-0.02	0.00	0.03	0.05	0.24	61,098
Market Cap. (in $m)	3,737	15,447	0.00	11.00	21.00	309.00	6,305	15,382	350,232	1,231,865
Shares Out. (in 1000s)	90.85	257.69	0.00	2.00	4.00	26.00	174.00	347.00	3,914	1,231,865
Trading Vol. (in 100,000s)	16,842	50,099	0.00	29.00	73.00	2,630	38,506	75,318	1,085,943	1,231,865

Notes: Monthly sample from 1998 to 2019. ΔCAPM $\widehat{\beta}$ is the difference between the average CAPM $\widehat{\beta}$ in the first and last quarter of a year. Variables are winsorized at the 0.5% and 99.5% level.

Table A2: Effect of Change in Benchmarking Intensity on CAPM $\widehat{\beta}$

Treatment Group:	Δ BMI>5p.p.							
Sample:	Market Equity $\geq$ P10 NYSE				Market Equity $\geq$ P20 NYSE			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treated $\times$ Post	0.111***	0.117***	0.111***	0.111***	0.102***	0.109***	0.102***	0.103***
	(0.013)	(0.012)	(0.012)	(0.012)	(0.014)	(0.012)	(0.013)	(0.013)
Controls	✓	✓	✓	✓	✓	✓	✓	✓
Fixed Effects								
Firm $\times$ Cohort	✓	✓	✓	✓	✓	✓		
Time $\times$ Cohort	✓				✓			
Size Decile $\times$ Time $\times$ Cohort		✓				✓		
Volume Decile $\times$ Time $\times$ Cohort			✓				✓	
Shrs. Out. Decile $\times$ Time $\times$ Cohort				✓				✓
Observations	291,822	291,754	291,688	291,617	249,916	249,840	249,745	249,703

Notes: This table reports coefficient estimates of Eq (8). Treated$\times$Post is the average of the post-treatment coefficients after 5 months (to account for the expanding-window estimation of CAPM $\widehat{\beta}$). Sample from 2000-01 to 2019-06. Standard errors in parentheses are double-clustered at firm and year-month level. + p<0.10, * p<0.05, ** p<0.01, *** p<0.001.

Table A3: Robustness to Alternative CAPM $\widehat{\beta}$ Estimators

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Panel A: CAPM β estimates using expanding windows of daily data with exponentially decaying weights of 3-months half life						
	Δ CAPM β_{EW}^{OLS}	Δ CAPM β_{EW}^{WEL}	Δ CAPM β_{EW}^{DIM}	Δ CAPM β_{EW}^{BLU}	Δ CAPM β_{EW}^{TOP}	$\Delta\ \rho(r_i, r_m)_{EW}$	$\Delta\ \sigma_{EW}^{i}$
Δ BMI (in p.p.)	0.0183***	0.0154***	0.0135***	0.0122***	0.0171***	0.00646***	-0.0000668*
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.000)	(0.000)
Firm FE	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓
Adj. R^2	0.15	0.16	0.11	0.15	0.26	0.41	0.59
Observations	28,514	28,514	28,514	28,514	28,514	28,514	28,514
	Panel B: CAPM β estimates using daily data with a 2-year rolling window (with equal weights)						
	Δ CAPM β_{RW}^{OLS}	Δ CAPM β_{RW}^{WEL}	Δ CAPM β_{RW}^{DIM}	Δ CAPM β_{RW}^{BLU}	Δ CAPM β_{RW}^{TOP}	$\Delta\ \rho(r_i, r_m)_{RW}$	$\Delta\ \sigma_{RW}^{i}$
Δ BMI (in p.p.)	0.00630***	0.00547***	0.00576***	0.00420***	0.00691***	0.00271***	-0.0000516**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)
Firm FE	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓
Adj. R^2	0.21	0.22	0.17	0.21	0.31	0.43	0.58
Observations	28,514	28,514	28,514	28,514	28,514	28,514	28,514

Notes: This table reports coefficient estimates of specifications of the form: $\Delta\beta_{i,t} = \alpha_i + \alpha_t + \gamma\Delta\text{BMI}_{i,t} + \varepsilon_{i,t}$. $\Delta\beta_{i,t}$ is between 1st and 4th quarter of each year. β^{WEL} is estimator of Welch (2022b), β^{DIM} is estimator of Dimson (1979), β^{BLU} is estimator of Blume (1975) (also known as Bloomberg $\widehat{\beta}$), β^{TOP} is $\widehat{\beta}$ with respect to ten largest stocks by market capitalization, EW stands for expanding window, RW for rolling window. Changes in BMI and CAPM $\widehat{\beta}$s are winsorized at the 2% and 98% level. Estimation sample is restricted to stocks within 300 ranks around Russell index cutoffs. Standard errors in parentheses are clustered at firm-level. + p<0.10, * p<0.05, ** p<0.01, *** p<0.001.

Table A4: Lag-selection based on Bayesian/Schwartz Information Criterion

Maximum lag length	L=0	L=1	L=2	L=3	L=4	L=5	L=6
Bayesian Information Criterion (OLS)	433	372	370	293	174	**144**	152
Bayesian Information Criterion (IV)	1,938	729	489	432	**388**	553	605
Observations	14,420	14,420	14,420	14,420	14,420	14,420	14,420

Notes: This table reports BIC for regression specifications of the form: ΔPerceived Cost of Capital$_{i,t} = \alpha_i + \alpha_t + \gamma\ \Delta\text{CAPM}\ \beta_{i,t} + \nu_{i,t}$ for OLS and IV regression specification in which changes in CAPM $\widehat{\beta}$ are instrumented by changes in BMI.

Table A5: Effect of Δ CAPM $\widehat{\beta}$ on Managers' Perceived Cost of Capital (unrestricted DL model)

	Dependent variable: Δ Perceived Cost of Capital (in p.p.)								
	RF			OLS			IV		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Δ BMI (in p.p.)	0.016***	0.017***	0.017***						
	(0.004)	(0.004)	(0.004)						
Δ CAPM β^A				1.202***	1.183***	1.135***	3.153***	3.694***	3.148***
				(0.057)	(0.059)	(0.075)	(0.825)	(0.920)	(0.769)
Fixed Effects									
Firm	✓	✓	✓	✓	✓	✓	✓	✓	✓
Time	✓			✓			✓		
Size Quartile $\times$ Time		✓			✓			✓	
Industry $\times$ Time			✓			✓			✓
Observations	19,501	19,501	18,940	19,501	19,501	18,940	19,501	19,501	18,940

Notes: This table reports $\lambda = \sum_{h=0}^{4} \hat{\gamma}_h$ for specifications of the form: ΔPerc. Cost of Capital$_{i,t} = \alpha_i + \alpha_{j,t} + \sum_{h=0}^{4} \gamma_h \Delta\text{CAPM}\ \beta_{i,t-h} + \varepsilon_{i,t}$ for reduced form, OLS, and IV regression in which the instrument is ΔBMI for stock i in year t. IV estimated via LIML. Standard errors in parentheses are clustered at firm-level. + p<0.10, * p<0.05, ** p<0.01, *** p<0.001.

Table A6: Effects of Benchmarking Intensity on Equal-Weighted Average CAPM $\widehat{\beta}^E$

	(1) OLS	(2) ADL(1)	(3) DOLS(3)	(4) DOLS(4)	(5) DOLS(5)	(6) DOLS(7)
BMI (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: Newey-West standard error in parentheses with L=21 lags. + p<0.10, * p<0.05, ** p<0.01, *** p<0.001.

Table A7: Weighted Average CAPM $\widehat{\beta}$ of Compustat Firms from 1975 to 2017

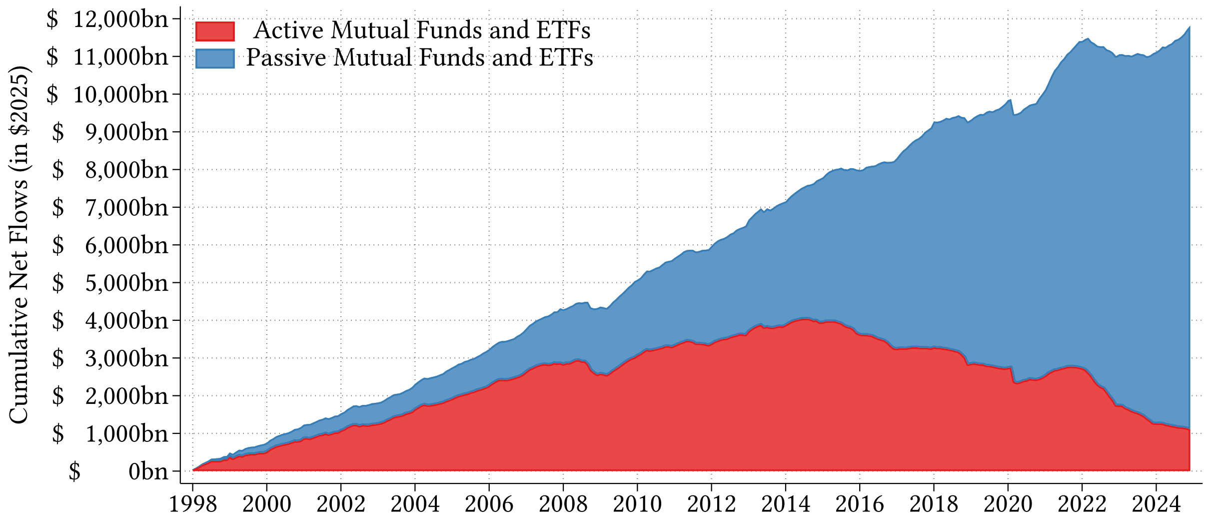
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
			Weighted CAPM β Estimates				
weighted by:	Market Cap.	Equal	PPENT	Cap. Ex.	Total Assets	Sales	Value Add.
$\mathbb{1}\{\text{Year} > 2003\}$	0.003	0.273***	0.196***	0.152***	0.216***	0.163***	0.130***
	(0.012)	(0.021)	(0.030)	(0.027)	(0.024)	(0.028)	(0.025)
Constant	1.001***	0.735***	0.854***	0.907***	0.849***	0.910***	0.927***
	(0.010)	(0.012)	(0.032)	(0.028)	(0.020)	(0.029)	(0.025)
Observations	43	43	43	43	43	43	43

Notes: This table reports coefficient estimates of yearly regressions of the form: Weighted CAPM $\beta_t = \alpha_0 + \mathbb{1}\{\text{Year} > 2003\} + \varepsilon_t$ from 1975 to 2017 in which Weighted CAPM $\beta_t = \sum_i \omega_i \times$ CAPM $\beta_{i,t}$ is the cross-sectional weighted average of Compustat firm's CAPM $\widehat{\beta}$. Firm-level CAPM $\widehat{\beta}$s are estimates from Welch (2022b). Newey-West standard errors with $8 = \lfloor 1.3\sqrt{43} \rfloor$ lags in parenthesis. . + p<0.10, * p<0.05, ** p<0.01, *** p<0.001.

B Flows Into Passive Mutual Fund and CAPM $\widehat{\beta}$s

This appendix documents a strong correlation between passive mutual fund flows and cross-sectional increases in CAPM $\widehat{\beta}$s using panel regressions. We also present simulation evidence showing that a two-factor model—with a passive flow factor scaled by BMI exposure—can replicate the observed rise in CAPM $\widehat{\beta}$s.

Figure B10: Cumulative Net Flows into Passive and Active Mutual Funds and ETFs

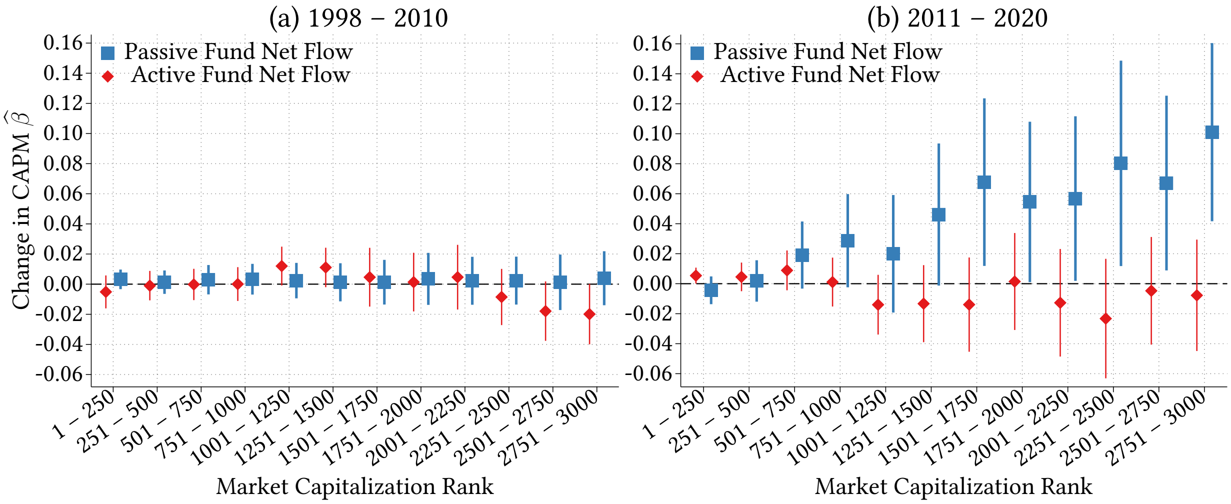


Notes: This figure show cumulative monthly net flows into active and passive mutual funds and ETFs from 1998 to 2024 deflated by the Consumer Price Index. Source: Morningstar Direct.

In 2024, total net assets in U.S. passive mutual funds and ETFs surpassed those in active funds for the first time (Morningstar Direct, 2025). Figure B10 illustrates the rapid growth of passive investing over the past 25 years, with cumulative net flows into passive funds exceeding those into active funds by more than $10 trillion since 1998. According to Investment Company Institute (2022), index funds held 16% of the U.S. stock market in 2021. However, Chinco and Sammon (2024) estimate that total passive ownership is roughly twice this figure, accounting for institutions managing index portfolios internally and active managers engaging in quasi-indexing.

Mutual Fund Flows We obtain monthly total net assets and net 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 (see Morningstar Direct, 2024). Rather, the flows present the net amount of money that investors put into or withdraw from mutual funds.

Figure B11: Impact of Net Flows into Passive and Active Mutual Funds and ETFs on CAPM $\widehat{\beta}$



Notes: This figure shows estimates of γ_j^A and γ_j^P from the monthly panel regression: CAPM $\widehat{\beta}_{i,t} = \alpha_i + \rho$ CAPM $\widehat{\beta}_{i,t-1} + \sum_j \gamma_j^A \, \mathbb{1}\{i \in \text{Bin } j\} \times F_t^A/A_{t-1}^A + \sum_j \gamma_j^P \, \mathbb{1}\{i \in \text{Bin } j\} \times F_t^P/A_{t-1}^P + \varepsilon_{i,t}$. Estimates are scaled to a 2 standard deviation net inflow ($\approx 1\%$ of A_{t-1}). 90% confidence intervals based on standard errors clustered at the stock and year-month level. CAPM $\widehat{\beta}$ estimated using a rolling window of 52 weeks.

B.1 Effect of Passive Mutual Fund Flows on CAPM $\widehat{\beta}$s

We test whether passive or active flows are correlated with the observed increase in CAPM $\widehat{\beta}$. We estimate the following panel regression at the monthly frequency (using end of month $\widehat{\beta}$s):

$$\begin{aligned}\text{CAPM } \widehat{\beta}_{i,t} =& \alpha_i + \rho \text{ CAPM } \widehat{\beta}_{i,t-1} \\ &+ \sum_j \gamma_j^A \, \mathbb{1}\{i \in \text{Bin } j\} \times F_t^A/A_{t-1}^A + \sum_j \gamma_j^P \, \mathbb{1}\{i \in \text{Bin } j\} \times F_{i,t}^P/A_{t-1}^P + \varepsilon_{i,t} \quad (24)\end{aligned}$$

in which F_t^A and $F_{i,t}^P$ are net flows into active and passive funds, respectively. We set $\mathbb{1}\{i \in \text{Bin } j\}$ to 1 if stock i is in bin j of the market capitalization rank and 0 otherwise.

Figure B11 plots the estimates γ_j^A and γ_j^P from Eq. (24). It shows how CAPM $\widehat{\beta}$s across the size distribution change in response to a 2 standard deviation net flow into active and passive funds. Panel (a) shows the period from 1998 to 2010. The increase in CAPM $\widehat{\beta}$ in response to net flows into both active and passive funds is minuscule and statistically insignificant. Panel (b) shows the period from 2010 to 2018. The increase in CAPM $\widehat{\beta}$ in response to net flows into passive funds is large and statistically significant for stocks beyond a market capitalization rank of 1000. This is consistent with the fact that a larger fraction of the Russell 2000 is owned by passive funds than the Russell 1000 (Pavlova and Sikorskaya, 2023). A 2 standard deviation net inflow into passive funds increases the CAPM $\widehat{\beta}$ of the small-caps stocks by 0.06 to 0.10. The effects of flows into

Table B8: Benchmarking Intensity and Net Flows into Active and Passive Mutual Funds

	(1) CAPM $\widehat{\beta}$	(2) CAPM $\widehat{\beta}$	(3) CAPM $\widehat{\beta}$	(4) CAPM $\widehat{\beta}$	(5) CAPM $\widehat{\beta}$
$\text{BMI}_{i,t-1}$ (as fraction of ME)	1.119***	1.980***	0.064	1.971***	0.135
	(0.237)	(0.309)	(0.198)	(0.309)	(0.202)
$\text{BMI}_{i,t-1} \times F_t/A_{t-1}$ (Pooled)	0.160**	0.034	0.201***		
	(0.062)	(0.063)	(0.073)		
$\text{BMI}_{i,t-1} \times F_t/A_{t-1}$ (Active Funds)				0.034	0.095
				(0.066)	(0.080)
$\text{BMI}_{i,t-1} \times F_t/A_{t-1}$ (Passive Funds)				0.024	0.245***
				(0.063)	(0.076)
Sample	1998 – 2018	1998 – 2010	2011 – 2018	1998 – 2010	2011 – 2018
Stock Fixed Effects	✓	✓	✓	✓	✓
Year-Month Fixed Effects	✓	✓	✓	✓	✓
Adj. R^2	0.47	0.52	0.54	0.52	0.54
Observations	699,752	409,095	290,638	409,095	290,638

Notes: This table reports coefficients from the panel regression: CAPM $\widehat{\beta}_{i,t} = \alpha_i + \alpha_t + \text{BMI}_{i,t-1} + \text{BMI}_{i,t-1} \times F_t/A_{t-1} + \varepsilon_{i,t}$ in which F_t are net flows and $A_{i,t}$ total net assets of mutual funds and EFTs from Morningstar Direct. F_t/A_{t-1} is standardized to have zero mean and unit variance. Observations are weighted by market capitalization. Standard errors clustered at the stock and year-month level in parenthesis. * p<0.10, ** p<0.05, *** p<0.01

active mutual funds on CAPM $\widehat{\beta}$s close to zero and statistically insignificant.

Prima facie, our results suggest that the relationship between passive flows and CAPM $\widehat{\beta}$s may have evolved over time. While official data show large passive fund flows only after 2010, Chinco and Sammon (2024) document substantial flows into passive strategies before 2010 that do not appear in official passive fund data. This suggests that passive flow's distortions of CAPM $\widehat{\beta}$ may have been present earlier but was not captured through traditional fund classifications.

Table B8 provides further insight. Before 2010, the effects on CAPM $\widehat{\beta}$s appear to have been intermediated primarily through BMI, whereas after 2010, the impact operates through direct interactions with observed net flows – specifically, the interaction between passive flows and benchmarking intensity. We interpret this result as suggesting that BMI is a good proxy for exposure to passive flows pre-2010.

B.2 Simulated CAPM $\widehat{\beta}$s in a Two-Factor Model

We use simulations to show that the emergence of a second (flow) factor explains the cross-sectional evolution of CAPM $\widehat{\beta}$s between 1998 and 2018. We propose a parsimonious two-factor model in which a stock's CAPM $\widehat{\beta}$ depends on its exposure to a fundamental factor and a flow factor. The fundamental factor is the first principal component of key macro-financial variables, with factor loadings fixed at the distribution of CAPM $\widehat{\beta}$s observed in May 1990—when passive index investing was still nascent. The flow factor captures net flows into passive mutual funds and ETFs, with exposures proxied by stocks' benchmarking intensity. We discipline the simulation using the time-series of market weights, conditional (co)variances, and flow-factor exposures.

The simulations yield three key findings: (i) A flow factor with loadings proportional to benchmarking intensity successfully captures both the cross-sectional distribution and the temporal evolution of CAPM $\widehat{\beta}$s from 1998 to 2018. (ii) Calibrating the flow factor using passive net flows replicates the conditional covariance structure which is able to match the observed time series of CAPM $\widehat{\beta}$s. (iii) In contrast, active fund flows fail to match the observed conditional moments of CAPM $\widehat{\beta}$s.

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

$$R_{i,t+1} - R_t^f = a_{i,t} + b_{i,t}\lambda_{t+1} + u_{i,t+1} \tag{25}$$

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 $\widehat{\beta} = \frac{Cov_t(R_{i,t+1}, R_{m,t+1})}{Var_t(R_{m,t+1})}$ where $R_{m,t+1} = \sum_j w_{j,t} R_{j,t+1}$ denotes the market-cap weighted average return on the universe of securities j. Plugging (25) into the CAPM β formula, one finds that

$$\begin{aligned}\widehat{\beta}_{it} &= \frac{Cov_t\left(b_{i,t}\lambda_{t+1} + u_{i,t+1}, \sum_j w_{jt}\left(b_{j,t}\lambda_{t+1} + u_{j,t+1}\right)\right)}{Var_t\left(\sum_j w_{jt}(b'_{j,t}\lambda_{t+1} + u_{j,t+1})\right)} \\ &= \frac{w_t' b_t \Sigma_\lambda b_t' e_i + w_{i,t}\sigma_{u,i}^2}{w_t' b_t \Sigma_\lambda b_t' w_t + w_t' \Sigma_u w_t}\end{aligned} \tag{26}$$

where e_i denotes the i-th unit vector.

To replicate Figure 1 in our simulation, we simulate Eq. (26) using the conditional means of CAPM $\widehat{\beta}s$ across market capitalization ranks rather than individual stocks $\widehat{\beta}_{it}$. We model conditional means of CAPM $\widehat{\beta}$ and BMI as flexible fifth-order polynomial functions of market capitalization ranks.[40] We then compare the simulated conditional means to the empirical conditional

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

means of CAPM $\widehat{\beta}$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 In order to simulate Eq. (26) 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 $b^1_{it} = \text{CAPM } \widehat{\beta}_{i1990m5} \, \forall \, t$. This ensures that time-variation in our simulated CAPM $\widehat{\beta}$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 B8 provides evidence that net flows into passive funds predict changes in CAPM $\widehat{\beta}$s. We therefore set the proportionality constant to 0.25, matching the coefficient of the BMI-passive flow interaction term from Column 5 of Table B8.

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 and Kuttner, 2005), unemployment rate (Kilic and Wachter, 2018), WTI oil price (Kilian and Park, 2009), the University of Michigan consumer sentiment index (Baker and Wurgler, 2006), and the consumer price index (Campbell and 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 $\widehat{\beta}$s from May 1990.[41]

We specify the flow factor as net flows into passive mutual funds and ETFs, scaled by their total net assets. We are motivated by our findings in Appendix B.1 which documents that net flows into passive funds predict changes in CAPM $\widehat{\beta}$s. 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 $\widehat{\beta}$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 $\sigma_{u,it} = 0.07 \, \forall \, i, t$.

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

Table B9: 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

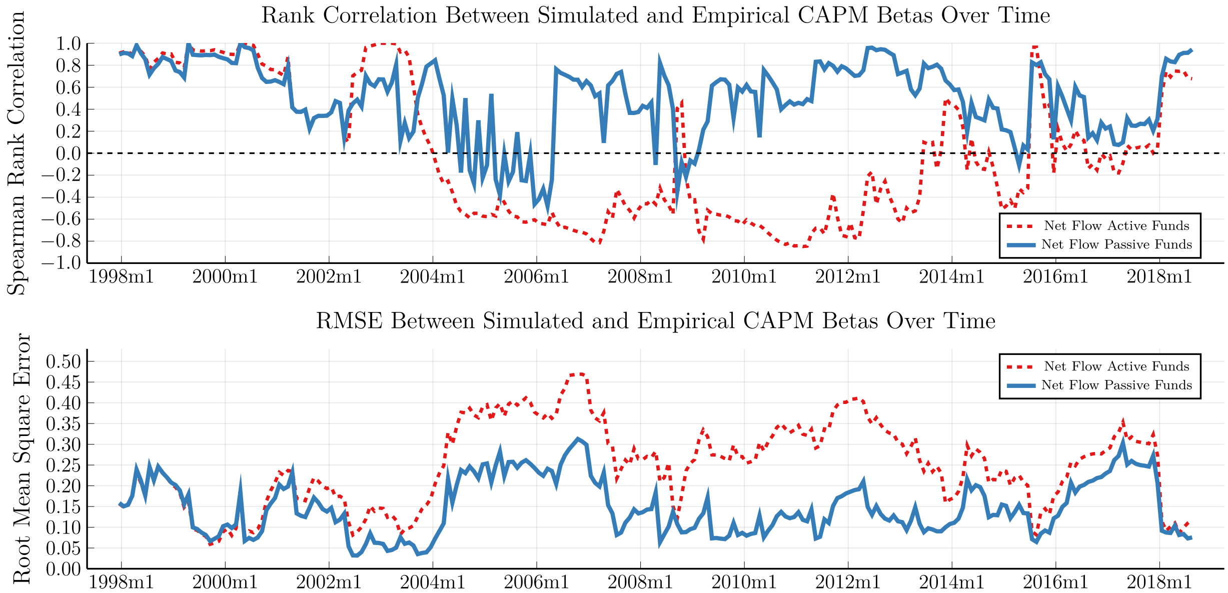
Notes: This table reports the average root mean square error (RMSE) and Spearman rank correlation between simulated and empirical CAPM $\widehat{\beta}$s from January 1998 to September 2018. Each month, we simulate conditional means of CAPM $\widehat{\beta}$ across market capitalization ranks and compare them with empirical conditional means. Results are reported separately 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, effectively explains both the cross-sectional distribution and the temporal evolution of CAPM $\widehat{\beta}$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 $\widehat{\beta}$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 $\widehat{\beta}$s.

Table B9 reports the average RMSE and Spearman rank correlations between simulated and empirical CAPM $\widehat{\beta}$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 $\widehat{\beta}$s correlate strongly with actual distributions when calibrated to passive flows (average correlation of 0.49), whereas correlations using active flows are close to zero (-0.02). Comparing different model specifications, results for passive flows remain robust. Eliminating the flow factor ($\sigma_f = 0$) substantially worsens model performance, increasing RMSE dramatically and implies negative correlations between simulated and observed $\widehat{\beta}$s. Figure B12 shows the time-series evolution of rank correlations and RMSE between simulated and empirical CAPM $\widehat{\beta}$s from 1998 to 2018. The passive-flow calibration consistently outperforms the active-flow calibration, particularly after 2007. This aligns with Table B8, which indicates a stronger correlation between passive flows, benchmarking intensity, and $\widehat{\beta}$s post-2010.

Figure B13 illustrates our two-factor model's ability to replicate CAPM $\widehat{\beta}$ 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 $\widehat{\beta}$s. Despite its simplicity, the model successfully captures key empirical patterns in the data. It is able to repli-

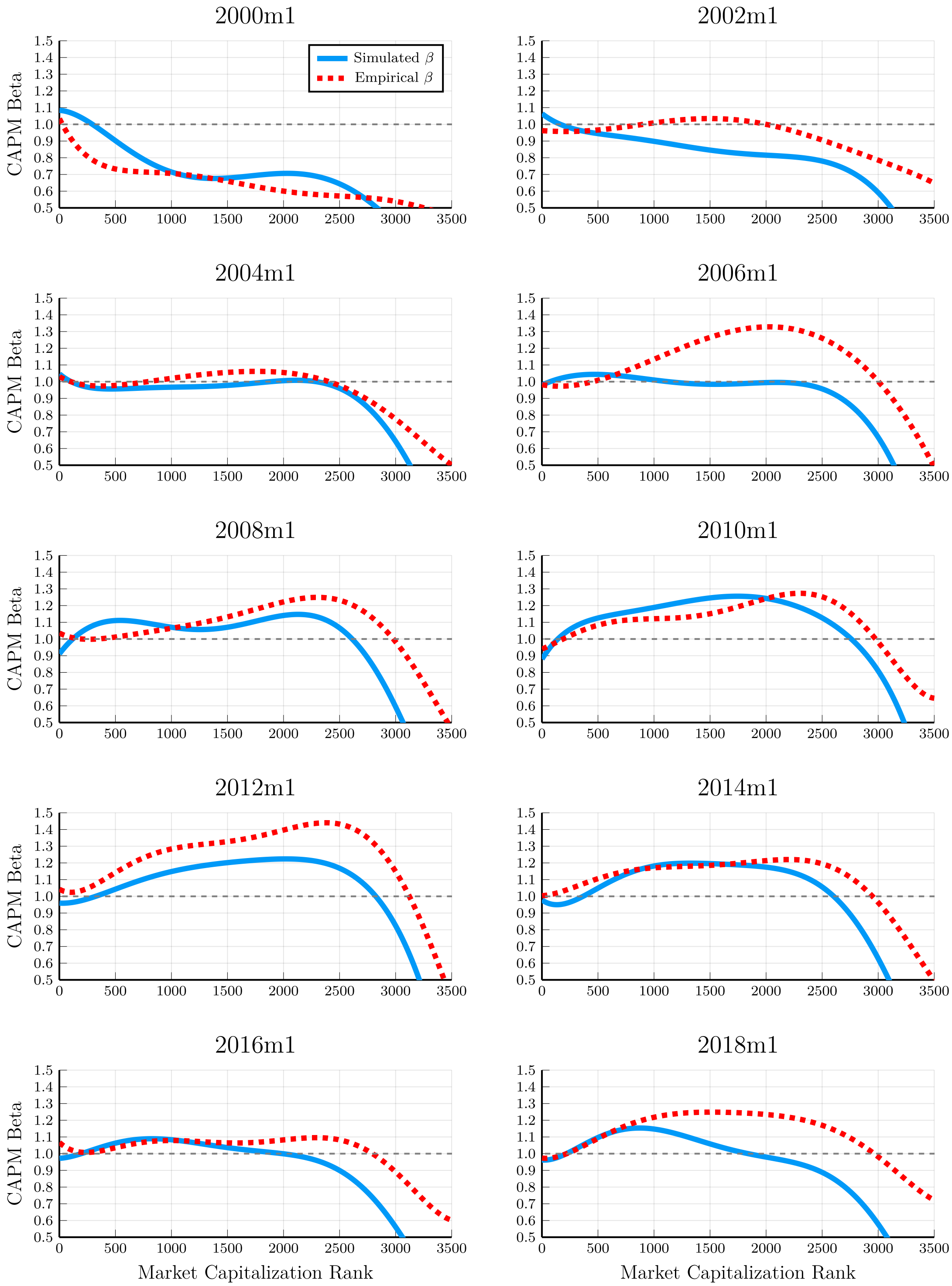
Figure B12: Time Series of Correlation and RMSE Between Simulated and Empirical CAPM $\widehat{\beta}$s



Notes: This figure plots Spearman rank correlation and root mean square error between the empirical and simulated conditional means of CAPM $\widehat{\beta}s$ 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 $\widehat{\beta}$s across market capitalization ranks from 2000 to 2018.

Figure B13: Simulated and Empirical CAPM $\widehat{\beta}$s Across Market Capitalization Ranks



Notes: This figure plots the empirical and simulated conditional means of CAPM $\widehat{\beta}s$ from 2000 to 2018. The flow factor is calibrated 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.

C Other Measures of Perceived Cost of Equity Capital

This section provides details on alternative measures of the perceived cost of equity capital. We use these alternative measures to validate our main results that the perceived cost of capital increases due to the CAPM $\widehat{\beta}$ distortions caused by benchmarking. Specifically, we show that benchmarking-induced changes of a stock's CAPM $\widehat{\beta}$ cause changes in the perceived cost of equity of stock analyst and regulators of public utilities and railroads.

C.1 Stock Analysts' Perceived Cost of Equity Capital

We collect stock analysts' perceived cost of equity capital 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 which are 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, Lehavy, and Michaely, 2005).

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

Table C10: 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.

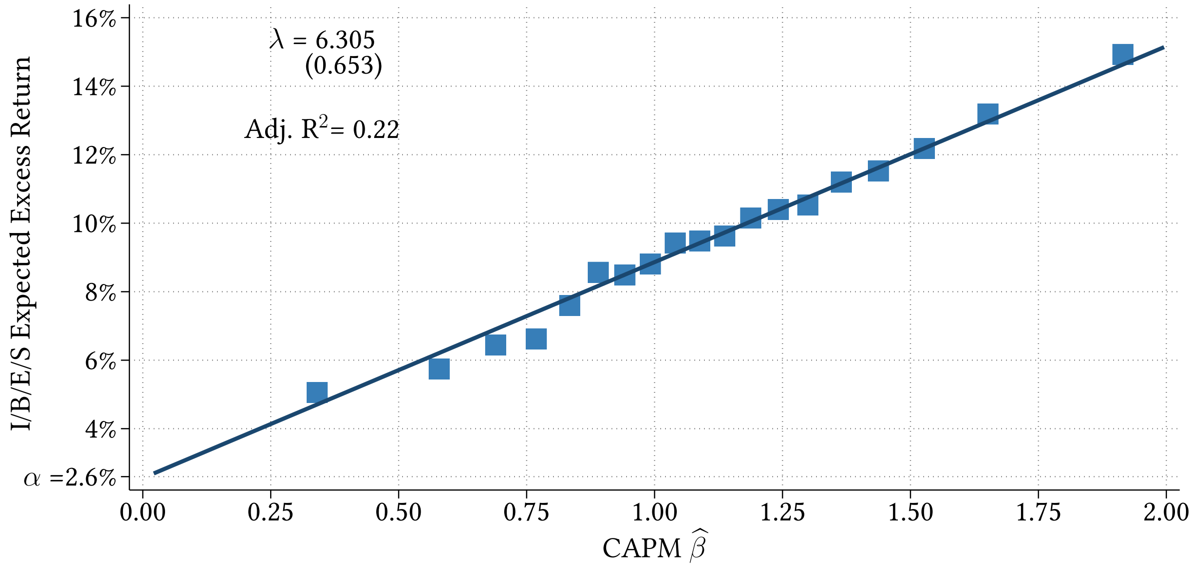
Table C10 reports the marginal effects from an ordered logit regression of the Value Line safety rank on exogenous changes in benchmarking intensity due to Russell index reconstitution. We restrict the sample to stocks within 400 ranks around the Russell index cutoffs. The coefficients indicate the change in the probability of each outcome category due to a 10 p.p. increase in BMI (from May to June) caused by the Russell index reconstitution. The results show that an exogenous increase in BMI causes 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 index 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 capital from their subjective expected returns. To do this we obtain 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

$$\mathbb{E}_t^\star\left[R_{i,t+1}\right] = \frac{\mathbb{E}_t^\star\left[p_{i,t+1}\right] - \mathbb{E}_t^\star\left[d_{i,t+1}\right]}{p_{i,t}} - 1 \tag{27}$$

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. (27) are based on analysts' forecasts of future stock prices and thus incorporate both perceived discount rates and perceived

Figure C14: 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 $\widehat{\beta}$. The conditional means of each bin are identified 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 $\widehat{\beta}$ from Welch (2022b). $N =$ 261,795 observations.

mispricing, that is, whether analysts think the stock is over- or undervalued (see Jensen, 2024).

Figure C14 plots the CAPM security market line using stock analysts' subjective expected returns using the CAPM $\widehat{\beta}$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 documented by Brav and Lehavy (2003).

C.2 Cost of Equity Capital of 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 capital from Regulatory Research Associates.

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 federal government (FERC Opinion No. 569, 2019) and most state public utility commissions—including those in

Table C11: Effect of Benchmarking on Utilities Requested 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, *** p<0.001.

California, Texas, Florida, New York, and Pennsylvania—endorse the CAPM for this purpose.

The utility's capital stock, or rate base, consists of the assets on which rates are calculated. Its opportunity cost is the return it could earn in competitive markets. Utilities typically finance operations with roughly equal parts debt and equity, and regulators use the weighted average cost of capital (WACC) to set the allowed return. The authorized return is almost always set as a percentage of the rate base. For example, with a $10 billion rate base and an 10% allowed return, the utility may recover $1 billion annually to cover debt costs and provide a return to shareholders.

D Additional Tests and Instrument Validity

D.1 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, Kogan, and Zhang, 2003) determine firm-level exposure to aggregate risk. We test whether the aggregate risk exposure of treated firms changes by estimating whether the CAPM $\widehat{\beta}$ 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.

Table D12: Placebo test using the CAPM $\widehat{\beta}$ 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's Δ CAPM β^E	(5) Peer n=2 Δ CAPM β^E	(6) Peer n=3's 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 $\widehat{\beta}$ 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 are 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.

Changes in CAPM $\widehat{\beta}$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 $\widehat{\beta}$ of peers. To avoid confounding our estimates, we exclude peers that also experience a change in BMI. Appendix Table D12 shows the results of this test using a firm's peers. The regression of changes in a firm's CAPM $\widehat{\beta}$ on changes in its peers' CAPM $\widehat{\beta}$ shows a significant positive coefficient, indicating common exposure to aggregate risk.[42] However, changes in a firm's BMI do not correlate with changes in peers' CAPM $\widehat{\beta}$s, with

[42] Levi and Welch (2017) similarly show that the CAPM $\widehat{\beta}$s of peer firms predict own firms' $\widehat{\beta}$ well.

insignificant coefficients close to zero. This suggests that benchmarking distortions cause the significant changes in a firm's CAPM $\widehat{\beta}$ rather than changes in aggregate risk exposure.

Table D13: Changes in CAPM $\widehat{\beta}$ and firm-level risk measures of Hassan et al. (2019)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
(in σ units)	Δ Risk		Δ Pol. Risk		Δ Pol. Risk - Econ.		Δ Pol. Risk - Secu.		Δ Pol. Risk - Tech.		Δ Pol. Risk - Trade	
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: ΔFirm-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 $\widehat{\beta}$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 D13 reports estimates of OLS regressions of changes in firm-level risk measures on changes in CAPM $\widehat{\beta}$ and changes in BMI. Two things are worth noting. First, changes in the CAPM $\widehat{\beta}$ 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 $\widehat{\beta}$ 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.

D.2 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 $\widehat{\beta}$, the exclusion restriction would be violated. However, we find no evidence of such correlations.

Text-based measures of financial constraints We collect text-based measures of financial constraints from Hoberg and Maksimovic (2015) and Linn and Weagley (2021). These measures

Table D14: Changes in measures of text-based financial frictions (Hoberg and 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, '23)	(6) Δ Inv. Delay & Debt (LW, '23)
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: ΔMeasure 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 and Maksimovic (2015) and Linn and Weagley (2021). Coefficients are standardized to unit variances. Changes in financial constraints measures, CAPM $\widehat{\beta}$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.

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 D14 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 D14 shows that changes in BMI do not correlate with firm statements about plans to delay investments.

Table D15: Changes in CDS Spreads and CAPM $\widehat{\beta}$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 $\widehat{\beta}$s are calculated on daily data from 2010 to 2019 using the weighted least squares estimator of Welch (2022b) with exponentially decay of 3 months half life. Changes in CDS spreads and CDS CAPM $\widehat{\beta}$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 $\widehat{\beta}$ We collect CDS spreads for senior unsecured debt with tenor of 5 year from 2010[43] to 2019. We calculate CDS CAPM $\widehat{\beta}$s on daily data using the estimator of Welch (2022b). We calculate changes in a firm's CDS spreads and firm's CAPM $\widehat{\beta}$ of CDS spreads as the difference between the average of daily observations in the first and last quarter of a year. Appendix Table D15 reports estimates of OLS regressions of changes in CDS spreads and changes in the CDS CAPM $\widehat{\beta}$ 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 $\widehat{\beta}$s. The estimated coefficients on BMI are insignificant and close to zero.

Table D16: 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.

D.3 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, Van Reenen, and Zingales, 2013). However, increased passive ownership may also decrease monitoring incentives, as in the model of Bebchuk and Hirst (2019). We test whether measures of governance change with changes in BMI but find no evidence of such an effect.

We obtain governance and ESG scores from S&P, Sustainalytics, and Refinitiv and test whether changes in BMI correlate with changes in those scores. Appendix Table D16 reports estimates 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.

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

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