The Real Cost of Benchmarking*

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Abstract

This paper provides causal evidence that benchmarking-induced asset price distortions have real effects on corporate investment. We exploit exogenous variation in stocks' benchmarking intensity around Russell index reconstitutions to establish causality. We find that increased exposure to benchmark-linked capital flows causes stocks' CAPM β to rise. Firm managers perceive this as an increase in their cost of capital and reduce investment. Treated firms have 7.1% less physical and 8.4% less intangible capital after six years. At the aggregate level, the asset price distortions caused by benchmarking can explain 10.7% lower capital accumulation from 2000 to 2016. Our findings highlight how benchmark-linked investing affects capital allocation in the real economy.

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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 capital. The growth of passive index funds and the evaluation of active funds against benchmarks means that a large share of capital 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, Boyer, 2011) 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' exposure to benchmark-linked capital flows to show that increased benchmarking raises stocks' CAPM βs. Firm managers interpret this CAPM β increase as a higher cost of capital and consequently reduce investment. Importantly, we show that these results are not driven by changes in firm fundamentals. Instead, we argue that firm managers rely on textbook guidance to set discount rates using their stock's CAPM β without accounting for distortions created by benchmarking. These distortions have a substantial impact on investment decisions at both the firm and aggregate level through their effect on the perceived cost of capital. Our study 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 increase in stock price lowers discount rates 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 invest in projects with positive net present value and use the weighted average cost of capital implied by

[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 firm's CAPM β to discount future cash flows.[2]

While the assumption that firm managers practice what textbooks teach may seem innocuous, it is key to our mechanism. Firm managers who set discount rates using their stocks' CAPM β will observe an increase in co-movement 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. As a consequence, benchmarking has an unambiguously negative impact on corporate investment.

We test the model's predictions using the benchmarking-intensity measure (BMI) developed by Pavlova and Sikorskaya (2023), which 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 β estimates from Welch (2022b), accounting data from Compustat, data on managers' perceived cost of capital from Gormsen and Huber (2024) and stock market data from CRSP from 1998 to 2018.

We begin by establishing the causal effect of changes in a stock's BMI on its CAPM β. We use a difference-in-differences design that compares the evolution of CAPM β between firms experiencing BMI changes around the Russell index reconstitution dates and those that do not. This approach does not require that index inclusion is random or common support in covariate levels across firms. It only requires that treated and control firms would have evolved similarly absent BMI changes. To ensure that our estimates are well-identified we include high-dimensional fixed effects that remove as much time-varying unobserved heterogeneity as possible.

The difference-in-differences results show that an increase in the BMI of a stock by at least 5 percentage points (p.p.) increases its CAPM β by 0.16. The treatment effects of index inclusion on CAPM β are increasing in BMI. Stocks with a BMI increase of at least 10 p.p. (20 p.p.) subsequently have 0.23 (0.35) higher CAPM βs. These effects are not driven by micro-cap stocks and are also present for stocks with market capitalizations above the 20th percentile of the New York Stock Exchange (NYSE). We confirm that changes in CAPM βs are not due to changes in fundamentals or increased risk exposure. Instead, our results indicate that increased co-movement with the market is explained by institutional ownership, similar to the findings of Antón and Polk (2014).

The increase in treated firms' cost of equity is substantial and persistent. Assuming an annual equity risk premium (ERP) of 6%, our baseline results imply an increase by 96 basis points (bps), with firms experiencing BMI increases of more than 10 p.p. seeing a 144 bps rise. These effects

[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.

persist over time: a 10 p.p. shock to BMI raises the cost of equity by 150 bps after one year, 110 bps after four years, and 61 bps after seven years. Compared to other discount rate shocks these effects are fast, large and persistent. For example, Bauer and Rudebusch (2020) estimate that the natural real rate of interest declined by 100 bps between 2002 and 2020. In contrast, effects on stock prices and the implied cost of capital (ICC) are short-lived, with a 41 bps decrease at index inclusion[3] fading to 11 bps after one year and becoming insignificant thereafter. Our findings suggest that benchmarking primarily affects the cost of capital through persistent changes in CAPM βs, rather than short-term fluctuations in the stock price. If managers rely on the CAPM for capital allocation decisions, these persistent changes in βs can have long-lasting effects on investment behavior.

We estimate the influence of benchmarking-induced distortions on corporate investment using changes in BMI as an instrumental variable (IV). We use Jordà's (2005) local projections (LP) to estimate the effects of an increase in CAPM β on capital allocation over horizons of up to 6 years. 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 use two methods to ensure that our estimates are well-identified. 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).

We conduct several tests to validate the IV exclusion restriction. We find no evidence that changes in BMI correlate with changes in risk exposure, debt market access, or corporate governance. The CAPM β of peer firms remains stable when a treated firm's BMI changes, and firm-level risk measures show no correlation with changes in BMI. Measures of financial frictions and cost of debt, including CDS spreads and their CAPM β, are unaffected by BMI changes. Corporate governance scores also do not change when BMI changes. These findings suggest that BMI changes are orthogonal to other factors that influence investment. This supports the use of BMI changes as valid instrument and allows for a causal interpretation of our results.

A benchmarking-induced increase in a firm's CAPM β leads to a substantial and persistent reduction in investment. Specifically, a 15% rise in CAPM β results in a cumulative decrease of 10.0% in capital expenditure over a six-year period. Instead of investing, treated firms first accumulate cash and subsequently increase payouts to shareholders. The treatment effects are consistent with firms using rolling window estimators that gradually update their CAPM β esti-

[3]The 41 bps decrease in ICC we observe at index inclusion implies a 4.85% stock price increase, close to the 5% documented by Chang, Hong, and Liskovich (2015).

mates: they are near zero for short horizons, grow over time, and become statistically significant after three years. Over six years the average treated firm's physical capital stock declines by 7.1%; its' intangible capital stock declines by 8.4%. The estimated response of the physical capital stock implies a user cost of capital elasticity of -1.09, close to the theoretical value of unity implied by Cobb-Douglas production technology.

Consistent with our mechanism and the observed change in corporate investment, we find that increases in benchmarking predict increases in the perceived cost of capital of firm managers reported by Gormsen and Huber (2023, 2024). As before, we use changes in BMI as IV to identify the causal effect of changes in CAPM β on a firm's perceived cost of capital. The estimates show that managers' perceived cost of capital is responsive to benchmarking-induced increases in CAPM β: a two standard deviation increase in a firm's CAPM β raises managers' perceived cost of capital by 80 bps.

An influential body of literature finds that U.S. investment has been low in recent decades relative to profitability and valuations (Gutiérrez and Philippon, 2017).[4] According to standard Q-theory, investment should have increased with an increase in Tobin's Q. However, investment has been low by historical standards. This has led researchers to argue that there is "missing investment", exceeding over 20% of the aggregate capital stock (Gormsen and Huber, 2023).

We argue that benchmarking has contributed to the missing investment puzzle. The difference-in-differences results show that BMI increases cause CAPM βs to rise. Extending this to the cross-section of stocks, we estimate that the average CAPM β increased by 0.46 over the past 25 years after being stable from 1975 to 2000. We attribute 80% of this increase to the more than 10 p.p. increase in average BMI since 1998. Counterfactuals show that the increase in CAPM βs caused by benchmarking raised the average firm's WACC by 162 to 199 bps from 1998 to 2018, which largely offset the decline in risk-free rates.

We support this argument with industry-level evidence from the NBER-CES manufacturing database. We measure the effects of CAPM β increases on capital accumulation using IV regressions in long-differences from 2000 to 2016. The estimates show that higher CAPM βs led to 10.7% lower capital accumulation at the aggregate-level during this period. Gormsen and Huber (2023) calculate that the cumulative investment shortfall in the U.S. from 2002 to 2016 was approximately 17.5%. Our results suggest that the increase in CAPM βs due to benchmarking can explain up to 57% of this investment shortfall.

Our study shines a new light on the importance of benchmarking for asset pricing and cor-

[4]Consistent with our results, Gutiérrez and Philippon (2017) find that "within industry-year, the investment gap is driven by firms owned by quasi-indexers". Our findings provide an explanation for why firms owned by quasi-indexers reduce investment: CAPM β increases with ownership by institutions that are benchmarked to an index.

porate 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.

The remainder of this paper is organized as follows. The remainder of this section discusses related literature. Section 2 illustrates our proposed mechanism in a stylized model. Section 3 describes the data. Section 4 establishes a causal link between BMI and CAPM β. Section 5 tests whether changes in BMI correlate with changes in firm fundamentals. Section 6 shows that BMI-induced changes in CAPM β affect real outcomes at the firm-level. Section 7 shows that the aggregate increase in BMI can partly explain the aggregate investment shortfall since the early 2000s. 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 (Vijh, 1994, Barberis et al., 2005, Boyer, 2011) increase after index inclusion (see Wurgler, 2010, for a survey). We add to this literature by providing causal evidence that the level of a stock's co-movement is determined by its BMI. We further document that the average co-movement of stocks increased in lockstep with the average BMI over the past 25 years.

Basak and Pavlova (2013) provide a theoretical framework showing that benchmarking of funds leads to asset class effects consistent with the observed index inclusion effects.[5] Building on this, Kashyap et al. (2021) derive optimal corporate investment policies in the presence of benchmarked funds, arguing that managers should internalize the inelastic demand for index stocks and over-invest 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 lower investment and a higher perceived cost of capital. Conceptually, we introduce a behavioral argument that reconciles our findings with Kashyap et al. (2021). We argue that managers, who rely on textbook guidance to estimate the cost of capital 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.

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

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

French, 2004),[6] it reigns supreme in practice. Welch (2008) reports that about 75% of finance professors recommend using the CAPM. 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), and mutual funds (Berk and Van Binsbergen, 2016) confirms that practitioners rely on the CAPM. We add by documenting that benchmarking induced CAPM distortions have first-order effects on the discount rates that managers use to make capital budgeting decisions. We argue that these distortions are large enough to affect the economy as a whole.

Despite the widespread use of the CAPM in practice, the effects of variation in CAPM βs on investment are not widely studied. The literature primarily focuses on how the cost of debt (Gilchrist and Zakrajšek, 2007, Philippon, 2009)[7] 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 βs 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 increases in CAPM β lead to lower investment.

Our findings also link to a literature on the corporate governance implications of passive investing. Appel, Gormley, and Keim (2016), Edmans and Holderness (2017), Bebchuk, Cohen, and Hirst (2017), Heath, Macciocchi, Michaely, and Ringgenberg (2021), and Lewellen and Lewellen (2022) examine the effects of the rise in passive investing on corporate governance, while Azar, Schmalz, and Tecu (2018) study the implications of common ownership for competition. Our results show that passive investing can affect corporate investment without an explicit corporate governance channel through its impact on the perceived cost of equity capital.

[6] Berk, Green, and Naik (1999) show that stock returns need not satisfy the CAPM even when the expected returns on all individual projects do, since a firm's stock has real options to abandon established projects and undertake new projects embedded. Da, Guo, and Jagannathan (2012) show that an option-adjusted CAPM does well empirically.

[7] De Fraisse (2024) finds that a higher supply of long-term government bonds increases firms' discount rates over long horizons, leading to crowding-out of long-duration investment.

2 A stylized model that highlights the mechanism

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).[8] 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. While most textbooks provide little guidance on estimating the former, they typically recommend using the weighted average cost of capital (WACC) as discount rate and to estimate the CAPM β to determine the cost of equity capital. The following stylized model highlights how the presence of benchmarked funds distorts the discount rate and thus affects capital allocation decisions.

Textbook investment policy The value of a firm $V_{i,t}$ 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 $\{R_{i,t\to t+h}\}_{h=1}^{\infty}$:

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

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 $\{R_{t+h}^f\}_{h=1}^{\infty}$.

$$R_{i,t\to t+h} = \prod_{j=1}^{h} \left(R_{t+j}^f + \beta_i^A ERP_{t+j} \right) \tag{2}$$

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):

$$\beta_i^A = \frac{\beta_i^E}{1 + (1-\tau)\frac{D_i}{E_i}} \tag{3}$$

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

[8] See Ben-David and Chinco (2023) for a model in which managers maximize earnings-per-share instead.

should invest in the project if it increases firm value, that is if

$$\mathbb{E}_t\left[\sum_{h=1}^{\infty}\frac{y_{i,t+h}}{\widehat{R}_{i,t+h}}\right]=\mathbb{E}_t\left[\sum_{h=1}^{\infty}\frac{y_{it+h}}{\prod_{j=1}^{h}\left(R^f_{t+j}+\frac{\widehat{\beta}^E_i}{1+(1-\tau)\frac{D_i}{E_i}}ERP_{t+j}\right)}\right]>C_{i,t}, \tag{4}$$

where $\widehat{R}_{i,t}$ results from substituting the empirical counterpart of (3) into (2).

Benchmarking distortions The presence of benchmarked funds distorts asset prices. Kashyap et al. (2021) show that benchmarked funds' inelastic demand for index constituents increases their price and thereby lowers the discount rate for index constituents. However, index membership also induces excess co-movement between index constituent stocks that is unrelated to the aggregate risk exposure of the firm's cash flows (Vijh, 1994, Barberis et al., 2005, Boyer, 2011).[9] The excess co-movement of index stocks increases β^E_i and thus the discount rate proportional to the equity risk premium.

We illustrate 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 index inclusion reduces the effective discount rate by $\Delta_I(BMI_{i,t})$. At the same time, β^E increases to $\widetilde{\beta}^E_{i,t}=\beta^E_i+\Delta_\beta(BMI_{i,t})$. 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

$$\widetilde{R}_{i,t\to t+h}=\prod_{j=1}^{h}\left(R^f_{t+j}+\frac{\beta^E_i+\Delta_\beta(BMI_{i,t})}{1+(1-\tau)\frac{D_i}{E_i}}ERP_{t+j}-\Delta_I(BMI_{i,t})\right). \tag{5}$$

The total effect of both discount rate wedges is ambiguous and depends on the functional forms of $\Delta_I(BMI_{i,t})$ and $\Delta_\beta(BMI_{i,t})$. Empirically, positive price effects at index inclusion (Chang et al., 2015) suggest that $\Delta_I(BMI_{i,t})$ dominates in the short-run.

CAPM investment policy with benchmarking distortions Whether the benchmarking distortions to the discount rate in Eq. (5) cause firm managers to invest more or less is ambiguous. The level-shift in discount rates by $\Delta_I(BMI_{i,t})$ (in blue) incentivizes investment, whereas the increase in CAPM β, Δ_β (in red), discourages investment.

What if firm managers do not internalize the inelastic demand of benchmarked funds for index constituent stocks but use the cost of capital implied by the CAPM to evaluate investment

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

opportunities as in Eq. (4)? In this case, the presence of benchmarked funds has an unambiguously negative effect on investment for index constituents. Firm managers, with expectations $\mathbb{E}_t^\star[\cdot]$, observe an increase in their stock's CAPM β from $\widehat{\beta}_i^E$ to $\widetilde{\beta}_i^E = \widehat{\beta}_i^E + \Delta_\beta(BMI_{i,t})$ and infer an increase in the firm's cost of capital. Firm managers now invest only in projects that satisfy

$$\mathbb{E}_t^\star\left[\sum_{h=1}^{\infty}\frac{y_{i,t+h}}{\widetilde{\widehat{R}}_{i,t+h}}\right] = \mathbb{E}_t^\star\left[\sum_{h=1}^{\infty}\frac{y_{i,t+h}}{\prod_{j=1}^{h}\left(R_{t+j}^f + \frac{\widehat{\beta}_i^E + \Delta_\beta(BMI_{i,t})}{1+(1-\tau)\frac{D_i}{E_i}}ERP_{t+j}\right)}\right] > C_{i,t}. \quad (6)$$

All else equal, a firm inside the 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 βs. Empirical CAPM βs, however, are distorted by benchmarking-induced co-movement and will thus lead index 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 β^E,
(ii) an increase in firm BMI increases the firm's perceived cost of capital,
(iii) and leads to a decline in investment.

3 Data and sample

We use four main sources in our empirical analysis: (1) the measure of benchmarking intensity developed by Pavlova and Sikorskaya (2023), (2) estimates of firm CAPM βs from Welch (2022b), (3) firm-level data from S&P's Compustat North America Fundamentals, and (4) additional firm-level variables from various sources.

Benchmarking Intensity We use the benchmarking intensity measure developed by Pavlova and Sikorskaya (2023) from 1998 to 2018. Benchmarking intensity (BMI) for stock i in month t is defined as

$$\text{BMI}_{i,t} = \sum_{j=1}^{J}\frac{\lambda_{j,t}\omega_{i,j,t}}{\text{Market Value}_{i,t}} = \sum_{j=1}^{J}\frac{\lambda_{j,t}\mathbb{1}\{\text{Stock is in Index}\}_{i,t}}{\text{Market Value of all Stocks in Index}_{j,t}} \quad (7)$$

Table 1: 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 β is the difference between the average CAPM β in the first and last quarter of a year. Variables are winsorized at the 0.5% and 99.5% level.

where $\lambda_{j,t}$ is the assets under management (AUM) of mutual funds and ETFs benchmarked to index j and $\omega_{i,j,t} = \frac{\text{Market Value}_{i,t}\mathbb{1}\{\text{Stock is in Index}\}_{i,t}}{\text{Market Value of all Stocks in Index}_{j,t}}$ is the stock's weight in value-weighted index j.

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. 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 index inclusion effects argues that after controlling for factors that determine index inclusion, most importantly the ranking variable (market value) that Russell uses for index assignment at the end of May, the index membership dummy is exogenous.

CAPM βs We use end-of-month estimates of the winsorized and exponentially weighted CAPM βs from Welch (2022b), calculated using daily data.[10] 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 days. Welch (2022b) shows that this estimator outperforms other well known β estimators like Bloomberg β or the Vasicek (1973) β in predicting future market βs. We focus on common equities that are traded on either the NYSE, AMEX, or NASDAQ, and exclude ADRs, REITs, and ETFs. Table 1 reports descriptive statistics for the matched BMI-CAPM dataset covering 1998 to 2019.

Firm-level data We use annual data for publicly listed companies incorporated and located in the U.S. from Compustat for the sample period from 1998 to 2018. We exclude financial firms (SIC codes 6000-6999) and firms in regulated industries (4900-4999), as well as firms with less

[10] Levi and Welch (2017) caution against using monthly data, showing that monthly CAPM βs have half the explanatory power of daily βs in forecasting future βs.

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.

Additional firm data We obtain stock returns and market data from the Center for Research in Security Prices (CRSP). Data on firm managers' perceived cost of capital is sourced from Gormsen and Huber (2024), who hand-collect these from earnings calls. Measures of firm-level intangible capital are from Peters and Taylor (2017). Executive compensation peer group information is collected 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). Governance scores are obtained from Sustainalytics, Refinitiv, and S&P. Estimates of stocks' implied cost of capital (ICC) are from Eskildsen, Ibert, Jensen, and Pedersen (2024).

4 Changes in a firm's CAPM β due to benchmarking

We estimate the causal effect of changes in a firm's BMI on its CAPM β using a difference-in-differences design. We compare the evolution of CAPM βs of (treated) stocks that experience BMI changes around Russell index reconstitution dates to (control) stocks that do not. Our treatment group consists of stocks that experience changes in BMI greater than ± 5 p.p.. The control group consists of stocks that experience changes in BMI smaller than ± 1.5 p.p..

The difference-in-differences results show that changes in a stock's BMI causally affect its CAPM β. 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 β by 0.16 (-0.14) relative to the control group. A stock whose BMI increases by 10 p.p. to 20 p.p. (more than 20 p.p.) experiences a 0.24 (0.35) increase in CAPM β. These effects are large and economically meaningful. The baseline treatment effect of an increase in BMI greater than 5 p.p. translates into a 96 bps increase in the cost of equity capital (assuming a 6% ERP). An increase in BMI by 10 p.p. to 20 p.p. (greater than 20 p.p.) translates into increase of 132 bps (210 bps).

In Appendix A.3 and A.4 we find qualitatively and quantitatively similar results using regression discontinuity designs that exploit discontinuities in BMI at Russell index cutoffs.

4.1 Difference-in-differences strategy

We analyze the effect of an increase in BMI on a firm's CAPM β by estimating a series of difference-in-differences specifications of the form:

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

where 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 β.

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 β. To ensure our results are not driven by micro-cap stocks, we exclude stocks with market values below the fifth percentile of those traded on the NYSE.[11]

The Russell indices reconstitute each year, and identification in (8) thus exhibits staggered treatment timing with potentially misleading estimates when 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.[12]

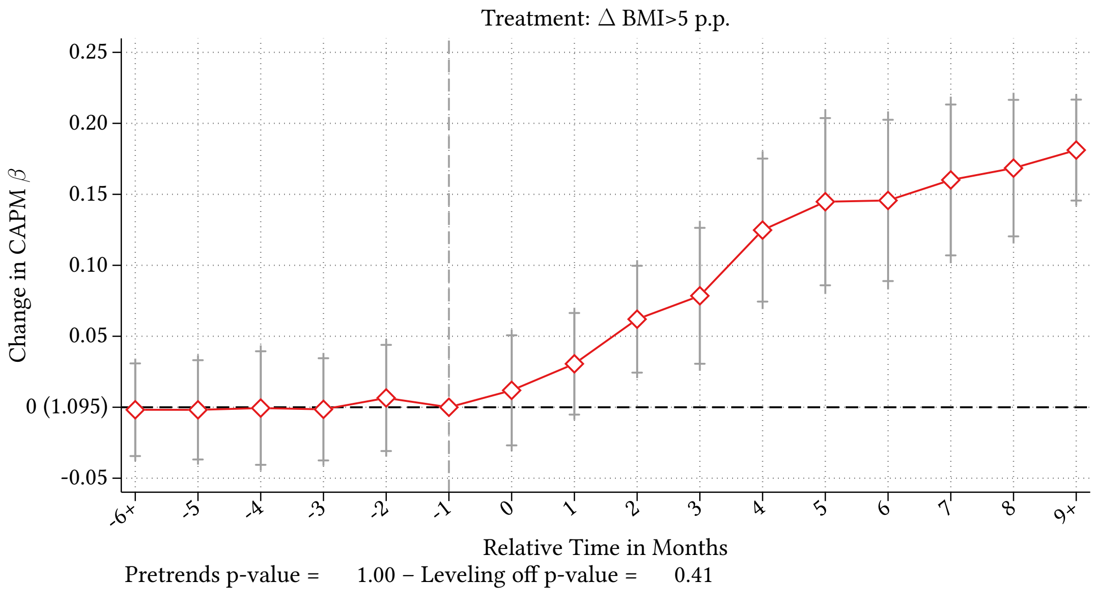
Identifying assumptions and threats to identification. Our identification strategy relies on the following assumption: conditional on the set of fixed effects, firms that experience changes in BMI are not differentially exposed to unobservable shocks that are correlated with BMI. The identification assumption does not require random assignment of index inclusion, nor does it require that firms have similar characteristics in levels. Rather, we rely on the parallel trends assumption that outcomes 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 1a and 1b and additionally perform a placebo test that compares firms with BMI increases between 0 p.p. and 1 p.p. to firms with BMI decreases between 0 p.p. and -1 p.p. in Figure A2. As expected, this placebo test finds no effects.

Results Figures 1a and 1b 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

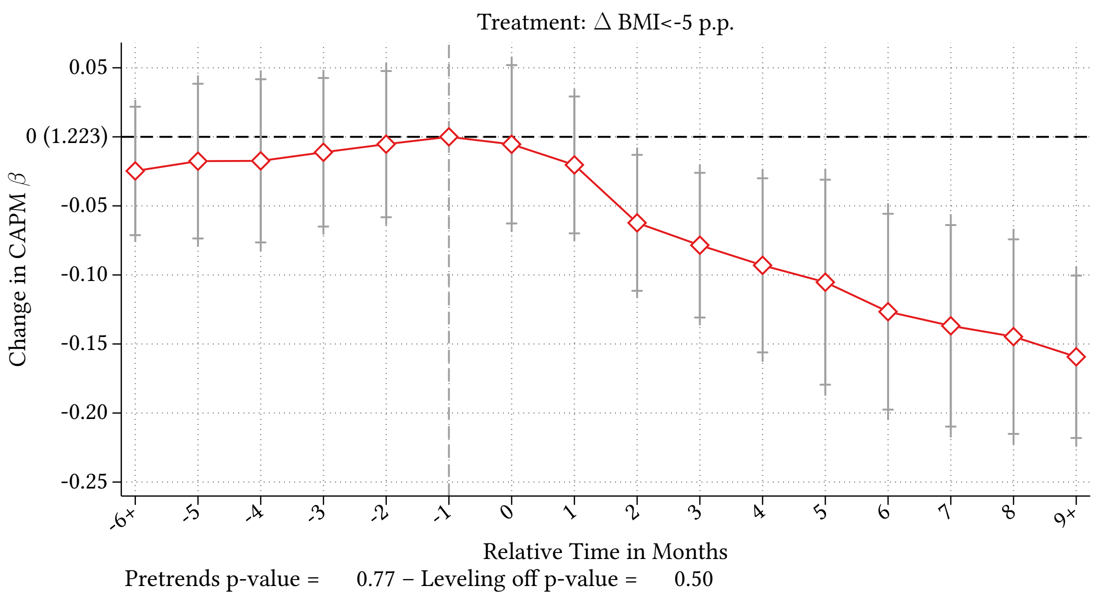
[11] We obtain similar results when using the 10th or 20th percentile of the NYSE as a cutoff (see Appendix Table A1).

[12] 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 1: Difference-in-differences Event Study



(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 β of treated stocks with an increase or decrease in BMI of at least 5 p.p. relative to a control group, where $|\Delta \text{ BMI}| < 1.5$ 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 β before treatment.

Table 2: Causal Effects of Changes in Benchmarking Intensity on CAPM βs

Treatment Group:	Δ BMI>5p.p.				Δ BMI<-5 p.p.			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treated $\times$ Post	0.158***	0.164***	0.161***	0.160***	-0.143***	-0.133***	-0.135***	-0.136***
	(0.014)	(0.014)	(0.014)	(0.014)	(0.021)	(0.021)	(0.020)	(0.020)
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	316,883	316,848	316,762	316,695	308,973	308,927	308,855	308,782

Notes: This table reports $\hat{\delta}$ for specifications of the form: CAPM $\beta_{i,t} = \delta$ Treated$_i$ $\times$ Post$_{t>\text{May}} + \theta_i + \theta_{t,s} + \varepsilon_{i,t}$. Treated×Post is average of post-treatment coefficients after 4 months (to account for the expanding-window estimation of CAPM β). Control group are firms with $|\Delta\text{BMI}| < 1.5$ p.p.. 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.

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 index inclusion.

Several facts are worth noting. First, the CAPM βs 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 0.77, respectively. Second, after index reconstitution, CAPM βs begin to diverge for both increases and decreases in BMI. The smooth event-time trend in Figure 1 is largely mechanical, as older information receives exponentially smaller weights.[13] Therefore, the treatment effect of a BMI increase on a firm's CAPM β is likely immediate, but our measurement captures it only when 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 2 reports the average estimated post-shock coefficient.[14] The coefficient estimate for the interaction Treated$i \times$ Post$t >$ 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, size, 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 β by 0.16, while Column (6) shows that a decrease in BMI by at least 5 p.p. lowers a firm's CAPM β by -0.14. These effects are large and economically meaningful. An increase of 0.16 in CAPM β implies a 96 bps increase in the cost of equity capital.

[13]The β estimator uses an expanding-window with exponential weights of 90 trading days half-life.

[14]We exclude the coefficients for $0 \leq t \leq 4$ since the CAPM βs by construction have a dynamic component.

The estimates of the average treatment effect in Table 2 mask substantial heterogeneity. Appendix Figure A1 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, which is equivalent to a 210 bps increase in the cost of equity capital.

Alternative CAPM β estimators To verify that our results are not driven by the choice of β estimator, we estimate the following reduced form specification for a set of alternative estimators:

$$\Delta\beta_{i,t}^{ALT} = \alpha_i + \alpha_t + \gamma \Delta \text{BMI}_{i,t} + \varepsilon_{i,t}$$

Appendix Table A2 shows reduced form regression results using different estimators for the unknown CAPM β. We compare the usual OLS estimator with alternative estimators proposed by Blume (1975) (the "Bloomberg β"), Dimson (1979), and Welch (2022b). We also report estimates of the β with the ten largest stocks by market capitalization, and correlation with the market and idiosyncratic volatility. For each estimator, we provide expanding-window (using exponentially decaying weights) estimates and 2-year rolling-window (using equal weights) estimates.

We find that *all* CAPM β estimators show a statistically significant (p<0.001) association with changes in BMI.[15] Estimates using rolling-windows with equal weighting are smaller in magnitude but highly statistically significant. Changes in CAPM β 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.

4.2 Persistence of effects and changes in stock's implied cost of capital

In our model 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 from 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.

[15] Online Appendix Table B1 shows that industry CAPM βs estimates react similar.

We further test whether the benchmarking distortions persist over long horizons. Our difference-in-differences results show that the distortionary effects of BMI increases on CAPM βs persist for at least 12 months. However, CAPM βs tend to revert to 1 in the long-run (Blume, 1975). If the distortionary effects of benchmarking on the cost of equity fade after a year, we would not expect any long-term impact on investment. We therefore test whether the effects on the ICC and on CAPM βs persist for horizons of up to 7 years.

Implied Cost of Capital Following Eskildsen et al. (2024),[16] we calculate the ICC by averaging four popular models from the accounting literature: 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). Note that the ICC only captures the implied cost of equity, we thus compare it to the cost of equity implied by the CAPM.

We test whether changes in BMI affect the ICC using the following specification:

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

for firm i in year t+h. Additionally, we estimate how long BMI induced CAPM β distortions persist using the following specification:

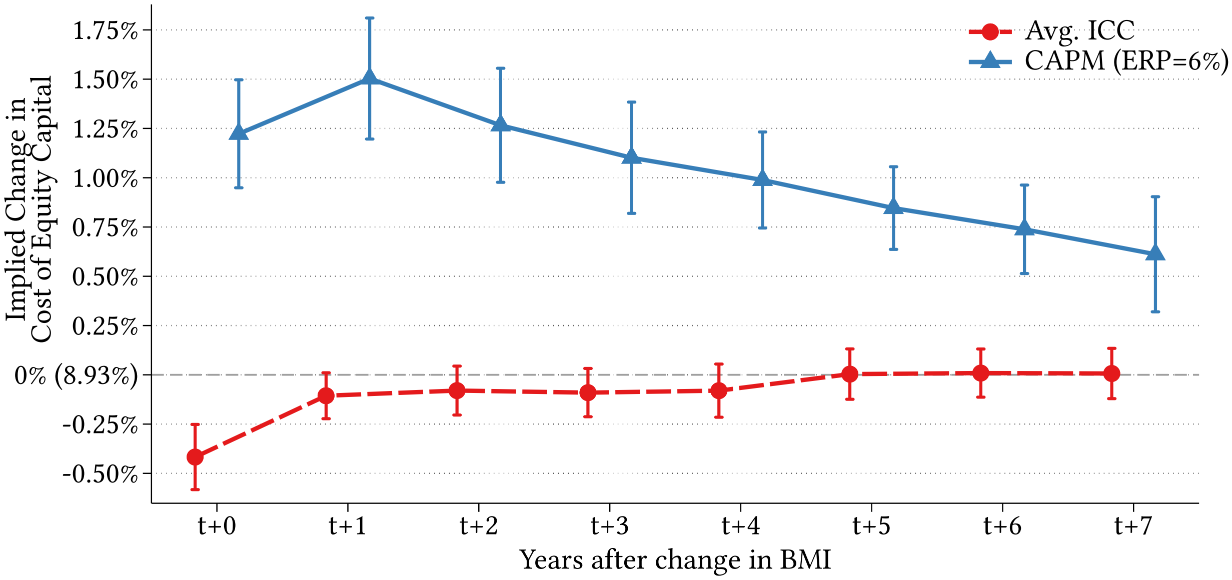
$$\text{CAPM } \beta_{i,t+h} = \gamma_0^h + \gamma_1^h \Delta\text{BMI}_{i,t} + \zeta^h X_{i,t} + \nu_{i,t+h}, \quad h = 0, \ldots, 7. \tag{10}$$

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 β or ICC after h years, respectively. The vector $X_{i,t}$ contains year 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. Standard errors are double-clustered at the year- and firm-level.

Results Figure 2 shows estimates for γ_1^h and θ_1^h of Eq. (10) and (10), respectively. The distortionary effects of BMI increases on CAPM βs persist for at least 7 years. At each forecast horizon, we find statistically significant ($p<0.001$) positive effects of BMI increases on CAPM βs. These effects gradually diminish over time but remain economically significant. One year after the initial BMI increase, the cost of equity capital is 150 bps higher. Four years later, it remains 110 bps higher, and even seven years later, it is still 61 bps higher. This prolonged impact suggests that benchmarking has a long-term effect on firms' perceived cost of capital, potentially leading to sustained changes in investment behavior.

[16] Using these measures, Eskildsen et al. (2024) estimate an annual green equity premium of -25 bps. Similarly, Kontz (2023) estimates a green convenience yield of 28 bps in auto asset-backed securities.

Figure 2: 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 a firm's cost of equity capital using the ICC and CAPM. Estimates are scaled to a 10 p.p. increase in BMI. Pointwise confidence intervals (95%) based on double-clustered standard errors. Value in parentheses on the Y-axis is the median ICC over the sample period.

The effects on the ICC are more short-lived. The estimate for the year of index inclusion shows that the implied cost of capital decreases by approximately 41 bps (p<0.001). The effect on the ICC fades to 11 bps (p<0.10) after one year and becomes statistically insignificant afterwards. The finding that the impact of BMI increases on the ICC is small and diminishes rapidly, implies that any effects on investment through this channel are unlikely.

Price Effects of Index Inclusion We perform a back-of-the-envelope calculation to estimate the implied stock return at index inclusion using Gordon's growth model, $P_0 = D_1/(r - g)$. 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:

$$4.85\% \approx \frac{P^{Post}}{P^{Pre}} - 1 = \frac{-\hat{\theta}_1^0 \times \Delta \text{ BMI}}{r + \hat{\theta}_1^0 \times \Delta \text{ BMI} - g} = \frac{0.41\%}{10.46\% - 0.41\% - 1.6\%},$$

where we set r to the long-run average of the ICC ($\approx 10.5\%$), g to the long-run average of real dividend growth ($\approx 1.6\%$), and ΔBMI to 10 p.p (as in Figure 2). The 41 bps decrease in the ICC at index inclusion implies a 4.85% increase in the stock price, close to the 5% documented by Chang et al. (2015). Our estimate is larger but not statistically different from the 2.8% increase in stock price for a 10 p.p. increase in BMI estimated by Pavlova and Sikorskaya (2023).[17]

5 Additional tests and instrument validity

Our first main result shows that increases in a stock's BMI cause its CAPM β to rise. We use changes in BMI between the Russell ranking day in May and the reconstitution day in June as an IV to exploit the effect of benchmarking on corporate investment. However, concerns may arise that other factors, such as risk exposure, access to debt markets, or governance, could change alongside CAPM βs when BMI changes, potentially violating the exclusion restriction. In this section, we test whether changes in BMI correlate with changes in risk, financial frictions, or governance, but find no evidence that they do.

5.1 Changes in BMI and measures of risk exposure

A potential concern with our IV identification strategy is that changes in BMI could correlate with changes in exposure to aggregate or idiosyncratic risk. Firm-level exposure to aggregate risk is influenced by an industry's aggregate risk (Karolyi, 1992) and by firm fundamentals (Gomes, Kogan, and Zhang, 2003). We test whether the aggregate risk exposure of treated firms changes by estimating whether the CAPM β 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.

Changes in CAPM βs 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 β of peers. To avoid confounding our estimates, we exclude peers that also experience a change in BMI. Appendix Table A3 shows the results of this test using a firm's peers. The regression of changes in a firm's CAPM β on changes in its peers' CAPM β shows a significant positive coefficient, indicating common exposure to aggregate risk.[18] However, changes in a firm's BMI do not correlate with changes in peers' CAPM βs, with insignificant coefficients close to zero. This suggests that the significant changes in a firm's CAPM β are driven by benchmarking distortions rather than by changes in aggregate risk exposure.

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

[17] Discrepancies between Pavlova and Sikorskaya (2023) and Chang et al. (2015) are primarily due to differing sample years and filters, see Pavlova and Sikorskaya (2023, Appendix A.15).

[18] Levi and Welch (2017) similarly show that the CAPM βs of peer firms are good predictors of own firms' β.

exposure to political risk stemming from economic policy, security policy, technological policy, and trade policy. Appendix Table A4 reports estimates of OLS regressions of changes in firm-level risk measures on changes in CAPM β and changes in BMI. Two things are worth noting. First, changes in the CAPM β 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 β 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 are not statistically significant.

5.2 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 β, 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 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 A6 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 A6 shows that changes in BMI do not correlate with firm statements about plans to delay investments.

Changes in CDS spreads and CDS CAPM β We collect CDS spreads for senior unsecured debt with tenor of 5 year from 2010[19] to 2019. CDS CAPM βs are calculated on daily data using the estimator of Welch (2022b). We calculate changes in a firm's CDS spreads and firm's CAPM β of CDS spreads as the difference between the average of daily observations in the first and last quarter of a year. Appendix Table A5 reports estimates of OLS regressions of changes in CDS spreads and changes in the CDS CAPM β 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 βs. The estimated coefficients on BMI are insignificant and close to zero.

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

5.3 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 A7 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, Sundaresan, and Wang (2021), who also find no evidence of changes in governance at index inclusion.

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 β raises the user cost of capital and should lead to a decline in investment. We therefore test whether changes in CAPM β affect firm outcomes like capital expenditure, physical and intangible capital stocks, cash holdings, and payouts.

The results show that firms react to BMI-induced changes in their CAPM β 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.

Consistent with this mechanism, managers' perceived cost of capital responds to benchmarking-induced increases in CAPM β. 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 βs on a firm's perceived cost of capital. The IV estimates imply that a two standard deviation change CAPM β increase managers' perceived cost of capital by 80 bps.

6.1 Empirical strategy

We use an instrumental variable (IV) local projections (LP) strategy to forecast the effects of a change in CAPM β on capital allocation over horizons of up to 6 years.[20] We instrument changes in CAPM β with changes in BMI, in an effort to identify causal effects. Pavlova and Sikorskaya (2023) argue that changes in BMI between the rank day of Russell indices in May and the reconstitution day in June serve as instruments for changes in institutional ownership. Our results in Section 4 show that changes in the level of institutional ownership cause changes in the firms' CAPM βs. Section 5 shows that these changes in CAPM β are orthogonal to aggregate risk exposure and fundamentals of the firm, thus acting as exogenous shock to the firm's cost of capital.

To analyze the effect of BMI-induced changes in a firm's CAPM β on real outcomes, we estimate a series of local projection instrumental variable regressions of the following form:

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

$$\log\left(Y_{i,t+h}\right) - \log\left(Y_{i,t-1}\right) = \alpha_i^h + \alpha_{j,t}^h + \gamma^h \Delta \widehat{\text{CAPM}}\,\beta_{i,t} + \xi^h X_{i,t} + \varepsilon_{i,t+h} \tag{12}$$

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 re-

[20] Similarly, LP-IVs are often used 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).

striction. 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 β. In Section 5 we find no evidence that changes in BMI correlate with changes in risk, financial constraints, or governance at the firm. Importantly, Column (1) of Appendix Table A6 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.[21] The literature on index inclusion effects generally finds positive but modest direct effects of index inclusion on real outcomes (e.g., Kacperczyk et al., 2021). Therefore, if anything, we 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.

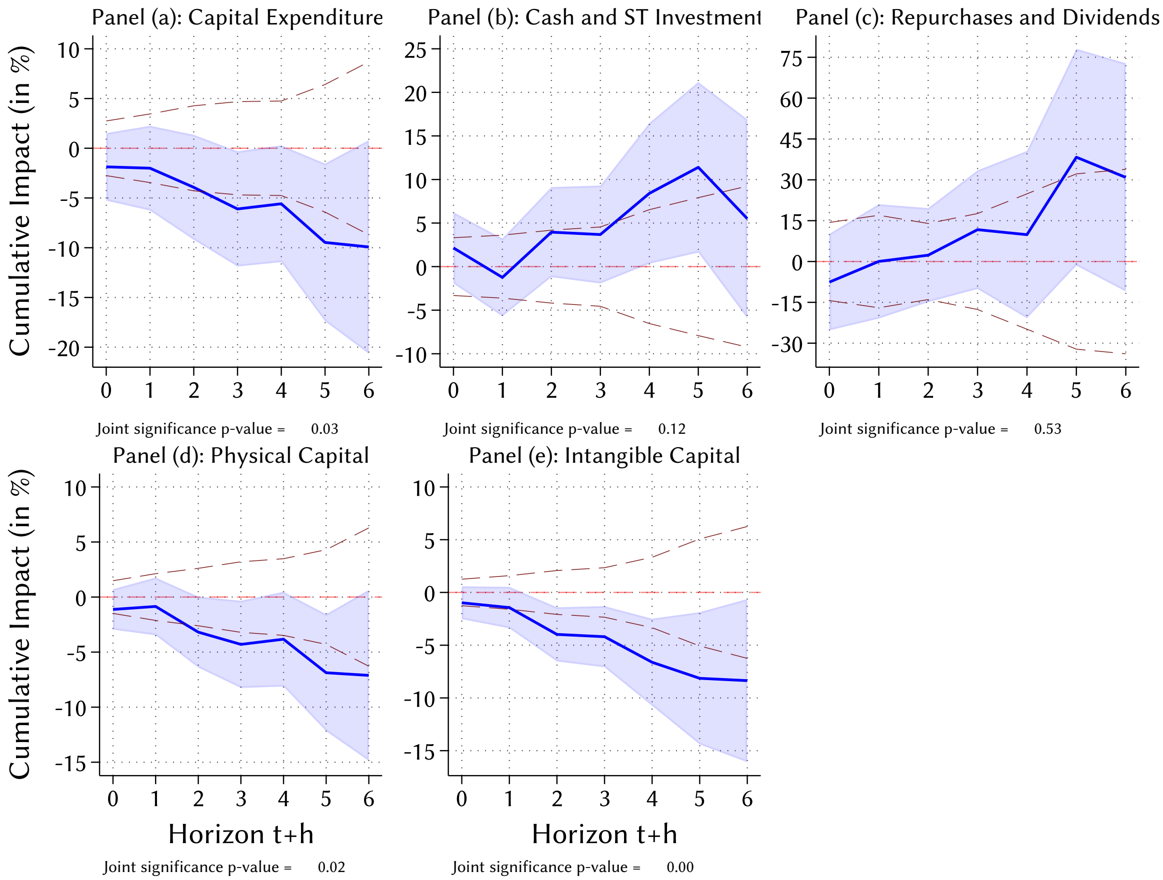
6.2 Results

Figure 3 shows estimates of the dynamic impulse response path of Eq. (12) to an increase in the CAPM β for capital expenditure, physical capital, intangible capital, and cash and short-term investments. The impulse is scaled to the average effect size for an increase of 5 p.p. in BMI in the Compustat sample (approximately a 15% increase in CAPM β^E). Note that the coefficients derived from local projection (LP) impulse responses are highly correlated. Similar to the case of regressions affected by near-collinearity, individual t-statistics may not appear significant, but a joint test for significance overwhelmingly rejects the null of zero treatment effect (see Jordà, 2023, for details). We therefore report F-statistics of joint-significant test and additionally display approximate 90% significance bands. The significance bands are calculated by inverting the F-statistic of the null that all impulse response coefficients are zero.

Several key results are evident in Figure 3. First, the impulse responses across all outcome variables have the expected signs: capital expenditure and physical and intangible capital stocks

[21]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 $y = \widehat{\Delta r}\beta + z\phi + \nu$ where $\mathbb{E}\left[\Delta r \nu\right] \neq 0$ but $\mathbb{E}\left[z\nu\right] \neq 0$. The exclusion restriction assumes that $\phi = 0$. If $\phi \neq 0$, we have $\hat{\beta}_{IV} \xrightarrow{p} \beta + \phi/b$. 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).

Figure 3: LP-IV: Impulse Response of Outcome Variables to CAPM β shock



Notes: This figure shows LP-IV coefficient estimates for $100\times$ cumulative log-changes of outcome variables. Intervention is a shock to CAPM β estimated with change in BMI as an instrumental variable. Dashed red lines represent 90% significance bands computed by inverting the F-statistic of joint significance around zero using Scheffé's method.

decrease in response to an equity cost shock, while cash and short-term investments increase. Firms also increase dividends and stock repurchases after several years. Second, firm responses to an increase in CAPM β are gradual and slow-moving, 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 βs. This gradual adjustment reflects how managers' estimated cost of capital incorporates older data points, even though the "true" CAPM β responds immediately. Third, the effects on capital expenditure and capital stocks are persistent and remain significant for at least six years after the shock.

Benchmarking-induced increases in CAPM βs lead to large and persistent declines in investment. We find that firms reduce their capital expenditure by approximately 10.0% over six years in response to a shock to their CAPM β of 15%. 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 around -1.09 and -1.28 for physical and intangible capital, respectively. These elasticities are larger but close to the theoretical elasticity of 1 implied by a Cobb-Douglas production function.

Appendix Table A8 reports the estimates of the LP-IV regressions of Eq. (12). We check whether the BMI instrument is weak with Kleibergen-Paap tests. We find that changes in BMI are strong instruments for changes in CAPM β with average first-stage F-statistics above 50. Finally, we test the null hypothesis that all ATE coefficients are jointly zero, reporting the p-value of the test in the row labeled H_0: ATE $= 0$. All average treatment effects are statistically significant at conventional levels, except for dividends and repurchases; reflecting the noise visible in Figure 3.

Robustness Checks We perform several robustness checks on the main results. First, we add firm-level controls, such as cash flow, Tobin's Q, and the debt-to-equity ratio, which are known predictors of investment, 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 A3 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 A4 shows the impact of a 15% increase in CAPM β on corporate investment rates. The investment rate[22] declines over time in response to the shock. Starting from a near-zero impact at $t+0$, gradually becoming more negative, reaching the lowest point after four to five years. The shock to the CAPM β leads to a significant (p<0.005) drop of -2.56 p.p. in investment rates after four years. In standard deviation units, corporate investments drops by 0.19 standard deviations. In terms of economic magnitudes this compares to Alfaro, Bloom, and Lin (2024) who find that uncertainty shocks lead to a 0.18 standard deviation drop in investment rates.

6.3 Changes in CAPM β and manager's perceived cost of capital

We document that changes in the CAPM β affect the perceived cost of capital of firm managers, using firm's self-reported data collected from earnings calls by Gormsen and Huber (2023, 2024).

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

We estimate the pass-through of changes in a firm's CAPM β on the perceived cost of capital using a series of instrumental variable (IV) regressions of the following form:

$$\Delta\text{CAPM } \beta_{i,t} = \delta_i + \delta_{j,t} + \theta\Delta\text{BMI}_{i,t} + \epsilon_{i,t} \tag{13}$$

$$\Delta\text{Perceived Cost of Capital}_{i,t} = \alpha_i + \alpha_{j,t} + \sum_{h=0}^{4} \gamma_h \Delta\widehat{\text{CAPM }}\beta_{i,t-h} + \varepsilon_{i,t} \tag{14}$$

where the coefficient of interest, $\sum_{h=0}^{4} \gamma_h$, provides a causal estimate of the pass-through of changes in a firm's CAPM β 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 characteristics 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 distributed lag model in Eq. (14) for both economic and econometric reasons. Managers typically estimate CAPM β using OLS regressions using two to five years windows, so changes in CAPM β are gradually incorporated into their 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. Additionally, the data supports a distributed lag model over a contemporaneous effect model, with Bayesian information criterion (BIC) values favoring fourth-order lags (Appendix Table A9).

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 β 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 Section 5, we find no evidence that BMI changes correlate with risk, financial constraints, or governance changes, supporting the validity of the exclusion restriction.

Table 3 reports coefficient estimates of Eq. (14) 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 ($p<0.001$). Columns (1) to (3) of Table 3 show that increases in BMI predict increases in managers' perceived

Table 3: Effect of ΔCAPM β on Managers' Perceived Cost of Capital (Gormsen and Huber, 2024)

	RF			OLS			IV		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Dependent variable: Δ Perceived Cost of Capital								
Δ BMI	1.643***	1.680***	1.667***						
	(0.375)	(0.373)	(0.402)						
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)
Firm	✓	✓	✓	✓	✓	✓	✓	✓	✓
Time	✓			✓			✓		
Size Quartile × Time		✓			✓			✓	
Industry × Time			✓			✓			✓
Observations	19,501	19,501	18,940	19,501	19,501	18,940	19,501	19,501	18,940

Notes: This table reports $\sum_{h=0}^{4} \hat{\gamma}_h$ for specifications of the form: ΔPerc. Cost of Capital$_{i,t} = \alpha_i + \alpha_{j,t} + \sum_{h=0}^{4} \gamma_h \Delta$CAPM $\beta_{i,t-h} + \varepsilon_{i,t}$ for reduced form, OLS, and IV regression where the instrument is ΔBMI for stock i in year t. IV estimated via LIML. Yearly sample from 2000 to 2018. Standard errors in parentheses are clustered at firm-level. + p<0.10, * p<0.05, ** p<0.01, *** p<0.001.

cost of capital. Comparing OLS to IV estimates shows that OLS estimates are downward-biased, likely due to classical measurement error. IV estimates using BMI changes as an instrument for CAPM β changes, are approximately three times larger than OLS estimates. Two mechanisms introduce measurement error. First, we do not observe how firms estimate their CAPM β when calculating their perceived cost of capital. We use the CAPM β estimates of Welch (2022b) due to their superior performance in predicting future CAPM βs out of sample. In practice, firms often simply estimate CAPM βs using equally-weighted observations on a rolling window of two to five years (Berk and DeMarzo, 2023). Second, any empirical measure of CAPM β is an *estimate* of the true CAPM β and thus subject to measurement error.

The IV estimates in column (8) imply that a two standard deviation change in a firm's CAPM β increases the manager's perceived cost of capital by 80 bps. The resulting increase in perceived cost of capital is substantial compared to typical financial price fluctuations. For example, Krishnamurthy and Vissing-Jorgensen (2011) find that the Fed's quantitative easing reduced corporate bond yields by up to 50 bps.

7 Aggregate Effects of increased benchmarking

A body of literature finds that U.S. investment has been low in recent decades relative to profitability and valuations. According to standard Q-theory, investment should have increased with the rise in Tobin's Q (Gutiérrez and Philippon, 2017). However, investment rates have been low by historical standards, leading researchers to argue that there is "missing investment", now exceeding 20% of the aggregate capital stock, even after accounting for intangibles and other measurement issues (Gormsen and Huber, 2023).

We argue that increased benchmarking has contributed to the missing investment puzzle. Our difference-in-differences results show that BMI increases due to index inclusion raise firms' CAPM βs. Extending this to the broader cross-section of firms, we estimate that the average CAPM β increased by 0.46 over the past 25 years after being stable for nearly 30 years. We attribute 80% of this increase to the 10.16 p.p. increase in average BMI since 1998. Counterfactuals show that the increase in benchmarking raised the average firm's WACC between 162 and 199 bps from 1998 to 2018, which largely offset the decline in risk-free rates.

We use the NBER-CES Manufacturing Industry Database to estimate the effect of increases in industries' average CAPM β on capital accumulation. Value-added weighted results indicate that higher CAPM βs led to 10.7% lower capital accumulation from 2000 to 2016 at the aggregate level. Thus, increases in CAPM βs can thus explain up to 57% of the missing investment.

7.1 Increase in average CAPM β over the past 25 years

Figure 4 shows the evolution of average CAPM β and average BMI from 1998 to 2018.[23] A casual inspection of the graphs suggests that both time-series are related. The average BMI increased from 8.16% in 1998 to 18.32% in 2018, while the average CAPM β increased from 0.63 to 1.09.

We estimate how an increase in the average cross-sectional BMI affects the average CAPM β using the following specification:

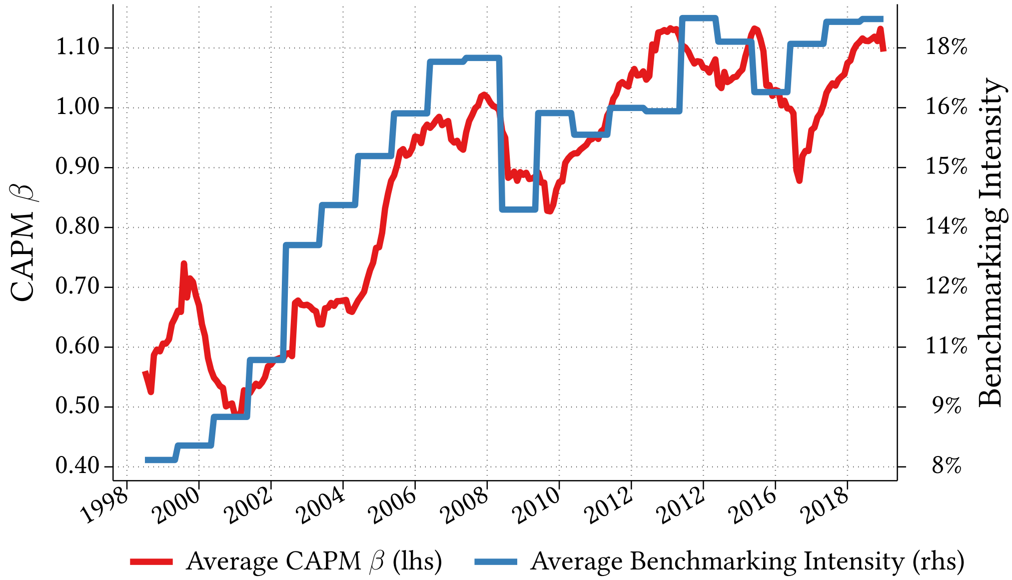
$$\overline{\text{CAPM }\beta}_{t+1} = \alpha + \gamma_1 \, \overline{\text{BMI}}_t + \gamma_2 \, \overline{\text{CAPM }\beta}_t + \varepsilon_t. \tag{15}$$

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.

Table 4a reports results of this time-series regressions in Columns (1) to (4). Column (1) shows that BMI is a statistically significant (p<0.01) predictor of CAPM β, even after considering the autocorrelation of CAPM βs. A 1 p.p. increase in average BMI is associated with a short-run increase of 0.021 in the average CAPM β. The short-run estimate of 0.021×10 p.p.=0.21 is nearly identical to the causally identified difference-in-differences estimate of 0.23 for a similar size increase in BMI, as shown in Figure A1. The long-run effect of a 1 p.p. increase is 0.036≈0.021/(1-0.413). Column (7) shows that the average BMI has increased by 10.16 p.p. from 1998 to 2018. Column (8) shows that a 10.16 p.p. increase in average BMI is associated with an 0.37 long-run increase in

[23] Appendix Figure A5 shows that the average CAPM β remained stable around a mean of 0.67 from 1975 to 2000.

Figure 4: Average Cross-Sectional CAPM β and BMI over the Past 25 Years



(a) Aggregate increase in CAPM βs due to increasing Benchmarking

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$\overline{\text{BMI}}_t$ (%)	$\overline{\text{CAPM } \beta}_t$	Cons.	Adj. R^2	$\overline{\text{BMI}}_{1998}$	$\overline{\text{BMI}}_{2018}$	$\Delta\ \overline{\text{BMI}}_{'98\to'18}$	$\widehat{\Delta \overline{\text{CAPM } \beta}}_{'98\to'18}$
$\overline{\text{CAPM } \beta}_{t+1}$	0.021**	0.413*	0.173*	0.81	8.16%	18.32%	10.16 p.p.	0.367***
	(0.006)	(0.169)	(0.062)		(0.10)	(0.16)		(0.046)

Notes: Columns (1), (2), (3) report $\hat{\gamma}_1$, $\hat{\gamma}_2$, and $\hat{\alpha}$ of the following regression: CAPM $\beta_{t+1} = \alpha + \gamma_1$ BMI$_t + \gamma_2$ CAPM $\beta_t + \varepsilon_{t+1}$. Column (5) and (6) report the average BMI in 1998 and 2018, respectively. Column (7) is the increase in BMI over the sample period. Column (8) reports the predicted increase in the CAPM β due to increasing BMI over the sample period ($\hat{\gamma}_1/(1-\hat{\gamma}_2)\times$10.16 p.p.). Newey-West standard error in parentheses with L=2 lags. Yearly sample from 1998 to 2018 (N=21). + p<0.10, * p<0.05, ** p<0.01, *** p<0.001.

average CAPM β. This implies that approximately 80% of the increase in average CAPM β from 1998 to 2018 is due to the rise in average BMI.[24]

7.2 The weighted average cost of capital over the past 25 years

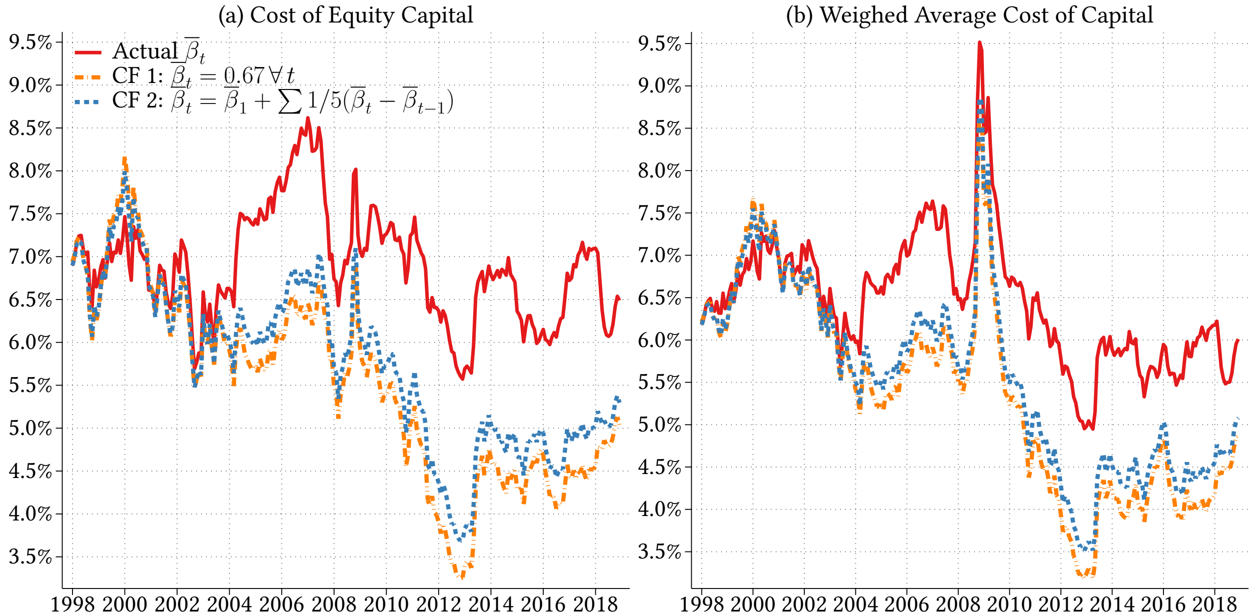
We next document that the benchmarking induced CAPM β distortions are large enough to affect the average firm's weighted average cost of capital (WACC) over the past 25 years. We calculate two counterfactuals to illustrate this point. First, we adjust the CAPM β for the increase in BMI and recalculate the WACC. Second, we set the CAPM β constant at its pre-2000 average.

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

$$\overline{\text{WACC}}_t = \overline{\omega}_t \times \overline{r}_t^E + (1 - \overline{\omega}_t) \times \overline{r}_t^D \times (1 - \overline{\tau}_t) \tag{16}$$

[24]We cannot statistically reject that 100% of the increase in CAPM β is driven by the increase in BMI.

Figure 5: 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 CAPM β_t. Blue and orange dashed lines show counterfactuals where CAPM β_t is adjusted for BMI increase (see Eq. 18) or set constant at its pre-2000 average, respectively.

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

The expected return on equity is given by the CAPM

$$\overline{r}_t^E = r_t^f + \overline{\beta}_t \times \left(\mathbb{E}_t \left[r^{Mkt} \right] - r_t^f \right), \tag{17}$$

where 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[25] and use the yield on the ICE-BofA High-Yield Bond Index to estimate the average expected return on debt, $\overline{r}_t^D$.[26]

We calculate two simple counterfactual WACCs motivated by our findings that increases in BMI cause CAPM βs to rise and that 80% of the aggregate increase in CAPM βs was driven by increases in the BMI (see Figure 4). In the first counterfactual, we set the CAPM β to its long-run average before the year 2000, i.e. $\overline{\beta}_t^{CF\ 1} = 0.67 \, \forall \, t$ (see Appendix Figure A5). In the second, we

[25] 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 β not increased (Appendix Figure A7).

[26] 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 A6 shows both time-series.

adjust the average CAPM $\overline{\beta}_t$ in Eq. (17) as follows:

$$\overline{\beta}_t^{CF\ 2} = \overline{\beta}_{1998/1} + \frac{1}{5} \times \sum_{i=1998/2}^{t} (\overline{\beta}_i - \overline{\beta}_{i-1}) \quad \forall\, t > 1998/1. \tag{18}$$

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

Results Figure 5 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 decline is driven by the secular decline in the risk-free rate over the past 25 years (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 between 162 and 199 bps from 1998 to 2018.

7.3 Long-term effects of CAPM β distortions on capital accumulation

We use the NBER CES Manufacturing Industry database to study the long-term effects of increasing CAPM βs due to increased benchmarking on capital accumulation at the aggregate-level.

We estimate the long-term effects of increasing CAPM βs 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:

$$\Delta\text{CAPM } \beta_i^{`00\rightarrow`16} = \delta_j + \theta\Delta\text{BMI}_i^{`00\rightarrow`16} + \zeta X_i^{`00} + \epsilon_i \tag{19}$$

$$\log\left(\text{Real Capital Stock}_i^{`16}/\text{Real Capital Stock}_i^{`00}\right) = \alpha_j + \gamma\widehat{\Delta\text{CAPM}\,\beta}_i^{`00\rightarrow`16} + \zeta X_i^{`00} + \varepsilon_i \tag{20}$$

where 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 β for industry i from 2000 to 2016 as the difference between the market equity-weighted average CAPM β of firms in that industry in 2016 and 2000. Similarly,

Table 4: Long-term Effects of Benchmarking on Capital Accumulation at the Industry-level

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Dependent variable: $\log\left(\text{Real Capital Stock}^{\text{`16}}\right) - \log\left(\text{Real Capital Stock}^{\text{`00}}\right)$							
ΔCAPM $\beta^{\text{`00}\to\text{`16}}$	-0.327^{+}	-0.300^{+}	-0.484*	-0.525**	-0.280*	-0.276*	-0.322*	-0.293*
	(0.172)	(0.155)	(0.188)	(0.195)	(0.132)	(0.128)	(0.147)	(0.147)
$\log\left(\text{Emp}^{\text{`00}}\right)$		-0.041		-0.003		0.0054		0.072*
		(0.034)		(0.037)		(0.035)		(0.030)
$\log\left(\text{TFP}^{\text{`00}}\right)$		0.057		-0.341^{+}		0.383**		-0.019
		(0.150)		(0.175)		(0.134)		(0.116)
Constant	0.266*	0.428*			0.213***	0.193		
	(0.104)	(0.211)			(0.063)	(0.213)		
Fixed Effects								
Subsector			✓	✓			✓	✓
FS F-stat.	20.14	26.33	17.71	18.32	25.64	30.70	29.23	27.29
Weights					VA$^{\text{`00}}$	VA$^{\text{`00}}$	VA$^{\text{`00}}$	VA$^{\text{`00}}$
Observations	111	111	107	107	111	111	107	107

Notes: This table reports coefficient estimates of regressions at the NAICS 5-digit industry-level of the form: $\Delta\log\left(\text{Real Capital Stock}\right)_i^{\text{`00}\to\text{`16}} = \alpha_j + \gamma\Delta\text{CAPM }\beta_i^{\text{`00}\to\text{`16}} + \zeta X_i^{\text{`00}} + \varepsilon_i$ where changes in CAPM β are instrumented with changes in BMI. Sub-sector fixed effects are at the NAICS 3-digit level. Columns (5) to (8) weighted by industry value added in 2000. FS F-stat is Kleibergen-Paap F-stat for weak instruments. All variables are winsorized 1% and 99% level to account for outliers. Standard errors in parentheses. + p<0.10, * p<0.05, ** p<0.01, *** p<0.001.

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. Perhaps the most significant change over the sample period was the U.S. economy's transition from a manufacturing-based economy to a technology- and information-based economy.

We address this concern by including NAICS 3-digit sub-sector[27] fixed effects in the regressions. Using sub-sector fixed effects, we identify the effects of changes in CAPM β on capital accumulation using variation across industries within the same sub-sectors.

Results Table 4 reports coefficient estimates of Eq. (20) for OLS and WLS, with observations weighted by their value added in 2000. Several things are worth noting. First, across all specifications, we find that increases in CAPM βs have a statistically significant (p<0.05) negative effect on long-term capital accumulation at the industry-level. Second, the estimated coefficients are economically meaningful. The weighted coefficient of Column (8) implies that a 0.37 increase in average CAPM β is associated with a 10.7% ($\approx$0.37$\times$0.29$\times$100%) lower aggregate capital stock

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

over the 17-year period. These magnitudes imply a user cost of capital elasticity of approximately -0.98, which is close to the value of unity implied by a Cobb-Douglas production function. 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 β even at the industry-level, with first-stage F-stats of at least 17.7.

Gormsen and Huber (Figure 10, 2023) calculate that the cumulative investment shortfall in the U.S. from 2002 to 2016 is approximately 17.5%. Our results suggest that the increase in CAPM βs due to the increase in benchmarking can explain up up to 57% of the cumulative investment shortfall.

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 βs to rise. Over the past 25 years, increased benchmarking has caused the average CAPM β to rise by 0.37, following nearly 30 years of stability. Firms reduce investment in response to benchmarking-induced increases in CAPM β. 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, managers report higher perceived costs of capital in earnings calls after their CAPM β 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 β 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.

In conclusion, 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 capital and its impact on the real economy.

References

Aghion, P., J. Van Reenen, and L. Zingales (2013): “Innovation and Institutional Ownership,” *American Economic Review*, 103, 277–304.

Alfaro, I., N. Bloom, and X. Lin (2024): “The Finance Uncertainty Multiplier,” *Journal of Political Economy*, 132, 577–615.

Antón, M. and C. Polk (2014): “Connected Stocks,” *Journal of Finance*, 69, 197–226.

Appel, I. R., T. A. Gormley, and D. B. Keim (2016): “Passive Investors, Not Passive Owners,” *Journal of Financial Economics*, 121, 111–141.

Azar, J., M. C. Schmalz, and I. Tecu (2018): “Anticompetitive Effects Of Common Ownership,” *The Journal of Finance*, 73, 1513–1565.

Baker, A. C., D. F. Larcker, and C. C. Wang (2022): “How Much Should We Trust Staggered Difference-in-differences Estimates?” *Journal of Financial Economics*, 144, 370–395.

Barberis, N., A. Shleifer, and J. Wurgler (2005): “Comovement,” *Journal of Financial Economics*, 75, 283–317.

Basak, S. and A. Pavlova (2013): “Asset Prices and Institutional Investors,” *American Economic Review*, 103, 1728–58.

Bauer, M. D. and G. D. Rudebusch (2020): “Interest Rates Under Falling Stars,” *American Economic Review*, 110, 1316–1354.

Bauer, M. D. and E. T. Swanson (2023): “A Reassessment of Monetary Policy Surprises and High-Frequency Identification,” *NBER Macroeconomics Annual*, 37, 87–155.

Bebchuk, L. A., A. Cohen, and S. Hirst (2017): “The Agency Problems Of Institutional Investors,” *Journal of Economic Perspectives*, 31, 89–102.

Bebchuk, L. A. and S. Hirst (2019): “Index Funds and the Future Of Corporate Governance: Theory, Evidence, and Policy,” NBER Working Paper 26543 26543, National Bureau of Economic Research.

Belo, F., X. Lin, and S. Bazdresch (2014): “Labor Hiring, Investment, and Stock Return Predictability In the Cross Section,” *Journal of Political Economy*, 122, 129–177.

Ben-David, I. and A. M. Chinco (2023): "Modeling Managers As EPS Maximizers," NBER Working Paper 31125, National Bureau of Economic Research.

Ben-David, I., F. Franzoni, and R. Moussawi (2018): "Do ETFs Increase Volatility?" *The Journal of Finance*, 73, 2471–2535.

Berk, J. B. and P. M. DeMarzo (2023): *Corporate Finance*, Boston: Pearson Education, 6th ed.

Berk, J. B., R. C. Green, and V. Naik (1999): "Optimal Investment, Growth Options, and Security Returns," *The Journal of finance*, 54, 1553–1607.

Berk, J. B. and J. H. Van Binsbergen (2016): "Assessing Asset Pricing Models Using Revealed Preference," *Journal of Financial Economics*, 119, 1–23.

Blume, M. E. (1975): "Betas and Their Regression Tendencies," *The Journal of Finance*, 30, 785–795.

Boyer, B. H. (2011): "Style-related Comovement: Fundamentals or Labels?" *The Journal of Finance*, 66, 307–332.

Brealey, R., S. Myers, F. Allen, and A. Edmans (2023): *Principles Of Corporate Finance. 14*, New York: McGraw Hill, 14th ed.

Buffa, A. M. and I. Hodor (2023): "Institutional Investors, Heterogeneous Benchmarks and the Comovement of asset Prices," *Journal of Financial Economics*, 147, 352–381.

Buffa, A. M., D. Vayanos, and P. Woolley (2022): "Asset Management Contracts and Equilibrium Prices," *Journal of Political Economy*, 130, 3146–3201.

Cengiz, D., A. Dube, A. Lindner, and B. Zipperer (2019): "The Effect Of Minimum Wages on Low-wage Jobs," *The Quarterly Journal of Economics*, 134, 1405–1454.

Chang, Y.-C., H. Hong, and I. Liskovich (2015): "Regression Discontinuity and the Price Effects Of Stock Market Indexing," *The Review of Financial Studies*, 28, 212–246.

Claus, J. and J. Thomas (2001): "Equity Premia as Low as Three Percent? Evidence From Analysts' Earnings Forecasts for Domestic and International Stock Markets," *The Journal of Finance*, 56, 1629–1666.

Conley, T. G., C. B. Hansen, and P. E. Rossi (2012): "Plausibly Exogenous," *Review of Economics and Statistics*, 94, 260–272.

Cuoco, D. and R. Kaniel (2011): "Equilibrium Prices in the Presence of Delegated Portfolio Management," *Journal of Financial Economics*, 101, 264–296.

Da, Z., R.-J. Guo, and R. Jagannathan (2012): "CAPM for Estimating the Cost of Equity Capital: Interpreting the Empirical Evidence," *Journal of Financial Economics*, 103, 204–220.

De Chaisemartin, C. and X. d'Haultfoeuille (2023): "Two-way Fixed Effects and Differences-in-differences with Heterogeneous Treatment Effects: a Survey," *The Econometrics Journal*, 26, C1–C30.

De Fraisse, A. H. (2024): "Long-term Bond Supply, Term Premium, and the Duration of Corporate Investment," Working paper, Available at SSRN 4064763.

Deshpande, M. and Y. Li (2019): "Who Is Screened Out? Application Costs and the Targeting Of Disability Programs," *American Economic Journal: Economic Policy*, 11, 213–248.

Dessaint, O., J. Olivier, C. A. Otto, and D. Thesmar (2020): "CAPM-Based Company (Mis)valuations," *The Review of Financial Studies*, 34, 1–66.

Dimson, E. (1979): "Risk Measurement When Shares Are Subject to Infrequent Trading," *Journal of Financial Economics*, 7, 197–226.

Easton, P. D. (2004): "PE ratios, PEG ratios, and estimating the implied expected rate of return on equity capital," *The Accounting Review*, 79, 73–95.

Edmans, A. and C. G. Holderness (2017): "Blockholders: A Survey of Theory and Evidence," in *The Handbook of the Economics of Corporate Governance*, ed. by B. E. Hermalin and M. S. Weisbach, Elsevier, vol. 1, chap. 8, 541–636.

Eskildsen, M., M. Ibert, T. I. Jensen, and L. H. Pedersen (2024): "In Search of the True Greenium," Working paper, Available at SSRN 4744608.

Fama, E. F. and K. R. French (2004): "The Capital Asset Pricing Model: Theory and Evidence," *Journal of Economic Perspectives*, 18, 25–46.

Frank, M. Z. and T. Shen (2016): "Investment and the Weighted Average Cost of Capital," *Journal of Financial Economics*, 119, 300–315.

Freyaldenhoven, S., C. Hansen, J. P. Pérez, and J. M. Shapiro (2021): "Visualization, Identification, and Estimation In the Linear Panel Event-study Design," NBER Working Paper 29170, National Bureau of Economic Research.

Gebhardt, W. R., C. M. Lee, and B. Swaminathan (2001): "Toward an Implied Cost of Capital," *Journal of Accounting Research*, 39, 135–176.

Gilchrist, S. and E. Zakrajšek (2007): "Investment and the Cost of Capital: New evidence from the Corporate Bond Market," NBER Working Paper 13174, National Bureau of Economic Research.

Golez, B. (2014): "Expected Returns and Dividend Growth Rates Implied by Derivative Markets," *The Review of Financial Studies*, 27, 790–822.

Gollier, C. (2021): "The Welfare Cost of Ignoring the Beta," CEPR Discussion Paper DP16007, Center for Economic and Policy Research.

Gomes, J., L. Kogan, and L. Zhang (2003): "Equilibrium Cross Section of Returns," *Journal of Political Economy*, 111, 693–732.

Gormley, T. A. and D. A. Matsa (2011): "Growing Out Of Trouble? Corporate Responses to Liability Risk," *The Review of Financial Studies*, 24, 2781–2821.

Gormsen, N. J. and K. Huber (2023): "Corporate Discount Rates," NBER Working Paper 31329, National Bureau of Economic Research.

——— (2024): "Firms' Perceived Cost Of Capital," NBER Working Paper 32611, National Bureau of Economic Research.

Graham, J. R. (2022): "Presidential Address: Corporate Finance and Reality," *The Journal of Finance*, 77, 1975–2049.

Gutiérrez, G. and T. Philippon (2017): "Investmentless Growth: an Empirical Investigation," *Brookings Papers on Economic Activity*, Fall, 89–169.

Hansen, B. E. (2023): *Econometrics*, Princeton: Princeton University Press, 1st ed.

Harris, L. and E. Gurel (1986): "Price and Volume Effects Associated with Changes in the S&P 500 List: New Evidence for the Existence Of Price Pressures," *The Journal of Finance*, 41, 815–829.

Hassan, T. A., S. Hollander, L. Van Lent, and A. Tahoun (2019): "Firm-level Political Risk: Measurement and Effects," *The Quarterly Journal of Economics*, 134, 2135–2202.

Heath, D., D. Macciocchi, R. Michaely, and M. C. Ringgenberg (2021): "Do Index Funds Monitor?" *The Review of Financial Studies*, 35, 91–131.

Hoberg, G. and V. Maksimovic (2015): "Redefining Financial Constraints: a Text-based Analysis," *The Review of Financial Studies*, 28, 1312–1352.

JORDÀ, Ò. (2005): "Estimation and Inference Of Impulse Responses by Local Projections," *American Economic Review*, 95, 161–182.

——— (2023): "Local Projections for Applied Economics," *Annual Review of Economics*, 15, 607–631.

JORDÀ, Ò., M. SCHULARICK, AND A. M. TAYLOR (2020): "The Effects Of Quasi-random Monetary Experiments," *Journal of Monetary Economics*, 112, 22–40.

KACPERCZYK, M., S. SUNDARESAN, AND T. WANG (2021): "Do Foreign Institutional Investors Improve Price Efficiency?" *The Review of Financial Studies*, 34, 1317–1367.

KAROLYI, G. A. (1992): "Predicting Risk: Some New Generalizations," *Management Science*, 38, 57–74.

KASHYAP, A. K., N. KOVRIJNYKH, J. LI, AND A. PAVLOVA (2021): "The Benchmark Inclusion Subsidy," *Journal of Financial Economics*, 142, 756–774.

KONTZ, C. (2023): "Do ESG investors care about carbon emissions? Evidence from securitized auto loans," Working paper, Stanford University.

KRISHNAMURTHY, A. AND A. VISSING-JORGENSEN (2011): "The Effects Of Quantitative Easing on Interest Rates: Channels and Implications for Policy," *Brookings Papers on Economic Activity*, Fall, 215–287.

KROEN, T., E. LIU, A. R. MIAN, AND A. SUFI (2021): "Falling Rates and Rising Superstars," NBER Working Paper 29368, National Bureau of Economic Research.

KRÜGER, P., A. LANDIER, AND D. THESMAR (2015): "The WACC fallacy: The Real Effects of using a Unique Discount Rate," *The Journal of Finance*, 70, 1253–1285.

KUEHN, L.-A. AND L. SCHMID (2014): "Investment-based Corporate Bond Pricing," *The Journal of Finance*, 69, 2741–2776.

LEVI, Y. AND I. WELCH (2017): "Best Practice for Cost-of-Capital Estimates," *Journal of Financial and Quantitative Analysis*, 52, 427–463.

LEWELLEN, J. AND K. LEWELLEN (2022): "Institutional Investors and Corporate Governance: the Incentive to Be Engaged," *Journal of Finance*, 77, 213–264.

LIMBURG, A. (2024): "Do Firms Self-select Into Russell Indices?" Working paper, Available at SSRN 4816038.

Linn, M. and D. Weagley (2021): “Uncovering Financial Constraints,” *Journal of Financial and Quantitative Analysis*, 1–36.

Mark, C. E., D. G. Garrett, E. Ohrn, K. A. Roberts, and J. C. Suárez Serrato (2021): “Capital Investment and Labor Demand: Evidence from 21st Century Tax Policy,” Working paper, Duke University.

Matray, A. (2023): “"Dividend Taxes, Firm Growth, and the Allocation of Capital",” NBER Working Paper 30099, National Bureau of Economic Research.

McCrary, J. (2008): “Manipulation Of the Running Variable In the Regression Discontinuity Design: a Density Test,” *Journal of Econometrics*, 142, 698–714.

Ohlson, J. A. and B. E. Juettner-Nauroth (2005): “Expected EPS and EPS Growth as Determinants of Value,” *Review of Accounting Studies*, 10, 349–365.

Pavlova, A. and T. Sikorskaya (2023): “Benchmarking Intensity,” *The Review of Financial Studies*, 36, 859–903.

Peters, R. H. and L. A. Taylor (2017): “Intangible Capital and the Investment-Q Relation,” *Journal of Financial Economics*, 123, 251–272.

Philippon, T. (2009): “The Bond Market’s Q,” *The Quarterly Journal of Economics*, 124, 1011–1056.

Ross, S., R. Westerfield, J. Jaffe, and B. Jordan (2016): *Corporate Finance*, New York: McGraw Hill, 11th ed.

Shleifer, A. (1986): “Do Demand Curves for Stocks Slope Down?” *The Journal of Finance*, 41, 579–590.

Vasicek, O. A. (1973): “A Note on Using Cross-sectional Information In Bayesian Estimation Of Security Betas,” *The Journal of Finance*, 28, 1233–1239.

Vijh, A. M. (1994): “S&P 500 Trading Strategies and Stock Betas,” *The Review of Financial Studies*, 7, 215–251.

Welch, I. (2008): “The Consensus Estimate for the Equity Premium by Academic Financial Economists in December 2007,” Working paper, Available at SSRN 1084918.

——— (2022a): *Corporate Finance*, Self-published, 5th ed.

——— (2022b): “Simply Better Market Betas,” *Critical Finance Review*, 11, 37–64.

Wurgler, J. (2010): "On the Economic Consequences Of Index-linked Investing," NBER Working Paper 16376, National Bureau of Economic Research.

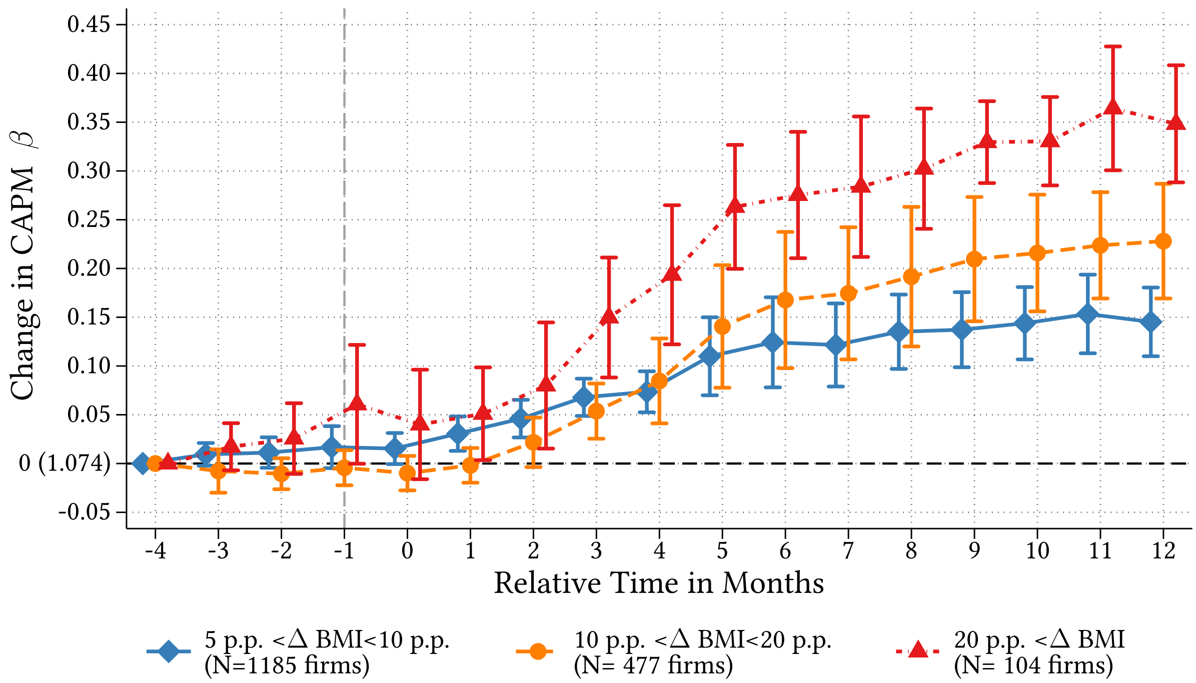
Zhang, L. (2005): "The Value Premium," *The Journal of Finance*, 60, 67–103.

Zwick, E. and J. Mahon (2017): "Tax Policy and Heterogeneous Investment Behavior," *American Economic Review*, 107, 217–248.

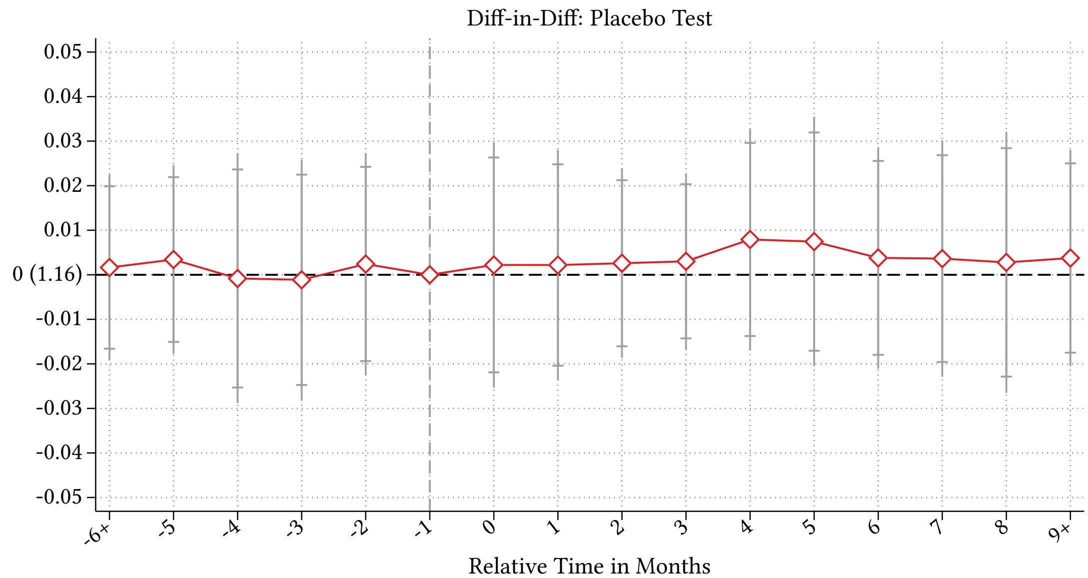
A Appendix

A.1 Appendix Figures

Figure A1: Difference-in-differences Event Study for Different Treatment Intensities

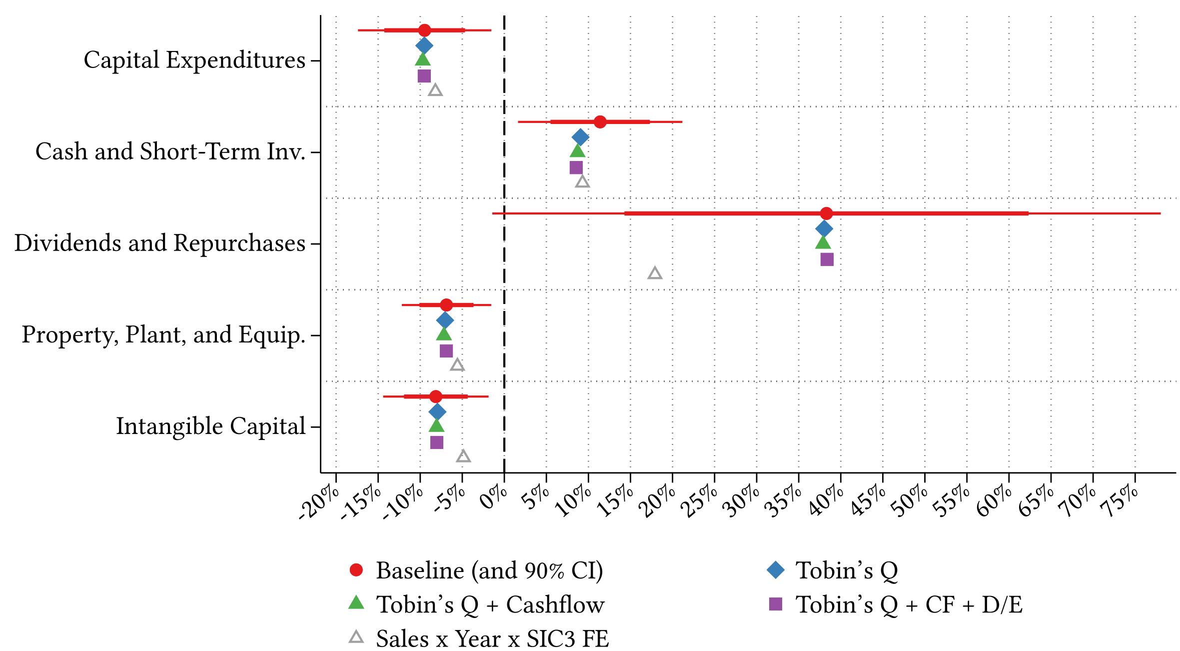


Notes: This figure shows difference-in-differences event study coefficients of Eq. (8) for different treatment intensities. Treatment effects are normalized to zero in t-4. Change in CAPM β of treated stocks relative to control group where $|\Delta$ BMI$|<1.5$ p.p.. Pointwise confidence intervals (90%) based on double-clustered standard errors. Values in parentheses on the Y-axis indicate the median CAPM β pre-treatment for all treatment intensities.



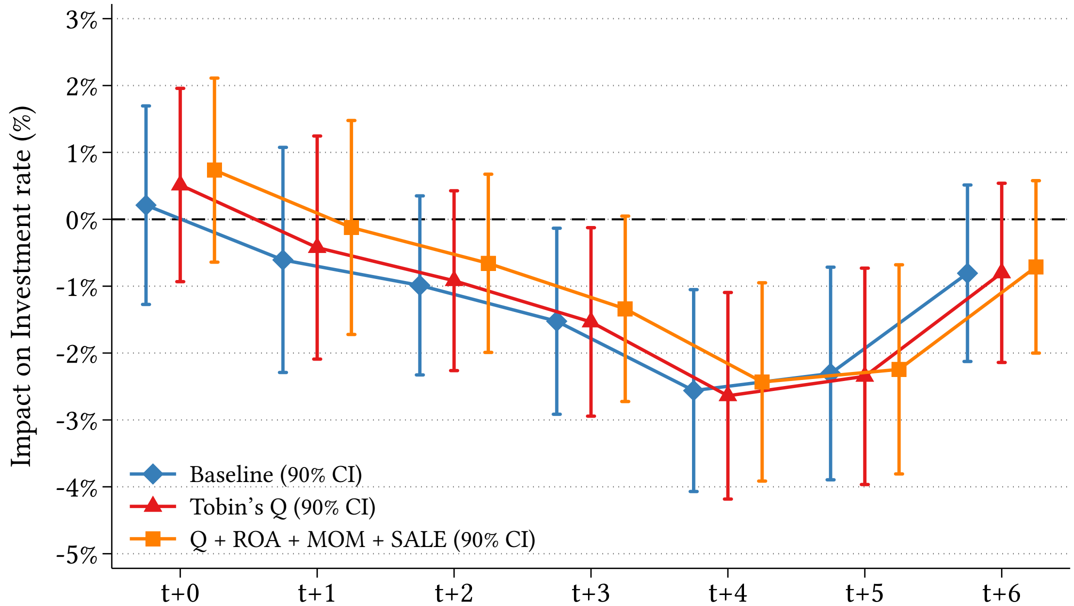
Notes: This figure shows difference-in-differences event study coefficients of Eq. (8). Treatment group: ΔBMI $\in (0\text{ p.p.}, 1\text{ p.p.}]$. Control group: ΔBMI $\in [-1\text{ p.p.}, 0\text{ p.p.}]$

Figure A3: LP-IV Robustness to various Alternative Specifications



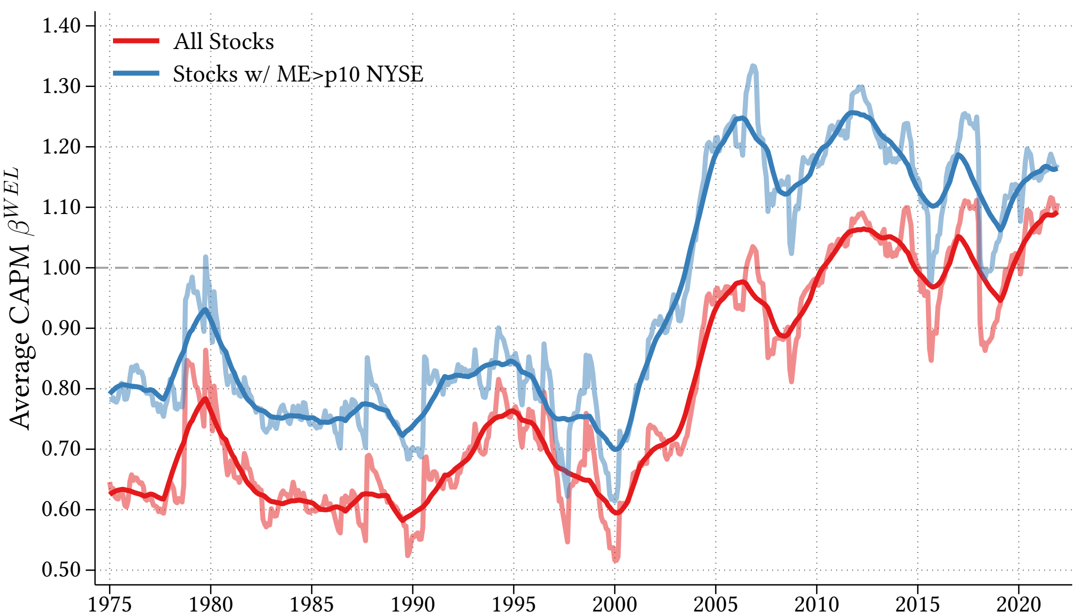
Notes: This figure shows estimates of LP-IV coefficient for h=5 from Eq. (12) for baseline and alternative specifications.

Figure A4: Impact of changes in CAPM β on investment rate



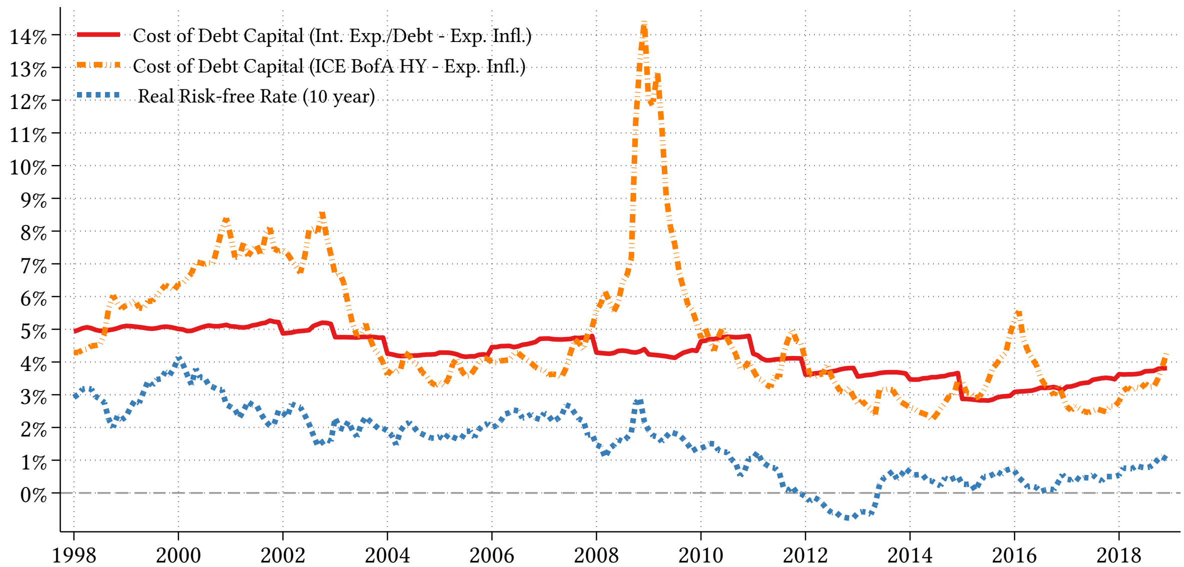
Notes: This figure shows estimates for γ^h of Investment Rate$_{i,t+h} = \alpha_i + \alpha_{j,t} + \gamma^h \widehat{\text{CAPM}}\,\beta_{i,t} + X'_{i,t}\xi + \varepsilon_{i,t+h}$, estimated using changes in BMI as an IV for changes in CAPM β. Estimates are scaled to a 0.16 change in CAPM β. Investment 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 is 19.9% and is 13.5% over the sample period from 2000 to 2018, respectively.

Figure A5: Time Series of Average CAPM β since 1975



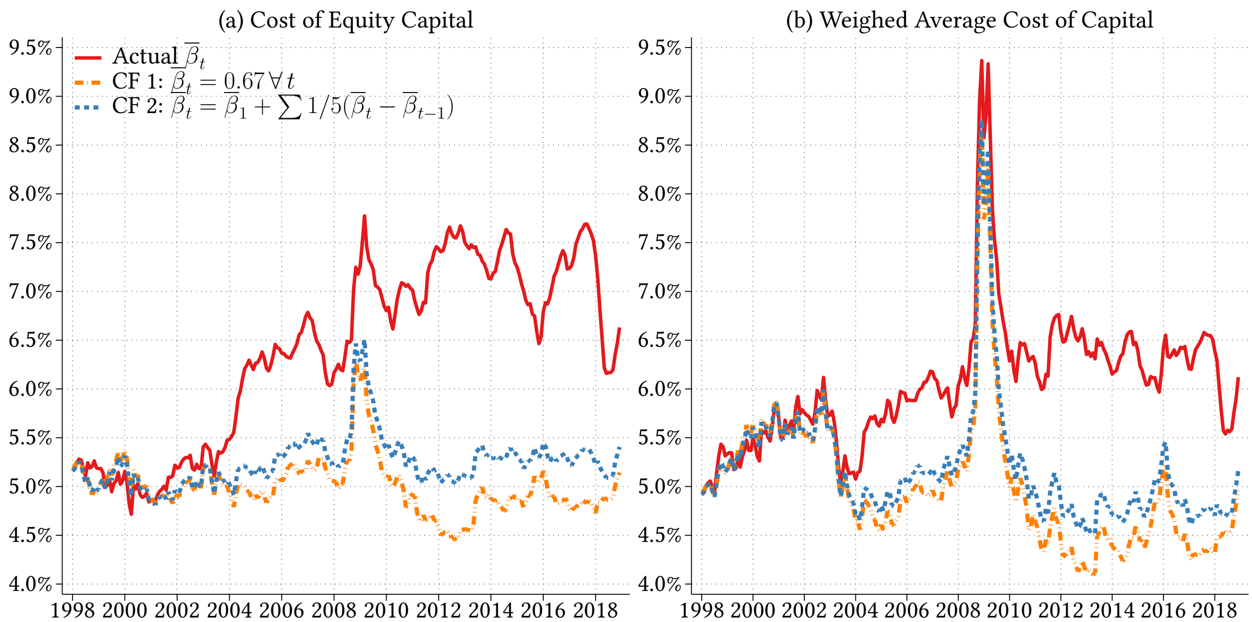
Notes: This figure shows the monthly cross-sectional average CAPM β of Welch (2022b) since 1975. Time-series are smoothed using a two-sided moving-average filter with 12 month window on either side.

Figure A6: 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 A7: 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)



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 where CAPM β_t is adjusted for BMI increase (see Eq. 18) or set constant at its pre-2000 average, respectively.

A.2 Appendix Tables

Table A1: Effect of Change in Benchmarking Intensity on CAPM β

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 shows 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 β). 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 A2: Robustness to Alternative CAPM β 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^{OLS}_{EW}	Δ CAPM β^{WEL}_{EW}	Δ CAPM β^{DIM}_{EW}	Δ CAPM β^{BLU}_{EW}	Δ CAPM β^{TOP}_{EW}	$\Delta\ \rho(r_i, r_m)_{EW}$	$\Delta\ \sigma^i_{EW}$
Δ BMI	1.146***	0.947***	0.752***	0.764***	1.056***	0.388***	-0.00222
	(0.059)	(0.047)	(0.080)	(0.039)	(0.055)	(0.019)	(0.002)
Firm FE	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓
Adj. R^2	0.19	0.20	0.14	0.19	0.30	0.38	0.55
Observations	36,095	36,095	36,095	36,095	36,095	36,095	36,095
	Panel B: CAPM β estimates using daily data with a 2-year rolling window (with equal weights)						
	Δ CAPM β^{OLS}_{RW}	Δ CAPM β^{WEL}_{RW}	Δ CAPM β^{DIM}_{RW}	Δ CAPM β^{BLU}_{RW}	Δ CAPM β^{TOP}_{RW}	$\Delta\ \rho(r_i, r_m)_{RW}$	$\Delta\ \sigma^i_{RW}$
Δ BMI	0.300***	0.247***	0.212***	0.200***	0.325***	0.140***	-0.00429***
	(0.040)	(0.032)	(0.055)	(0.027)	(0.038)	(0.013)	(0.001)
Firm FE	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓
Adj. R^2	0.24	0.25	0.18	0.24	0.33	0.39	0.53
Observations	36,095	36,095	36,095	36,095	36,095	36,095	36,095

Notes: This table reports coefficient estimates of specifications of the form: $\Delta\beta_{i,t} = \alpha_i + \alpha_t + \gamma\Delta\text{BMI}_{i,t} + \varepsilon_{i,t}$. 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 β), β^{TOP} is β with respect to ten largest stocks by market capitalization, EW stands for expanding window, RW for rolling window. Changes in BMI and CAPM βs are winsorized at the 1% and 99% level. Standard errors in parentheses are clustered at firm-level. + p<0.10, * p<0.05, ** p<0.01, *** p<0.001.

Table A3: Placebo test using the CAPM β 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 β 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.

Table A4: Changes in CAPM β and firm-level risk measures of Hassan et al. (2019)

(in σ units)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	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 βs, 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.

Table A5: Changes in CDS Spreads and CAPM βs 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 $\times$ Size Decile			✓				✓	
Year $\times$ 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: ΔCDS 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 βs 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 βs 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.

Table A6: 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 βs, 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.

Table A7: 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.

Table A8: LP-IV: Point Estimates of the Real Effects of Changes in β

Horizon	Capital Expenditure	Cash & Short-Term Inv.	Dividends & Repurchases	Physical Capital	Intangible Capital	No Obs.
t+1	-2.00	-1.24	0.04	-0.85	-1.44	13,829
	(2.59)	(2.71)	(12.75)	(1.59)	(1.19)	
t+2	-3.93	3.96	2.33	-3.18	-3.98*	11,943
	(3.21)	(3.14)	(10.49)	(1.96)	(1.56)	
t+3	-6.10+	3.68	11.70	-4.30+	-4.20*	10,342
	(3.52)	(3.42)	(13.23)	(2.41)	(1.76)	
t+4	-5.58	8.41+	9.86	-3.83	-6.62**	8,881
	(3.57)	(4.91)	(18.66)	(2.61)	(2.51)	
t+5	-9.47*	11.40+	38.30	-6.87*	-8.14*	7,518
	(4.82)	(5.94)	(24.16)	(3.23)	(3.81)	
t+6	-9.92	5.50	30.89	-7.12	-8.36+	6,327
	(6.52)	(6.93)	(25.43)	(4.72)	(4.69)	
H_0: ATE = 0	0.03	0.12	0.53	0.02	0.00	
Avg. FS F-stat.			50.48			

Notes: This table reports coefficient estimates of LP-IV specifications of the form: $\log\left(Y_{i,t+h}/Y_{i,t-1}\right) = \alpha_i^h + \alpha_{j,t}^h + \gamma^h \Delta\widehat{\text{CAPM}\,\beta}_{i,t} + \xi^h X_{i,t} + \varepsilon_{i,t+h}$ for $h = 1, \ldots, 6$. Specifications include lags of outcome variables and shocks of up to 3th order. All variables are winsorized at the 2.5% and 97.5% level. FS F-stat is Kleibergen-Paap F-statistic for weak instruments. H_0 ATE $= 0$ refers to the null that the coefficients for $h = 1, \ldots, 6$ are jointly zero. Standard error in parentheses are clustered at the firm-level. + p<0.10, * p<0.05, ** p<0.01, *** p<0.001.

Table A9: 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)	451	391	389	310	187	**157**	165
Bayesian Information Criterion (IV)	1,970	755	518	460	**411**	577	628
Observations	14,495	14,495	14,495	14,495	14,495	14,495	14,495

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

A.3 RDD at the Russell 3000 cutoff

We employ an alternative strategy to estimate the change in a firm's CAPM β due to a change in the stock's BMI using a regression discontinuity design at the Russell 3000 cutoffs.[28] To do so, we translate monthly estimates of CAPM βs to the year-firm-level using the following procedure.

$$\Delta\text{CAPM } \beta = \text{Avg. post-period } \hat{\beta} - \text{Avg. pre-period } \hat{\beta}$$

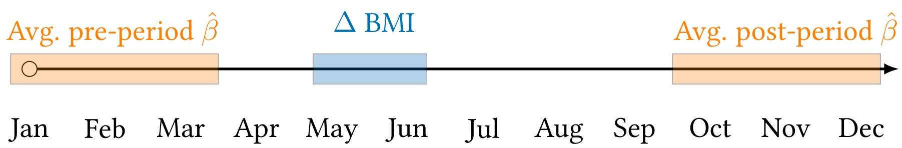


Figure A8: Timeline of Changes in CAPM

We define the change in a firm's CAPM β as the difference between the average β in the period before the BMI changes[29] (December to March) and a post-period (August to November). We drop April to July to avoid the potentially confounding effects of trading related to the index inclusion or exclusion on the β estimates. Figure A8 provides a visual representation of the timeline.

We estimate the local average treatment effect of Russell 3000 index inclusion on a firm's CAPM β by estimating a series of regression discontinuity specifications using the following form:

$$\Delta\text{CAPM } \beta_i = \alpha_0 + \alpha_1 D_i + f(\text{Rank} - \text{Cutoff})_i + f(\text{Rank} - \text{Cutoff})_i \times D_i + \eta_i \tag{21}$$

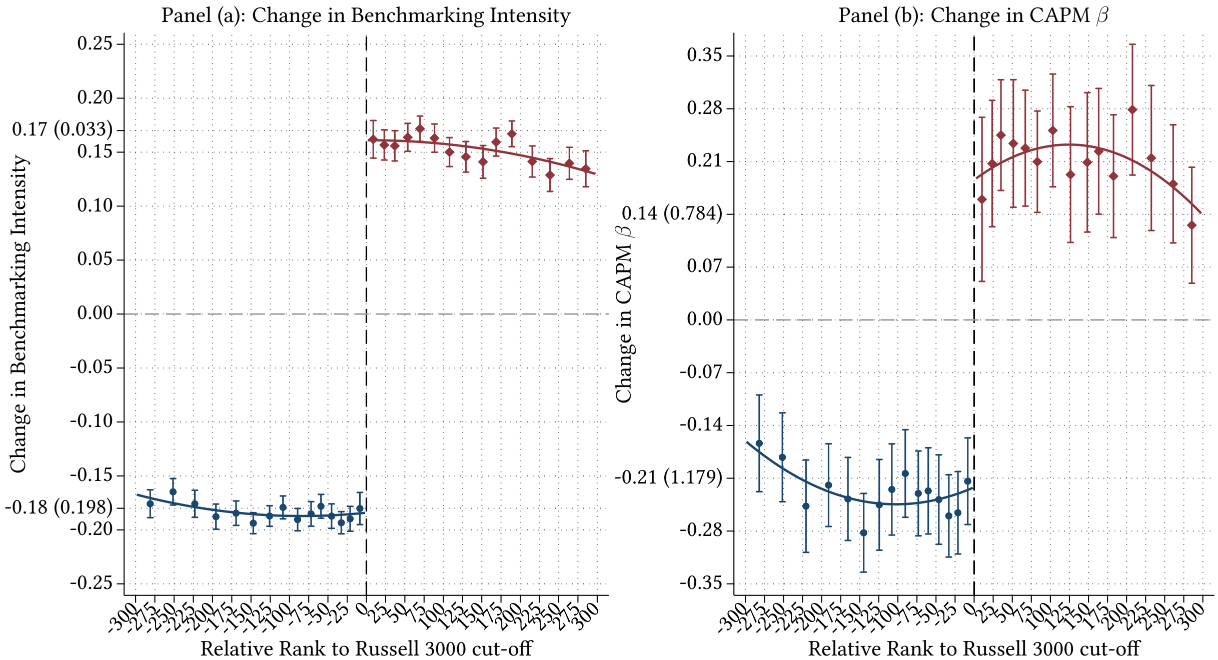
where D_i is an indicator variable for whether firm i's market value rank exceeds the Russell 3000 inclusion cutoff in year t. The coefficient of interest, α_1, summarizes the local average treatment effect of changes in BMI due to index reconstitution on a firm's CAPM β.

Identifying assumptions and threats to identification Our identification assumes that firms are not able to manipulate their market equity rank relative to the index cutoff with precision. This assumption is typically tested by checking for bunching around the cutoff with the McCrary (2008) test. However, bunching is not possible because the assignment variable is a rank. Moreover, an idiosyncratic shock to the market value on the rank date can bring the stock to the other side of the cutoff. Taken together, these two points imply that index assignment near the cutoff is

[28] Appendix A.4 repeats this exercise at the Russell 1000 cutoffs for the years from 2002 to 2006 with similar results.

[29] We again focus on stocks for which the BMI changes by at least 5 p.p. in absolute value to ensure that we select stocks that are affected by the index reconstitution.

Figure A9: Regression discontinuity study at Russell 3000 cutoffs



Notes: This figure shows changes in BMI and CAPM β relative to index inclusion cutoffs. Y-axis values in parentheses are average of variables in levels pre-treatment within 50 ranks of cutoff. Changes in BMI are calculated as the difference in BMI between May and June. Changes in CAPM β is difference between the average in the first and fourth quarter. Standard errors are clustered at firm-level. Sample from 2008 to 2018.

as good as random (Chang et al., 2015). Limburg (2024) tests if firm try to manipulate their equity rank to become index members but finds no evidence of such behavior.

Results Panel (a) of Figure A9 shows that the BMI discontinuously changes at the Russell 3000 inclusion cutoff. The BMI for stocks included in the Russell 3000 increases on average by 17 p.p.; an approximately five-fold increase relative to their pre-treatment average (measured within 50 ranks of the cutoff) of 3% BMI. Conversely, stocks dropped from the Russell 3000 see an average decrease of 18 p.p. in BMI.

Panel (b) of Figure A9 shows that this increase in BMI associated with index reconstitution drastically change the CAPM βs of treated firms. The CAPM β of stocks that experience an increase in BMI due to index inclusion increases by 0.14 on average. Conversely, the CAPM β of stocks that experience a decrease in BMI at index reconstitution decreases by 0.21; a decrease of 18% relative to their pre-treatment average CAPM β of 1.18.

Table A10 reports the results of the regression discontinuity specification in (21). The coefficient estimate of the local average treatment effect, α_1, is positive and always statistically significant at the 5% level or higher. Columns (1) to (7) use a parametric regression discontinuity

Table A10: Regression Discontinuity

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Dependent variable: Δ CAPM β							
LATE	0.363***	0.305**	0.342**	0.311*	0.342**	0.289*	0.303***	0.218*
	(0.0740)	(0.0963)	(0.0880)	(0.105)	(0.0995)	(0.102)	(0.0783)	(0.101)
$f(X)$	Linear	Quadratic	Linear	Quadratic	Linear	Quadratic	Poly(1)	Poly(2)
Window width	300	300	200	200	150	150	300	300
Kernel							Triangular	Triangular
Bandwidth							122.4	111.2
Adj. R^2	0.415	0.417	0.440	0.441	0.437	0.440		
Observations	1,185	1,185	914	914	737	737	1,185	1,185

Notes: This table reports the local average treatment effect (α_1) of Russell 3000 index inclusion on a firm's CAPM β from regression discontinuity specifciations: $\Delta\text{CAPM } \beta_i = \alpha_0 + \alpha_1 D_i + f(\text{Rank} - \text{Cutoff})_i + f(\text{Rank} - \text{Cutoff})_i \times D_i + \eta_i$. Standard errors in parentheses are double-clustered at firm and year level. + p<0.10, * p<0.05, ** p<0.01, *** p<0.001.

designs, while (7) and (8) are show non-parametric estimates using local polynomial regressions of order 1 and 2 using triangular kernels with automatic bandwidth selection. Columns (1), (2), (7), (8) estimate treatment effects around the index cutoffs with a window of 300 ranks on each side. Columns (3) and (4) use a window of 200 ranks, and columns (5) and (6) use a window of 150 ranks. The estimated coefficients are reasonably stable across columns (1) to (7) but around one third smaller for the local quadratic non-parametric estimate of column (8). The local average treatment effect, however, are again all large and economically meaningful. For example, the coefficient estimate of 0.289 in Column (6) implies an increase of 1.73 p.p. in the cost of equity capital using the CAPM (assuming an ERP of 6%).

A.4 RDD at the Russell 1000 cutoff

Table A11: Regression Discontinuity at Russell 1000 cutoffs

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Dependent variable: Δ CAPM β							
LATE	-0.114*	-0.142*	-0.124+	-0.131+	-0.126+	-0.167+	-0.233***	-0.262***
	(0.0354)	(0.0509)	(0.0551)	(0.0488)	(0.0490)	(0.0641)	(0.0573)	(0.0642)
f(X)	Linear	Quadratic	Linear	Quadratic	Linear	Quadratic	Poly(1)	Poly(2)
Window width	300	300	200	200	150	150	300	300
Kernel							Triangular	Triangular
Bandwidth							52.8	86.4
Adj. R^2	0.104	0.106	0.124	0.132	0.159	0.162		
Observations	474	474	390	390	322	322	474	474

Notes: This table reports the local average treatment effect (α_1) of Russell 1000 index inclusion on a firm's CAPM β from regression discontinuity specifciations: $\Delta\text{CAPM } \beta_i = \alpha_0 + \alpha_1 D_i + f(\text{Rank} - \text{Cutoff})_i + f(\text{Rank} - \text{Cutoff})_i \times D_i + \eta_i$. Standard errors in parentheses are double-clustered at firm and year level. + p<0.10, * p<0.05, ** p<0.01, *** p<0.001.

B Online Appendix (for online publication only)

Table B1: Robustness to Industry CAPM β Estimators (scaled to 10 p.p. increase in BMI)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Δ CAPM β^{OLS}_{RW}		Δ CAPM β^{WEL}_{RW}		Δ CAPM β^{DIM}_{RW}		Δ CAPM β^{BLU}_{RW}	
Δ BMI	0.193^{*}	0.169^{**}	0.157^{*}	0.140^{**}	0.281^{**}	0.221^{***}	0.129^{*}	0.113^{**}
(scaled to 10 p.p. incr.)	(0.071)	(0.051)	(0.060)	(0.043)	(0.085)	(0.060)	(0.047)	(0.034)
Industry Classification	FF30	FF48	FF30	FF48	FF30	FF48	FF30	FF48
Industry FE	✓	✓	✓	✓	✓	✓	✓	✓
Adj. R^2	0.03	0.03	0.03	0.04	0.05	0.04	0.03	0.03
Observations	507	753	507	753	507	753	507	753

Notes: This table reports coefficient estimates of specifications of the form: $\Delta\beta_{i,t} = \alpha_i + \gamma\Delta\text{BMI}_{i,t} + \varepsilon_{i,t}$ at the industry level i for Fama-French's 30 and 48 industries. Estimates are scaled to a 10 p.p. increase in BMI at the industry level. 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 β), RW stands for rolling window. Changes in BMI and CAPM βs are winsorized at the 1% and 99% level. Standard errors in parentheses are clustered at industry-level. + p<0.10, * p<0.05, ** p<0.01, *** p<0.001.