Benchmarking Intensity

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Abstract

Benchmarking incentivizes fund managers to invest a fraction of their funds' assets in their benchmark indices, and such demand is inelastic. We construct a measure of inelastic demand a stock attracts, *benchmarking intensity (BMI)*, computed as its cumulative weight in all benchmarks, weighted by assets following each benchmark. Exploiting the Russell 1000/2000 cutoff, we show that changes in stocks' BMIs instrument for changes in ownership of benchmarked investors. The resulting demand elasticities are low. We document that both active and passive fund managers buy additions to their benchmarks and sell deletions. Finally, an increase in BMI lowers future stock returns.

JEL Classification: G11, G12, G23

Keywords: Benchmark, preferred habitat, index effect, demand elasticity, mutual funds, Russell cutoff

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1 Introduction

The asset management industry has been growing in size and importance over time. To date, it has amassed more than $100 trillion in assets under management (AUM) worldwide.[1] A large fraction of these funds are managed against benchmarks (e.g., the S&P 500, FTSE-Russell indices, etc.). Benchmarks convey to fund investors information about the types of stocks the fund invests in and act as a useful tool for performance evaluation of fund managers. With a growing investor appetite for different investment styles, benchmarks are becoming increasingly heterogeneous. In 2018, the AUM share of U.S. mutual funds benchmarked to the S&P 500 was 35%, the next 34% was split between the Russell indices, followed by 22% benchmarked to the CRSP indices.[2] Our objective is to link membership in multiple benchmarks to stock prices and expected returns, as well as demand by fund managers.

In this paper, we argue that stocks included in a benchmark form a preferred habitat for fund managers evaluated against that benchmark. In our model, benchmarked fund managers have an incentive to hold stocks in their benchmarks, which makes a fraction of their demand for these stocks inelastic. We derive a measure, which we term *benchmarking intensity* (BMI), that captures the aggregate inelastic demand of all benchmarked managers. We define the benchmarking intensity of a stock as the cumulative weight of the stock in all benchmarks, weighted by assets under management following each benchmark, relative to the stock's market capitalization. For the former, we use the historical composition of 34 U.S. equity indices. For the assets, we use the AUM of U.S. equity mutual funds. We extract the history of fund benchmarks directly from their prospectuses.[3]

We exploit the variation in the benchmarking intensity of stocks that transition across the Russell 1000/2000 index cutoff to establish the effects of BMI on stock prices, expected returns, fund ownership, and demand elasticities. First, we show that the change in BMI resulting from an index reconstitution is positively related to the size of the index effect.[4] Second, we argue that a change in a stock's BMI predicts the change in ownership of benchmarked investors in this stock. Specifically, it accounts for both active and passive managers' demand and for all relevant benchmarks that include this stock, which allows us to establish

[1] Based on Willis Towers Watson report, https://www.thinkingaheadinstitute.org/news/article/global-asset-manager-aum-tops-us100-trillion-for-the-first-time/.

[2] Figure 5 in the Appendix plots assets under management of US domestic equity mutual funds, by benchmark. The heterogeneity of benchmarks is apparent from the figure, especially for mid-cap and small stocks.

[3] Details of the procedure and methods used to validate our benchmark data are described in the text. Previous research has used a snapshot of fund benchmarks or assumed S&P 500 as a universal benchmark.

[4] A boost to a company's share price when it is added to an index.

a lower bound for the price impact of benchmarked managers' trades. We then use changes in BMI as an instrumental variable to estimate the price impact of institutional investors' trades (or the price elasticity of demand). Third, we highlight that active managers contribute substantially to the benchmarking intensity and document that they buy additions to their benchmarks and sell deletions. Finally, we show that, consistent with our theory, an increase in a stock's benchmarking intensity leads to underperformance relative to comparable stocks for a period of one to five years. The literature has only considered shorter-term 'reversals' of the index inclusion effect, attributing this pattern to limits to arbitrage, while we argue that index membership permanently lowers the risk premium on a stock due to the inelastic demand of fund managers investing in it.

We start with a simple model that highlights the channel through which a stock's benchmarking intensity affects its price and expected return. The model features fund managers alongside standard direct investors. All investors are risk-averse. A fund manager's compensation depends on performance relative to her benchmark. The model predicts that such performance evaluation makes benchmark stocks the preferred habitat of managers evaluated against that benchmark. The fund manager's higher demand for her benchmark stocks makes prices of these stocks higher in equilibrium and their expected returns lower. This effect is permanent, persisting for as long as the stocks remain in the benchmark. In an equilibrium with heterogeneous benchmarks, the variable that captures the additional (inelastic) demand of benchmarked managers – beyond what the standard risk-return trade-off would predict – is exactly the benchmarking intensity.

In our empirical analysis, we explore how a shock to a stock's BMI affects its price and ownership. Isolating the effects of this variation is challenging because, through index membership, BMI may be related to other stock characteristics, most importantly size and liquidity. Our solution is to exploit the cutoff between the Russell 1000 and 2000 indices, which separates stocks that are very similar in size and other characteristics but differ significantly in terms of their benchmarking intensities. Mechanical index reconstitution rules lead to the close-to-random index assignment into the Russell 1000 and 2000 indices, which serves as a source of (conditionally) exogenous variation in benchmarking intensity. So our tests compare stocks close to the cutoff that experience different changes in BMI.

We empirically link the size of the price pressure experienced by a stock to the change in its benchmarking intensity. Corroborating the results of Chang, Hong, and Liskovich (2015), we document price pressure upon index reconstitution (the index effect). As in the rest of the index effect literature, Chang, Hong, and Liskovich look only at the average effect.[5] Our contribution is to show, in the cross-section of stocks around the Russell cutoff,

[5]The exceptions are Greenwood (2005) and Wurgler and Zhuravskaya (2002) who link the size of the index

that stocks whose BMI changed the most experience the largest index effect. We then use our regression estimates from this analysis to establish a lower bound on the price impact of benchmarked fund managers' trades and find that a 1% change in BMI leads to a 27bps higher return in the month of index reconstitution. It is a lower bound because, in practice, fund managers incur transaction costs, which often prevents them from trading as BMI would predict, especially if the funds are active.

We show that BMI predicts changes in institutional ownership and we can therefore estimate the actual price impact of institutional investors' trades. Ownership changes are, of course, endogenous, and we argue that changes in BMI act as a valid instrument for them. The literature has used the Russell 1000/2000 index membership (dummy) as an instrument for institutional ownership, but this instrument is rather coarse. The advantage of BMI is that it is a continuous measure, which makes it a stronger instrument, and we argue that it remains (conditionally) exogenous. The instrumental variable approach yields an estimate of 1.5 for the price impact of institutional investors' trades. This estimate is roughly in line with that of Koijen and Yogo (2019), obtained via the demand system approach to asset pricing, and highlights that the demand for stocks is quite inelastic.

BMI allows us to measure the price elasticity of demand for stocks more precisely than in the related literature, not only because it is continuous but also because it takes into account the inelastic demand of active managers stemming from different benchmarks that include these stocks. To measure the price elasticity of demand, most papers have exploited index reconstitutions and have used the resulting change in passive assets as a shock to net supply. If active managers' demand features an inelastic component, measures of elasticity based on a passive demand change upon index reconstitution will be inaccurate. We also argue that accounting for heterogeneous benchmarks (e.g., that each Russell 1000 stock also belongs to the Russell 1000 Value and/or Growth, and often to the Russell Midcap) is important when estimating the elasticity of demand for stocks.

We show that both active and passive investors have a considerable fraction of holdings concentrated in their benchmarks and that their rebalancing around the Russell cutoffs is consistent with changes to their benchmarks. The majority of recent studies attributed the discontinuities in ownership around the cutoff to passive investors, i.e., index and exchange-traded funds. In line with the literature, we find highly significant rebalancing of index additions and deletions for passive funds in the direction imposed by their benchmarks. For example, passive funds benchmarked to the Russell 2000 purchase 77bps of shares of stocks added to the Russell 2000. These funds also sell deleted stocks in similar proportions. Using the data on funds' benchmarks, we are able to demonstrate the same pattern in active funds.

effect to arbitrage risk.

We find that active funds benchmarked to the Russell 2000 also sell deletions, decreasing their ownership share by 55bps. Active funds benchmarked to the Russell 1000 and Russell Midcap increase their ownership shares in stocks added to the Russell 1000 and Midcap by 12bps and 39bps, respectively. We do not have an identification strategy of comparable quality for other benchmarks but we show that aggregate active fund portfolios indeed resemble their benchmarks. So in line with our theory, stocks inside the benchmarks serve as both active and passive funds' preferred habitats.

We also find that, consistent with our theory, stocks whose BMIs have gone up significantly underperform in the long run. Exploiting again the Russell cutoff, we show that increased inelastic demand of benchmarked fund managers leads to lower expected returns of these stocks for horizons of up to 5 years relative to their peers close to the cutoff. The economic magnitudes are sizeable, averaging 2.8% lower return in the first year for additions to the Russell 2000 index. We rule out alternative explanations of this finding.

Related research. This paper is related to several strands of literature, including equilibrium asset pricing with benchmarked fund managers, index effect, and empirical research on the effects of institutional ownership.

Among theoretical contributions, the first paper to study benchmarking is Brennan (1993). Brennan derives a two-factor asset pricing model in a two-period economy with a benchmarked fund manager. Cuoco and Kaniel (2011), Basak and Pavlova (2013) and Buffa, Vayanos, and Woolley (2014) investigate equilibrium asset pricing effects of delegated portfolio management in dynamic economies. The closest paper to ours in this strand of literature is Kashyap, Kovrijnykh, Li, and Pavlova (2021). None of these works, however, considers heterogeneous benchmarks. The only paper that does is Buffa and Hodor (2018), but they focus primarily on asset return comovement. In our model, heterogeneous habitats of fund managers arise because of the heterogeneity in benchmarks. Such habitats could also be driven by optimal narrow investment mandates in delegated asset management (e.g., van Binsbergen, Brandt, and Koijen (2008), He and Xiong (2013)) or different investor styles (Barberis and Shleifer (2003)). A related idea of studying how investor habitats affect asset prices is exlored in preferred habitat models of the term structure of interest rates (e.g., Vayanos and Vila (2021)).

Both our theoretical and empirical results are related to the index effect literature. The index effect was first documented by Shleifer (1986) and Harris and Gurel (1986) for additions to the S&P 500 index and subsequently found in many other markets and asset classes.[6] This literature typically measures the average size of index effect, while we show

[6]Most of the studies focus on S&P 500 and Russell composition changes, though others also cover such index families as MSCI, DJIA, Nikkei, FTSE, CAC, Toronto Stock Exchange Index, etc. For example,

how it varies in the cross-section with the change in BMI.

The existence of the index effect challenges the standard theories, which predict that demand curves for each stock are very elastic and therefore index inclusion should have no effect on asset prices and expected returns. The index effect literature has converged to the view that stocks are not perfect substitutes, which suggests that the demand curves for stocks are downward-sloping. Our preferred habitat model provides a microfoundation for why stocks are imperfect substitutes.[7] In the model, fund managers' demand features an inelastic component due to benchmarking. This affects stock prices and expected returns for as long as the stocks remain in the benchmark.

Our analysis delivers an alternative estimate of stock price elasticity of demand based on an index inclusion event. Most of the known estimates are based on a single index membership, while the BMI measure accounts for the demand related to all large benchmarks in a comprehensive way. Furthermore, the change in a stock's BMI helps measure the price elasticity of demand more accurately in a world where active managers' demand has both elastic and inelastic components. Recent literature stresses the importance of incorporating downward-sloping demand curves for stocks in the asset pricing and macro-finance models (for example, Gabaix and Koijen (2020)), and our results may inform such models.

Our instrumental variable approach to computing demand elasticities is related to that in Koijen and Yogo (2019), who propose a characteristics-based demand-system approach which can be used to estimate price impact of a given institutional investor. We focus on aggregate demand of benchmarked institutions and perform estimation in changes. Our estimate of the aggregate price impact is slightly lower than theirs, most likely because we consider stocks around the Russell 1000/2000 cutoff, which are closer substitutes.

The closest empirical work to ours is Chang, Hong, and Liskovich (2015). It is the first paper to build a regression discontinuity design (RDD) on the cutoff between the Russell 1000 and 2000 indices in order to quantify the price pressure stemming from institutional demand. The paper finds a 5% index effect in the month of addition to ~~and deletion from~~ the Russell 2000. It also documents a decreasing trend in this index effect and attributes it to the alleviation of limits to arbitrage. Even though we use the same cutoff for identification, we are the first to document the resulting difference in the long-run returns (twelve months to five years) of stocks that moved indices and those that did not. We view the duration of this effect as evidence that index membership affects the risk premium of a stock. Furthermore,

Chen, Noronha, and Singal (2005) document a long-lasting price increase of the S&P 500 additions, which increases in magnitude through time. Hacibedel and van Bommel (2007) also find permanent price increase for emerging markets indices within the MSCI family. Greenwood (2005) documents an index effect for a redefinition of the Nikkei 225 index in Japan.

[7] Petajisto (2009) offers a complemetary view, also based on asset manager demand.

we discuss the advantages of using BMI over the index membership dummy to measure demand elasticities and show how the estimates of Chang, Hong, and Liskovich change in a setting with heterogeneous benchmarks.

There is a growing body of literature studying implications of passive ownership for corporate governance using the Russell cutoff.[8] This literature documents predictable rebalancing of passive funds around the cutoff, but not active. In line with the findings of this literature, we find that the *total* active ownership in stocks that switched indices does not change. However, our granular data allows us to show that the identities of active funds change as benchmarks would predict. For example, a stock that is deleted from the Russell 2000 is sold by the active funds benchmarked to the Russell 2000 and bought by active funds benchmarked to the Russell 1000 and Midcap. As a result, monitoring incentives of active managers may change and this may affect corporate governance.

The paper proceeds as follows. Section 2 explains the implications of heterogeneous benchmarks for stock returns. In Section 3, we construct the measure of benchmarking intensity, show how it is linked to the size of the index effect and the elasticity of demand. We discuss funds' preferred habitats and rebalancing in Section 4. In Section 5, we inspect the relationship between BMI and long-run returns. Omitted details and further robustness exercises are relegated to the Appendix.

2 Model of Delegated Asset Management with Heterogeneous Benchmarks

To illustrate the main mechanism, we first develop a simple model of asset prices in the presence of benchmarking. It builds upon Brennan (1993) and Kashyap, Kovrijnykh, Li, and Pavlova (2021) and introduces heterogeneous fund managers whose performance is evaluated relative to a variety of benchmarks. The goal of the model is to characterize a relationship between benchmarking intensity, our measure of capital that is inelastically supplied by fund managers, and stock returns.

2.1 Model

Except for the presence of fund managers, our environment is standard. There are two periods, $t = 0, 1$. The financial market consists of a riskless asset with an exogenous

[8] The list of papers includes but is not limited to: Heath, Macciocchi, Michaely, and Ringgenberg (2021), Appel, Gormley, and Keim (2019), Glossner (2021), Schmidt and Fahlenbrach (2017), Appel, Gormley, and Keim (2016).

interest rate normalized to zero (e.g., a storage technology) and N risky assets paying cash flows $D_i,\ i = 1, \ldots, N$ in period 1. The cash flows of the risky assets are given by

$$D_i = \overline{D}_i + \beta_i Z + \epsilon_i, \quad \beta_i > 0,\ i = 1, \ldots, N,$$

where $Z \sim N(0, \sigma_z^2)$ is a common shock and $\epsilon_i \sim N(0, \sigma_\epsilon^2)$ is an idiosyncratic one. The vectors $D \equiv (D_1, \ldots, D_N)'$ and $S \equiv (S_1, \ldots, S_N)'$ denote vectors of period-1 cash flows and period-0 risky asset prices, respectively. Period-1 risky asset prices equal D. The risky assets are in fixed supply of $\overline{\theta} \equiv (\overline{\theta}_1, \ldots, \overline{\theta}_N)'$ shares. It is convenient to introduce the notation $\Sigma \equiv \Sigma_z + I_N \sigma_\epsilon^2$ for the variance-covariance matrix of cash flows D, where Σ_z is a $N \times N$ matrix with a typical element $\beta_i \beta_j \sigma_z^2$ and I_N is an $N \times N$ identity matrix. We also set $\overline{D} \equiv (\overline{D}_1, \ldots, \overline{D}_N)'$ and $\beta \equiv (\beta_1, \ldots, \beta_N)'$.

There are J benchmark portfolios that are used for performance evaluation. Each benchmark j is a portfolio of $\omega_j \equiv (\omega_{1j}, \ldots, \omega_{Nj})'$ shares of the assets described above. Some components of ω_j can be zero.

There are two types of investors: direct investors and fund managers. Direct investors, whose mass in the population is λ_D, manage their own portfolios. Fund managers manage portfolios on behalf of fund investors. Fund investors can buy the riskless asset directly, but cannot trade stocks; they delegate the selection of their portfolios to portfolio managers. The managers receive compensation from fund investors. Each manager is evaluated relative to a benchmark. We denote the mass of managers evaluated relative to benchmark j by λ_j.[9] All investors have a constant absolute risk aversion utility function over terminal wealth (or compensation), $U(W) = -\exp^{-\gamma W}$, where γ is the coefficient of absolute risk aversion.

The terminal wealth of a direct investor is given by $W = W_0 + \theta_D'(D - S)$, where the $N \times 1$ vector θ_D denotes the number of shares held by the direct investor, and W_0 is the investor's initial wealth. The direct investor chooses a portfolio θ_D to maximize his utility $U(W)$. A fund manager's j compensation w_j consists of three parts: one is a linear payout based on absolute performance of the fund, the second piece depends on the performance of the fund relative to the benchmark portfolio j, and the third is independent of performance (c). Specifically,

$$w_j = aR_j + b(R_j - B_j) + c, \quad a \geq 0,\ b > 0$$

where $R_j \equiv \theta_j'(D - S)$ is the performance of the fund's portfolio and $B_j \equiv \omega_j'(D - S)$ is the performance of benchmark j.[10] The parameters a and b are the contract's sensitivities to

[9]For simplicity, we assume that each fund investor employs one fund manager, but this can easily be relaxed.

[10]Ma, Tang, and Gómez (2019) and Evans, Gómez, Ma, and Tang (2020) analyze compensation of fund managers in the US mutual fund industry and provide evidence supporting our specification here. Endogenizing this compensation structure is beyond the scope of this paper; see Kashyap, Kovrijnykh, Li,

absolute and relative performance, respectively. The fund manager chooses a portfolio of θ_j shares to maximize his utility $U(w_j)$.

2.2 Portfolio Choice and Asset Prices

The portfolio demand of the direct investors is the standard mean-variance portfolio:[11]

$$\theta_D = \frac{1}{\gamma}\Sigma^{-1}\left(\overline{D} - S\right). \tag{1}$$

In contrast, the fund managers do not have the same risk-return trade-off as direct investors, because of their compensation contracts. The portoflio demand of manager j is given by

$$\theta_j = \frac{1}{\gamma(a+b)}\Sigma^{-1}\left(\overline{D} - S\right) + \frac{b}{a+b}\omega_j. \tag{2}$$

The fund manager splits his risky asset holdings across two portfolios: the mean-variance portoflio (the first term in (2)) and the benchmark portfolio (the second term). The latter portfolio arises because the manager hedges against underperforming the benchmark. Consistent with the preferred habitat view, the manager thus has a higher demand for stocks in her benchmark. Notice that the demand for the benchmark portfolio ω_j is inelastic. It does not depend on the riskiness of the assets and depends only on the parameters of the compensation contract. It follows that, *ceteris paribus,* stocks with a higher benchmark weight have a higher weight in the fund manager's portfolio.

By clearing markets for the risky assets, $\lambda_D\theta_D + \sum_{j=1}^{J}\lambda_j\theta_j = \overline{\theta}$, we compute equilibrium asset prices.

$$S = \overline{D} - \gamma A\Sigma\left(\overline{\theta} - \frac{b}{a+b}\sum_{j=1}^{J}\lambda_j\omega_j\right), \tag{3}$$

where $A \equiv \left[\lambda_D + \frac{\sum_j \lambda_j}{a+b}\right]^{-1}$ modifies the market's effective risk aversion.[12]

and Pavlova (2020) who derive it as part of an optimal contract. Finally, see Kashyap, Kovrijnykh, Li, and Pavlova (2021) (Online Appendix B) for an alternative specificaton of a benchmark, in which constituents are value-weighted. Such specification is not as analytically tractable as ours, but it delivers similar insights.

[11] We omit proofs in the main text and relegate them to Appendix B, available upon request.

[12] Our model can be extended to incorporate passive managers, who simply hold the benchmark portfolio. Suppose the total mass of fund managers benchmarked to index j, λ_j, consists of a mass λ_j^P of passive managers and a mass λ_j^A of active. Then the expression for stock prices is:

$$S = \overline{D} - \gamma A\Sigma\left(\overline{\theta} - \sum_{j=1}^{J}\left[\frac{b}{a+b}\lambda_j^A\omega_j + \lambda_j^P\omega_j\right]\right), \text{ where } A \equiv \left[\lambda_D + \frac{\sum_j \lambda_j^A}{a+b}\right]^{-1}.$$

Equation (3) elucidates the determinants of the index effect in our model. The index effect manifests itself through the benchmarking-induced price pressure term $\frac{b}{a+b}\sum_{j=1}^{J}\lambda_j\omega_j$. This term reflects the cumulative inelastic demand of fund managers and motivates our benchmarking intensity measure used in the empirical part of the paper. Equation (3) implies that if a stock gets added to a benchmark or if its weight in a benchmark increases, its price goes up. Another implication is that the larger the mass of fund managers (λ_j's) following a benchmark, the higher the benchmarking-induced price pressure and hence the bigger the index inclusion effect. The more benchmarks a stock belongs to and the bigger its weight in the benchmarks, the more demand from fund managers it attracts and therefore the higher the stock's price.

Our next set of predictions is about the expected stock returns (or the cost of equity). The expected return of stock i, expressed as a per-share return $\Delta S_i \equiv \overline{D}_i - S_i$, is given by[13]

$$E[\Delta S_i] = \gamma A \beta_i \sigma_z^2 \beta' \left(\overline{\theta} - \frac{b}{a+b}\sum_{j=1}^{J}\lambda_j\omega_j \right) + \gamma A \sigma_\epsilon^2 \left(\overline{\theta}_i - \frac{b}{a+b}\sum_{j=1}^{J}\lambda_j\omega_{ij} \right). \tag{4}$$

Equation (4) implies that the price pressure we discussed above is permanent, and it lasts for as long as a stock remains in the fund managers' benchmarks. Therefore, *ceteris paribus*, stocks with higher benchmarking intensities, defined in our model as $\sum_{j=1}^{J}\lambda_j\omega_{ij}$, have lower expected returns. Furthermore, if a stock's benchmarking intensity goes up (e.g., due to an index inclusion), its price should rise upon announcement and the expected return after the announcement should be lower.

In summary, our model produces the following predictions:

Prediction 1: Stocks with higher benchmarking intensities have lower expected returns.

Prediction 2: If a stock's benchmarking intensity goes up (e.g., due to an index inclusion), its price should rise.

Prediction 3: If a stock's benchmarking intensity goes up, the funds' ownership of the stock ($\sum_j \theta_{ij}$) should rise.

Prediction 4: If a stock enters benchmark j and exits benchmark k, funds benchmarked to index j increase their demand for the stock (θ_{ij}) while those benchmarked to index k decrease their demand (θ_{ik}).

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[13]In models with CARA preferences and normally distributed cash flows, the return is usually expressed in per-share terms. In our empirical analysis, however, we use per-dollar returns, $r_{it+1} \equiv (S_{it+1} - S_{it})/S_{it}$, as in the empirical literature. We acknowledge this inconsistency, but we still prefer to keep our theoretical results in terms of per-share returns, for expositional clarity.

3 Benchmarking Intensity in the Data

In this section, we use data on US domestic equity mutual funds and their prospectus benchmarks to build a measure of benchmarking intensity. We document its basic properties and apply this measure to the computation of the price elasticity of demand for stocks.

3.1 Dataset

The main sample is an annual panel of stocks which were the Russell 3000 constituents in 1998-2018.[14] The main three pillars of data are historical benchmark weights, mutual fund and institutional holdings, and stock characteristics. The second and third are standard, we report details on them in Section A.2 of Appendix.

In contrast to the previous studies, the dataset is granular with respect to benchmark information. It includes primary prospectus benchmarks scraped directly from historical fund prospectuses available on the website of the U.S. Securities and Exchange Commission[15] and augmented with a Morningstar snapshot. The scraping procedure and its validation are described in detail in Section A.3 in the Appendix. We obtain benchmark constituent data from the following sources. All the constituent weights for 22 Russell benchmark indices are from FTSE Russell (London Stock Exchange Group). The Russell indices include (all total return in USD): Russell 1000, 2000, 2500, 3000, 3000E, Top 200, Midcap, Small Cap Completeness (blend) as well as their Growth and Value counterparts. Constituent weights for the S&P 500 TR USD and S&P MidCap 400 TR USD are from Morningstar and available from September 1989 and September 2001, respectively, to October 2015. We construct constituent weights for S&P 500 after October 2015 manually from constituent lists and prices available through CRSP. We generate the S&P 400 weights from holdings of index funds (Dreyfus and iShares).[16] The constituent weights for the CRSP US indices are from Morningstar and available from 2012. These indices include (all total return in USD): Total Market, Large Cap, Mid Cap, Small Cap (blend) as well as their Growth and Value counterparts.

Our benchmark data has two advantages to prior research. First, the benchmark

[14] Our main sample starts in 1998 because before that we do not have benchmark data of sufficient quality. Even though the SEC's electronic archives date back to 1994, many funds do not report their benchmarks in files available prior to 1998. Please find the details in Section A.3. Our sample ends in December 2018 because the holdings data used for the analysis of fund ownership is available with a lag.

[15] Follow https://www.sec.gov/edgar/searchedgar/mutualsearch.html

[16] Since the S&P 400 index is relatively small, these weights do not contribute much to the analysis. We do not include the S&P 600 index because its share is even smaller and the holdings-based weights are not of sufficient quality.

information is a dynamic panel encompassing benchmark changes.[17] Therefore, it accurately reflects the benchmark used by funds at any point in time.[18] Secondly, we obtain Russell index data from FTSE Russell directly: our dataset includes proprietary total market values (capitalization) as of the rank day in May and provisional constituent lists available before the reconstitution day in June.

We report the descriptive statistics of the main calculated variables used in analysis in Tables 8 and 9 in the Appendix.

3.2 Empirical Measure of Benchmarking Intensity

Guided by the model, we calculate the *benchmarking intensity (BMI)* for stock i in month t as

$$BMI_{it} = \frac{\sum_{j=1}^{J} \lambda_{jt}\omega_{ijt}}{MV_{it}}, \tag{5}$$

where λ_{jt} is the assets under management (AUM) of mutual funds benchmarked to index j in month t, ω_{ijt} is the weight of stock i in index j in month t and MV_{it} is the market capitalization of stock i in month t. In our theory, the price impact of additional inelastic demand ($\Delta S_i/\Delta \sum_{j=1}^{J} \lambda_j\omega_{ij}$) is constant and does not depend on the stock's supply (equation (4)), which is unrealistic. This feature of CARA models makes them tractable, but in our empirical analysis, to be consistent with the empirical literature on price impact, the natural object to work with is the total inelastic demand the stock attracts, *as a fraction of the stock's market capitalization*. An additional advantage of this scaling of our theoretical measure is that, for value-weighted indices, the MV_{it} terms cancel out from (5) and we can rewrite BMI as

$$BMI_{it} = \sum_{j=1}^{J} \frac{\lambda_{jt}\mathbf{1}_{ijt}}{\sum_{k=1}^{N} MV_{kt}\mathbf{1}_{kjt}} = \sum_{j=1}^{J} \frac{\lambda_{jt}\mathbf{1}_{ijt}}{\text{IndexMV}_{jt}}, \tag{6}$$

where the index membership dummy $\mathbf{1}_{ijt}$ is equal to one if stock i belongs to index j at time t and IndexMV_{jt} is the total market cap of all stocks in index j at time t. Related literature has established that a stock's transitions between the Russell 1000 and 2000 indices, captured by $\mathbf{1}_{ijt}$, can be used as an instrument for changes in the stock's ownership. Since our BMI depends additionally only on aggregated variables such as the total AUM of each index the stock belongs to and the total market capitalization of each index, it is plausible that ΔBMI

[17] See Appendix, in which we show that our scraping procedure picked up such important benchmark changes as Vanguard's move from the MSCI to CRSP indices in 2013.

[18] We attribute funds with benchmarks with non-value weighted constituents and SRI screened funds to their 'parent' benchmarks, e.g. the S&P 500 equal-weighted index to the S&P 500 index. These funds are small in our sample and removing them does not change the results.

is also a valid instrument for changes in stock ownership.[19] We examine this conjecture in detail in Section 3.3.4.

Notice that the computation of BMI does not rely on holdings data. Holdings data are available at best quarterly and can be noisy while index composition and funds' AUM are observed monthly.

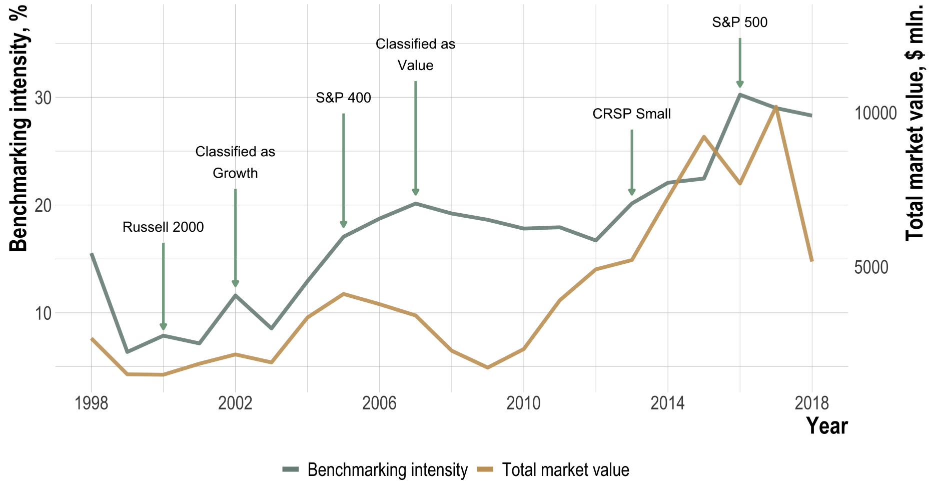
Even though benchmarking intensity is typically slow-moving, considerable variation comes from index membership. A useful illustration is a retailer Foot Locker Inc. (ticker FL). Figure 1 depicts a year-on-year evolution of its benchmarking intensity. Despite the evident comovement between size and benchmarking intensity, the latter has more variation due to the changing index membership and index asset flows: in 2000 FL joins the Russell 2000, in 2005 – the S&P 400, in 2012 FL gets into the CRSP Small, in 2016 it gets added to the S&P 500.

Figure 2 illustrates the contribution of membership in each index to the benchmarking intensity of FL (Panel (a)). Even though the stock's addition to S&P 500 clearly increases its BMI, the size and variation of other components are significant. Panel (b) of the same Figure shows how much different benchmark styles (i.e., value, growth, and blend) contribute to FL's BMI. In our data, we only have style indices for the Russell and CRSP families, so the rest is attributed to blend. Even with this limitation, it is apparent that style benchmarks occupy a considerable fraction of BMI. These two illustrations highlight one of the key contributions of our measure – it takes into account the heterogeneity of benchmarks and overlaps between them.

Since the benchmarking intensity measure is built using the AUM of both active and passive funds, there is a variation coming from the relative importance of these two fund types as depicted in Panel (c) of Figure 2. The BMI of FL is dominated by the inelastic demand

[19] There are two potential caveats. First, some index providers use the float-adjusted market cap for the purposes of index construction. That is, strictly speaking, (6) should be $BMI_{it} = \sum_{j=1}^{J} \frac{\lambda_{jt} FF_{ijt} \mathbf{1}_{ijt}}{\sum_{k=1}^{N} MV_{kt} FF_{kjt} \mathbf{1}_{kjt}}$, where FF_{ijt} denotes the float factor of stock i in index j at time t (the float factor may be index-specific). Because this float factor reflects stock liquidity, it could be a potential source of endogeneity. Russell uses primarily companies' SEC filings to compute their free float. In our regression analysis, we use the official Russell free float in May, provided to us by Russell, as one of our control variables and supplement it with bid-ask spread to account for any stale information in the float factor. We could also scale BMI by float-adjusted market value provided by Russell instead of the total market value from CRSP to completely exclude FF from the numerator. Our results are robust to this alternative scaling and we choose the total market value scaling as our baseline because it makes our measure easy to replicate. Second, value and growth indices typically include only a fraction of the market value of the stock that they deem related to value or growth style. We see that, on average, this split of shares between Russell value and growth indices does not strongly affect changes in BMI around the Russell cutoff (the necessary assumptions are discussed in Appendix A.18). Furthermore, all our results are robust to controlling for the stock's Russell proprietary value ratio in May, M/B, and sales growth. To further alleviate possible concerns about endogeneity of ΔBMI, in Section 3.3.4 we perform overidentifying restrictions tests.

Figure 1: Benchmarking Intensity of Foot Locker Inc.



This figure plots the benchmarking intensity (left axis) and the total market value (right axis) of Foot Locker Inc. stock over time. Arrows point to the years when the stock was added to the benchmarks.

from active funds, even though the contribution of passive funds has grown. This illustrates another important advantage of BMI – unlike passive ownership, a measure of institutional demand used in the extant literature – the BMI accounts for the inelastic demand of active funds as well.

Table 1 documents descriptive statistics for BMI in our sample. S&P 500 stocks have the highest average BMI, while membership in the Russell 2000 contributes the most to the BMI of an average stock. The reported statistics also highlight the increasing heterogeneity of benchmarks for U.S. equities: the average number of benchmarks increased from 7 to 10 and the concentration of benchmark shares in BMI went down (as shown in Panel B). Together, value and growth indices are at least as important as blend indices, contributing on average over 50% to the BMI. Furthermore, active funds contribute 83% to the BMI over the full sample period, even though their share declined to an average of 65% in the recent 5 years.[20]

BMI is not free of limitations. Empirically, we only observe benchmarks of the U.S. funds, while U.S. firms have seen an increasing share of foreign owners. This implies that the BMI we compute is a proxy of the true BMI which should include foreign funds benchmarked to U.S. stock indices. We focus on mutual funds but other investors, such as pension funds and insurance companies, may also invest through benchmarked managers. Because BMI is

[20]The maximum value of BMI above 100% corresponds to the few cases when the benchmarking demand is indeed larger than the market value of a stock. In our model, such cases would imply that some direct investors or fund managers are short the stock.

additive and only the numerator depends on AUM, the omission of foreign funds and other benchmarked institutions scales BMI down. While we do not have data for assets under management across all benchmarked institutions, we have checked data for separate accounts available in Morningstar. The distribution of assets across benchmarks is remarkably similar to that for mutual funds, with the exception of CRSP benchmark indices. It gives us some comfort that adding such benchmarked institutions will maintain the cross-sectional ranking in our sample. On the theory side, we assume that there are no transaction costs and fund mandates only differ in the benchmark used. In practice, however, trading is costly and funds may have other constraints, such as bounds on sector exposure. This is expected to skew the weights used to compute BMI. We discuss the consequences of considering trading costs at the end of Section 5.1.

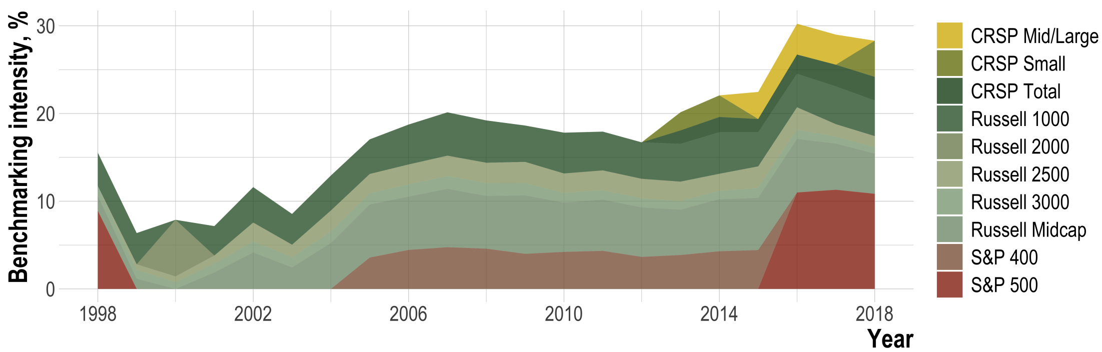
Table 1: Properties of benchmarking intensity

	By time period					**By benchmark**					
	Full sample	1998-2000	2001-2006	2007-2012	2013-2018	S&P 500	Russell 1000	Russell 2000	Russell Midcap	Russell Value indices	Russell Growth indices
Panel A: Descriptive statistics											
Average BMI, %	15.4	10.1	15.2	17.1	15.5	19.6	16.4	17.3	16.6	16.8	17.1
St. dev. of BMI, %	8.9	5.1	5.8	9.3	10.7	6.7	7.2	8.1	7.6	7.9	7.7
Minimum BMI, %	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Maximum BMI, %	120.4	61.4	57.4	98.7	120.4	120.4	120.4	108.2	120.4	98.7	120.4
Average no. of benchmarks	9.0	7.5	9.0	8.3	10.0	9.7	11.0	9.4	11.4	10.5	10.6
Panel B: Average contribution of indices, %:											
- S&P 500	8.4	9.6	9.6	9.7	6.3	53.5	26.1	0.2	17.8	9.5	8.3
- S&P 400	2.0	0.0	2.0	2.8	1.8	0.0	4.7	0.7	5.9	2.2	1.9
- Russell 1000	8.6	12.2	9.2	7.5	7.8	21.8	26.6	0.1	26.1	9.7	8.2
- Russell Midcap	7.4	6.6	8.1	9.2	5.8	12.6	23.1	0.1	28.7	7.4	8.2
- Russell 2000	50.5	49.1	53.0	56.3	44.4	0.7	0.4	78.9	0.6	52.8	52.5
- Russell 2500	8.5	11.6	10.6	8.8	5.7	1.2	6.2	10.2	7.8	7.7	10.3
- Russell 3000	6.1	10.9	7.5	5.9	3.8	6.0	7.4	5.9	7.2	6.4	6.5
- CRSP Large and Mid	0.4	0.0	0.0	0.0	1.2	1.6	1.3	0.0	1.5	0.4	0.4
- CRSP Small	1.5	0.0	0.0	0.0	4.4	0.1	1.6	1.6	2.0	1.6	1.5
- CRSP Total	6.6	0.0	0.0	0.0	18.9	2.4	2.6	2.3	2.5	2.4	2.3
Panel C: Average contribution of styles, %:											
- blend	48.6	37.1	42.3	49.0	56.7	63.2	45.7	46.6	40.4	47.9	44.3
- value	25.3	25.3	25.1	27.3	23.5	20.7	28.0	25.7	30.9	38.8	11.9
- growth	26.1	38.6	32.5	23.7	19.8	16.1	26.4	27.7	28.7	13.3	43.9
Panel D: Average contribution of fund types, %:											
- active	82.9	96.5	93.4	89.9	65.0	80.4	83.3	88.3	84.3	86.3	87.3
- passive (index and ETFs)	17.1	3.5	6.6	10.1	35.0	20.0	16.7	11.7	15.7	13.7	12.7

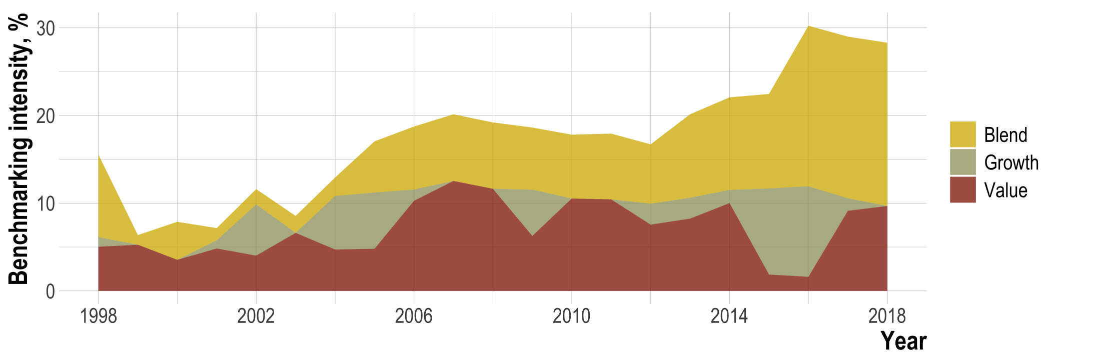
This table reports the descriptive statistics for benchmarking intensity. Columns 'By time period' show statistics for the respective period. Columns 'By benchmark' show statistics for stocks that belong to the respective benchmark. BMI statistics (average, standard deviation, minimum, and maximum) are in percentage points. Contribution is in percentage points. Contribution of indices is the average of the ratios of BMI coming from the AUM benchmarked to an index to the total BMI of the stock. Contribution of indices is across index styles, e.g., line for the Russell 1000 includes blend, value, and growth. Average number of benchmarks is for a stock. Averages are simple arithmetic means across stock-years.

Figure 2: Decomposition of the Benchmarking Intensity of Foot Locker Inc.

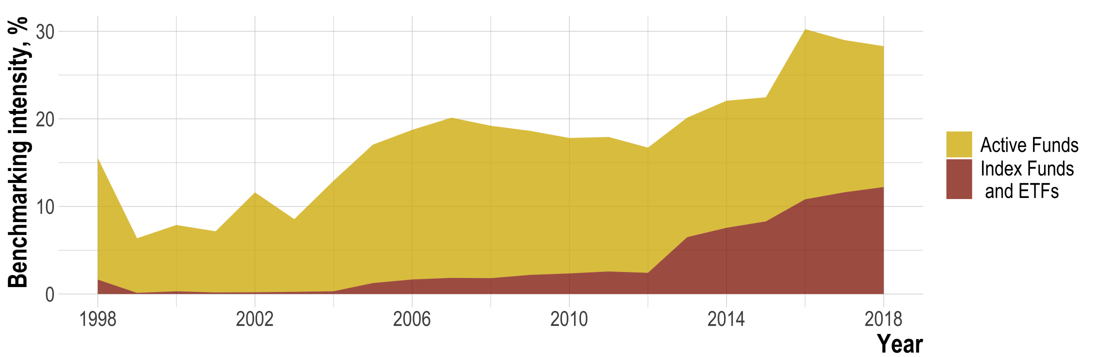
(a) Index Group



(b) Index Style



(c) Fund Type



These figures plot the evolution of each component of the benchmarking intensity of Foot Locker Inc. stock over time. Figure (a) plots index groups, each including blend, value, and growth indices. Figure (b) plots Russell and CRSP style components. Figure (c) plots the contribution of active and passive funds.

3.3 Benchmarking Intensity and the Price Elasticity of Demand

In this section, we explore the relationship between the benchmarking intensity, the size of the index effect, and demand elasticities. We exploit the cutoff between the Russell 1000 and 2000 indices, which separates stocks that are very similar in size and other characteristics but differ significantly in terms of their benchmarking intensities.

3.3.1 The Russell Index Cutoff

The Russell indices undergo an annual reconstitution every June. All eligible stocks get ranked based on their market cap value, and the top 1000 stocks get assigned to Russell 1000. The ranking is based on a fixed date in May so any shock to a stock next to the cutoff can send it to one or the other side.[21] Figure 3 (a) plots index weights of stocks on the rank day (May 31^{st}) in 2006. All stocks to the right of 1000^{th} rank cutoff in May are assigned to the Russell 2000 in June. To the left of the cutoff, stocks will have smaller index weights because they are the smallest constituents of the value-weighted Russell 1000 index. Similarly, to the right of the cutoff are the largest stocks of the Russell 2000 index, so their weight is high.

It is important to note that it is not the discontinuity in index weights at the Russell cutoff that drives the variation in our benchmarking intensity measure.[22] The averaged benchmarking intensity plotted in Panels (b) and (d) of Figure 3 also has a discontinuity around the Russell cutoff and it is larger for larger stocks. This pattern is, however, driven by stock membership in different indices as well as the variation in the ratio of AUM to Index MV. The latter is significantly larger to the right of the cutoff. Furthermore, larger stocks are more likely to be in the S&P 500 and S&P 400 indices, which makes the curves downward sloping.[23]

In contrast to the literature, which typically accounts only for the Russell 1000 (blend) and Russell 2000 (blend), we consider all nine Russell indices that contribute to the discontinuity at the cutoff. These indices include the Russell 1000 (blend, value, and growth) and Russell Midcap (blend, value, and growth) to the left of the cutoff and the Russell 2000 (blend, value, and growth) to the right of it.[24] Style funds (i.e., value and growth) have his-

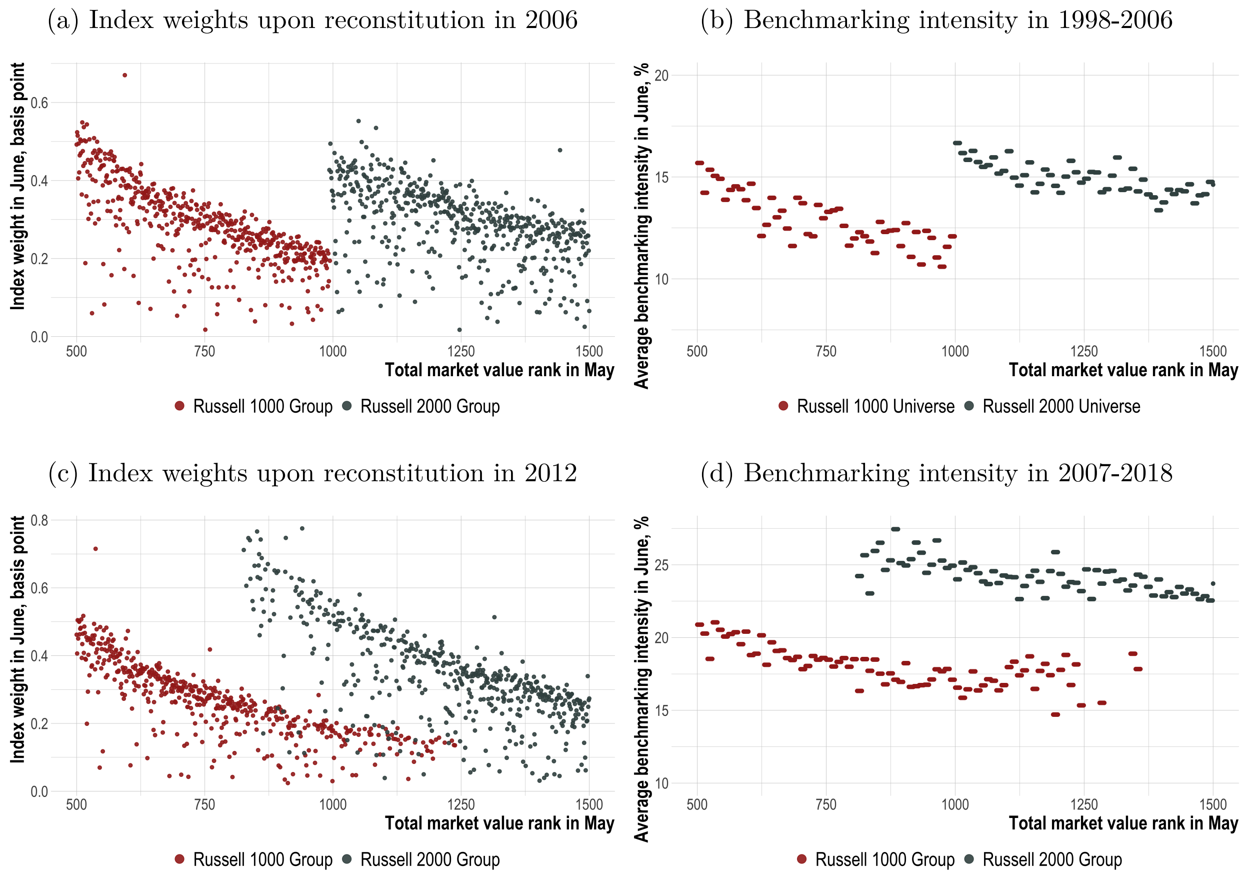
[21] Extensive details on the Russell reconstitution are reported in Section A.9 of the Appendix. The introduction of 'banding' policy is discussed therein.

[22] If BMI of a stock were scaled differently, e.g., using total benchmarked AUM instead of the stock's market value, it would pick up the variation in index weights too.

[23] Even though S&P 500 is designed to represent 500 largest companies, we see that it includes some of the Russell 2000 stocks in our sample because of the differences in the S&P and Russell index construction methodologies. All our results are robust to excluding changes in S&P and CRSP indices.

[24] This set does not include Russell indices that do not contribute to the discontinuity near the 1000/2000 cutoff. These are, for example, Russell 3000, Russell 2500, and Russell Small Cap Completeness. However,

Figure 3: Discontinuities in Index Weights and BMI before and after 2006



This figure plots index weights and benchmarking intensity against the total market value rank on the rank day in May. Index weights are a snapshot on the reconstitution date in 2006 (June 30^{th}) and 2012 (June 29^{th}). Benchmarking intensity is averaged for constituents of each index across bins of 10 stocks and over the relevant period. Russell 1000 Group includes the Russell 1000 and Russell Midcap (blend, value, and growth). Russell 2000 Group includes the Russell 2000 (blend, value, and growth).

torically had a larger market share on the Russell 1000 side of the cutoff, while blend funds have been more important on the Russell 2000 side. Moreover, we include funds benchmarked to the Russell Midcap – an index that spans stocks smaller than rank 200 within the Russell 1000. It assigns a higher weight to the stocks near the cutoff than the Russell 1000 index because it excludes its 200 largest constituents. The AUM of funds benchmarked to the Russell Midcap in our sample is almost as high as that of all Russell 2000 funds (Figure 5 and Table 10 in the Appendix).

Due to the updated reconstitution methodology, since 2007 there is a market value region in which both Russell 1000 and Russell 2000 stocks are present. Figure 3 (c) plots the index weights around the cutoffs on the rank day (May 31^{st}) in 2012. In that year, the band

all these indices are still accounted for in the BMI, they just do not contribute to the discontinuity.

is between ranks 823 and 1243. The discontinuity is still apparent: Russell 2000 stocks (in grey) have higher index weights. BMI mirrors the new pattern due to higher AUM/IndexMV ratio of the Russell 2000 indices: the curve for Russell 2000 stocks lies above that for the Russell 1000 (Figure 3 (d)).

What we exploit in most of our analysis is the increase in BMI for stocks added to the Russell 2000 or the decrease in BMI for stocks just deleted from it. We argue that this variation is exogenous in Section 3.3.4.

We use a local linear regression approach, i.e., our samples are restricted to the neighborhood of the cutoff (rectangular kernel). Our default bandwidth is 300 stocks around the cutoff and we report the robustness with respect to this choice for all our tests. For the period up to 2006, the cutoff rank around which we center the analysis is 1000. For each year starting from 2007, we compute the left and right cutoffs based on the Russell methodology.[25]

We also exclude stocks that move more than 500 ranks in one year. Our results are not sensitive to this filter but we prefer to keep it in place to ensure the comparability of stocks.

3.3.2 BMI and Index Effect

In this section, we show that a higher benchmarking intensity change leads to a larger price pressure (short-term return) upon an index inclusion event. This corresponds to Prediction 2 of our model. We first confirm the result in the literature that, on average, stocks added to the Russell 2000 index experience a positive return in June. Second, we present novel results suggesting that the size of the index effect is linked to the change of a stock's BMI in the cross-section.

Similarly to Chang, Hong, and Liskovich (2015), we see a positive return upon addition to the Russell 2000 and a negative return following deletion from it in our data.[26] Identification details and estimation results are presented in Table 12 in the Appendix.

Next, we show stocks with larger changes in BMI experience higher returns in June. We estimate the following specification:

$$Ret_{it}^{June} = \alpha \Delta BMI_{it} + \zeta logMV_{it} + \phi' BandingControls_{it} + \xi Float_{it} + \delta' \bar{X}_{it} + \mu_t + \varepsilon_{it}. \quad (7)$$

In this specification, Ret_{it}^{June} is the return of stock i in June of year t,[27] winsorized at

[25] Market value levels for the cutoffs we compute are reported in Table 7 in the Appendix, we almost fully match historical values reported by Russell on the website: https://www.ftserussell.com/research-insights/russell-reconstitution/market-capitalization-ranges.

[26] We get lower magnitudes due to using proprietary ranking variable and a different methodology.

[27] Consistent with Chang, Hong, and Liskovich (2015), June is the month when we expect the price pressure

1%. ΔBMI_{it} is the difference between the BMI of stock i in May of year t and its BMI in June of the same year. As we discuss later in Section 3.3.4, conditional on $logMV$, $BandingControls_{it}$ and $Float_{it}$ in May, the change in BMI due to the Russell reconstitution is exogenous. $logMV_{it}$ is the logarithm of total market value, the ranking variable as of May provided by Russell. BandingControls$_{it}$ include dummies for being in the band, being in the Russell 2000, and their interaction in May of year $t-1$. $Float_{it}$ is the Russell float factor, a proprietary liquidity measure affecting index weight. $\bar{X}$ is a vector consisting of: 5-year monthly rolling β^{CAPM} computed using CRSP total market value-weighted index and 1-year monthly rolling average bid-ask percentage spread. We include β^{CAPM} because, as implied by our model, it affects expected returns. We supplement the controls with bid-ask spread to account for any stale information in the float factor. μ_t are year fixed effects. In the baseline analysis, we perform this estimation for all stocks within 300 ranks around the cutoff.

Table 2: BMI change and return in June

	Return in June					ΔBMI, %
	(1)	(2)	(3)	(4)	(5)	(6)
ΔBMI	0.201***	0.271**	0.282**			
	(2.88)	(2.73)	(2.74)			
1(ΔBMI quartile 1)				-0.010***	-0.011***	-2.92
				(-3.36)	(-3.40)	
1(ΔBMI quartile 2)				-0.002	-0.005***	-0.31
				(-1.27)	(-3.02)	
1(ΔBMI quartile 3)				0.005***	0.004***	0.57
				(2.95)	(2.62)	
1(ΔBMI quartile 4)				0.006***	0.008**	4.08
				(2.43)	(2.54)	
Fixed effect	Year	Year	Stock & Year	N	N	
$\bar{X}$ controls	N	Y	Y	N	Y	
Observations	16,405	15,135	14,549	16,405	15,135	
Adj. R^2, %	15.6	16.5	19.2	1.1	1.5	

This table reports the results of estimating equation (7) for stocks in the full sample (1998-2018). The dependent variable is the winsorized return of stock i in June in year t (in columns (1)-(3) and demeaned by year in (4)-(5)). The independent variable is ΔBMI_{it}, the change in the BMI of stock i between June and May of year t, or the dummies for its quartiles. All regressions include $logMV$ (the logarithm of proprietary total market value), $Float$ (proprietary float factor), $BandingControls$ (being in the band, being in the Russell 2000 and their interaction in May). Columns (2), (3) and (5) include controls in $\bar{X}$ (β^{CAPM} and bid-ask spread). All controls are demeaned by year in columns (4)-(5). The constant is excluded. Band width is 300 around both cutoffs. The last column reports the mean percentage ΔBMI_{it} in each quartile. t-statistics based on standard errors double-clustered by stock and year are in parentheses. Significance levels are marked as: *p<0.10; **p<0.05; ***p<0.01.

due to the Russell reconstitution. In Section 3.3.4, we also consider quarterly return, for April-June.

Estimation results are presented in Table 2. Consistent with our model's Prediction 2, price pressure is the highest for stocks experiencing the largest increase in BMI, all else equal. Specifically, a 1% increase in BMI leads to a 27bps higher return in June. To better understand the magnitudes, we report the estimates of price pressure in quartiles of BMI change. A stock in the top quartile has an 80bps higher return in June relative to an average stock in that year, while a stock in the bottom quartile has a 110bps lower return. These magnitudes are consistent with the average index effect size we get with a dummy approach in Table 12 in the Appendix. The results are robust to alternative specifications and band widths[28] as well as using a deflated version of the change in BMI.[29]

Therefore, in contrast with the existing literature which looks at the average index effect for stocks added to the index or deleted from it, our analysis suggests that the size of index effect is proportional to the stock's BMI change.[30] It is a natural result because, as we show in the following section, the change in BMI, in fact, allows us to compute the price elasticity of demand.

3.3.3 Implications for the Price Elasticity of Demand

Our heterogeneous benchmarks model has nontrivial implications for the stock price elasticity of demand. Even though this parameter enters many macroeconomic models, the literature offers a rather wide range of its estimates (e.g., Wurgler and Zhuravskaya (2002)) and sometimes focuses on the demand curves of different groups of investors. Importantly, previous research has studied single stock demand curves using only one benchmark (starting from Shleifer (1986)) and, in most cases, assumed that only passive managers (index funds and ETFs) have inelastic demand.

For the experiment below, consider a one-stock version of our model ($N = 1$). Additionally, to fix ideas, we separate fund managers into active and passive ones, as in foot-

[28] Column (1) in Table 2 only includes controls specific to the Russell index membership ($logMV$ and banding controls). Column (3) adds stock fixed effects. Estimates for narrower bands are presented in Table 13 in the Appendix. In unreported analysis, we ran the regression with terciles and quintiles of BMI change instead of quartiles and the results are similar.

[29] As discussed above, prices do not enter BMI. However, to alleviate any concern about the mechanical relationship between returns in June and change in BMI, we report the estimates of (7) using deflated change in BMI in Table 14 in the Appendix. Specifically, deflated BMI is computed using index composition in June but with May prices; that is, it accounts for the new index membership of stock i but not its return in June. Estimates are not significantly different from those in Table 2.

[30] Greenwood (2005) and Wurgler and Zhuravskaya (2002) perform a cross-sectional analysis for one benchmark and show that arbitrage risk is positively associated with the index effect for Nikkei 225 and S&P 500 stocks, respectively. Motivated by their work, we explore implications of arbitrage risk, as proxied by stock idiosyncratic volatility or short interest, for our results. We also find that the larger the arbitrage risk, the higher the index effect. Controlling for either of these proxies does not change the economic or statistical importance of BMI.

note 12.

Most of the existing literature implicitly assumes that active investor demand (corresponding to benchmarked active managers and direct investors in our model) is fully elastic. If it is the case, the change in passive investor demand due to index reconstitution can be used as a shock to the supply of shares available to the rest of the market (effective supply). This is illustrated in Figure 4 (a). When the passive investor demand increases, the effective supply reduces from $\tilde{\theta}_0$ to $\tilde{\theta}_1$, and the new equilibrium price is higher, $S_1 > S_0$. Using the change in passive benchmarked assets that corresponds to $\tilde{\theta}_1 - \tilde{\theta}_0$ and the size of the index effect, i.e., $(S_1 - S_0)/S_0$, allows us to measure the price elasticity of demand of the rest of the market, typically computed as $(\tilde{\theta}_1 - \tilde{\theta}_0)/(S_1 - S_0) \times S_0/\tilde{\theta}_0$. We refer to the demand of the rest of the market as residual demand.

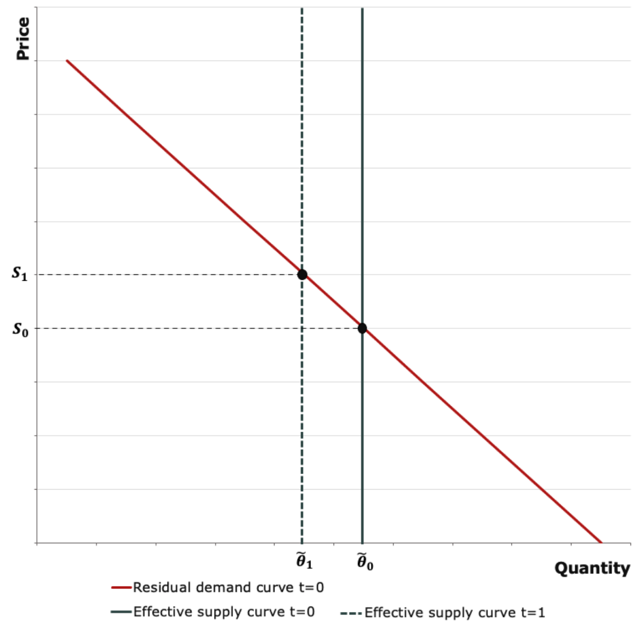
In our model, however, the standard approach will not recover the price elasticity of demand. The demand of passive managers benchmarked to index j for any particular stock is fully inelastic: $\theta_j^P = \omega_j$. Then, the effective supply of shares available to benchmarked active managers and direct investors is $\tilde{\theta} = \bar{\theta} - \sum_j \lambda_j^P \omega_j$. Due to benchmarking, the aggregate demand function of benchmarked active managers and direct investors features an inelastic component, the last term in the equation below.

$$\Theta^{Active+Direct} = \frac{1}{\gamma} A^{-1} \Sigma^{-1} (\bar{D} - S) + \frac{b}{a+b} \sum_j \lambda_j^A \omega_j.$$

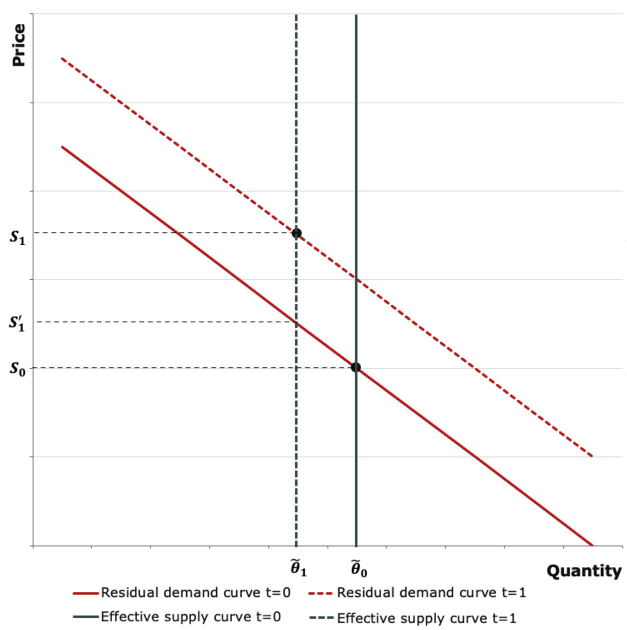
This equation as a function of S represents the demand curve in Figure 4 (b). With benchmarking, an index inclusion event will not only trigger a parallel shift in effective supply to the right but also an upward parallel shift in residual demand. As illustrated in Figure 4 (b), the observed price pressure will be $(S_1 - S_0)/S_0$, not $(S_1' - S_0)/S_0$. If we use the former price pressure with the change in passive demand to compute elasticities, we will conclude that the residual demand curve is steeper than it actually is. Therefore, if the world is close to our model economy, using the benchmarked passive asset change and the observed price pressure does not deliver the correct estimate of the price elasticity of demand. As shown in Section 4, active managers indeed have inelastic demand for stocks in their benchmarks and constitute, on average, 80% of asset managers in our sample.

Figure 4: Demand Curves and Index Effect

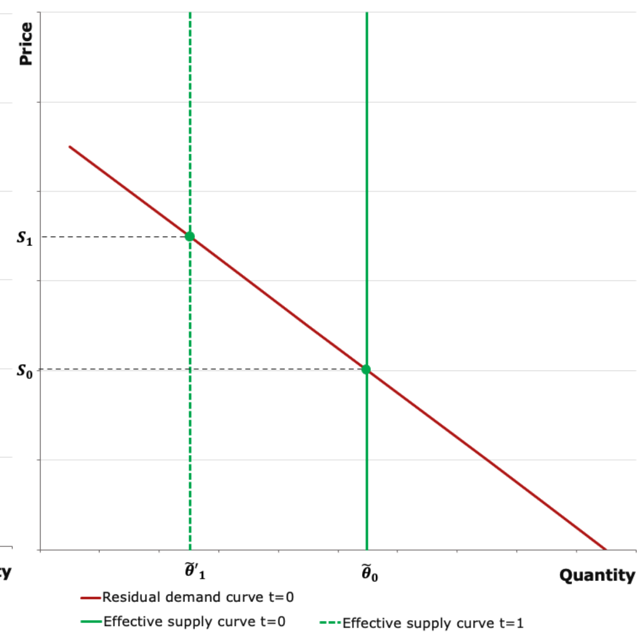
(a) Only passive demand is inelastic



(b) Inelastic component in active demand



(c) Using BMI to shift effective supply



This figure illustrates index reconstitution implications when (a) only passive investors' demand reacts inelastically, (b) active investors also have inelastic component in demand function, and (c) when BMI change is used to shift effective supply. Effective supply in (a) and (b) is the total supply of shares, $\bar{\theta}$, minus the holdings of passive managers. In (c), it additionally excludes the inelastic component of holdings of active managers. Residual demand is the total demand of the rest of the market, i.e., (elastic) active managers and direct investors.

What is the appropriate way to compute elasticity? One could separate elastic and inelastic components of active managers' demand and subtract the latter from the effective supply: $\tilde{\theta}' = \bar{\theta} - \left[\sum_j \lambda_j^P \omega_j + \frac{b}{a+b} \sum_j \lambda_j^A \omega_j\right]$. But in the data, we normally do not observe these components individually. In our model, however, BMI is exactly $\sum_{j=1}^{J} \left[\lambda_j^P \omega_j + \frac{b}{a+b} \lambda_j^A \omega_j\right]$. In other words, the change in BMI due to an index reconstitution event directly measures the shift in effective supply resulting from the inelastic response of both passive and active managers.[31] This is illustrated in Figure 4 (c). The difference between the solid green and dashed green lines is the total change of effective supply due to the inelastic demand of both active and passive managers. Since this change in BMI is observable, it allows us to trace the correct slope of the residual (elastic) demand function.

The BMI-based estimate of elasticity can be derived from Table 2. Since $Ret^{June}/\Delta BMI = 0.27$, the corresponding price elasticity of demand is $-1/0.27 = -3.7$. This estimate is an upper bound for elasticity because our calculation of BMI is based on $\frac{b}{a+b} = 1$.[32] Our estimates are regression-based, we also compare them with those computed in Chang, Hong, and Liskovich (2015) in Appendix A.18, which are based on averages.

Importantly, the heterogeneity of benchmarks has significant quantitative implications for the measures of elasticity relative to a single-benchmark case. Appendix A.18 shows that the BMI change is the same as the change in total benchmarked assets used by Chang, Hong, and Liskovich (2015) only if a stock does not enter any benchmark other than the Russell 1000 and 2000 and if all its shares are floated. The literature has not considered the demand that stems from such large indices as the Russell 1000 Growth and Russell Midcap,[33] and hence the change in demand is typically mismeasured. As shown in Table 17 in the Appendix, accounting for all benchmarks in the same sample and with the same price

[31] Data on manager compensation are generally not available. The only estimate of $\frac{b}{a+b}$ in the literature is provided in Ibert, Kaniel, Nieuwerburgh, and Vestman (2018) on Swedish data, which exhibits structural differences to the US. We assume that $\frac{b}{a+b} = 1$ in our main results but also provide a sensitivity analysis to this ratio.

[32] This implies that active managers are strongly concerned about relative performance and the sensitivity of their compensation to absolute performance, a, is small. If a is higher, the inelastic component constitutes a smaller fraction of their demand for risky stocks. Therefore, they contribute less to the overall inelastic demand in the economy. In the language used in this section, it means that the shift in effective supply of a stock due to an index inclusion is smaller. In our calculation, the corresponding change in the stock's price is fixed, as estimated in the data. Hence, the same change in price is associated with a smaller change in demand, resulting in lower elasticity of residual (elastic) demand. For example, for $\frac{b}{a+b} = 0.5$ and $\frac{b}{a+b} = 0.8$, the price elasticity of the residual demand would be -2.06 and -2.92, respectively. If the shift in the dashed green line in Figure 4 (c) is smaller, the residual demand curve (red line) must be steeper to result in the same (observed) price change.

[33] Benchmarked assets of the Russell indices are shown in Table 10. Russell Value and Growth indices are even larger than blend indexes in terms of the assets benchmarked to them. Moreover, since the Russell Midcap represents the smallest 800 stocks in the Russell 1000, the stock would exit it too. The size of the investor base of the Russell Midcap is just as large as that for the Russell 2000. It is therefore surprising that most of the literature studying the Russell cutoff has not taken all these indices into account.

pressure estimate as in Chang, Hong, and Liskovich, we obtain elasticity of -1.02 (30% less elastic than -1.46 in their paper).

Our estimates of the price elasticity of demand in this section should be viewed as an upper bound for two reasons. First, as explained above, our baseline calculation of the change in BMI assumes the strongest benchmarking incentives for active funds, i.e., we use $\frac{b}{a+b} = 1$. For any other $\frac{b}{a+b} \in (0, 1)$, the change in BMI is lower and, therefore, elasticity is lower as well. Second, not all of the changes in stocks' BMI, a theoretical measure, translate into changes in actual ownership of mutual funds. In practice, mutual funds incur transaction costs, which often prevent them from trading as our frictionless model would predict. In the section that follows, we provide estimates of the actual price impact, using ΔBMI as an instrument for stock ownership.

3.3.4 BMI as an IV

In this section, we estimate price impact of benchmarked investors' trades by examining directly how changes in their ownership of a stock affect the stock's price. Of course, as our theory illustrates, stock ownership and prices are jointly determined in equilibrium. In this section, we address this identification challenge with an instrumental variable approach. We propose to use changes in BMI—a measure of inelastic demand that a stock attracts—as an *instrument* for changes in institutional ownership.[34] Changes in BMI should therefore predict how benchmarked investors rebalance their portfolios in response to a Russell index reconstitution (relevance condition). Intuitively, a change in BMI acts as a shock to the effective supply of a stock.

Our best proxy for the total ownership of a stock i at time t by benchmarked investors is institutional ownership, available from the Thomson Reuters Institutional Holdings (13F) Database, which reports total institutional holdings. Institutional ownership is defined as

$$IO_{it} = \frac{\sum_{j=1}^{\bar{J}} \lambda_{jt} \theta_{ijt}}{MV_{it}}, \tag{8}$$

where θ_{ijt} denotes the actual weight of stock i held by institutional investor j and $\bar{J}$ is the total number of institutional owners. The definition in (8) mirrors that of our BMI (equation (5)), except that it has actual portfolio weights θ_{ijt} as opposed to benchmark index portfolio weights ω_{ijt}. We acknowledge that IO_{it} also contains holdings of non-benchmarked institutional investors, but as long as our instrument is sufficiently strong, this should not pose a problem for our estimation.

[34]We thank Moto Yogo for this insight, which has inspired this section.

We would like to estimate the following structural equation:

$$Ret_{it}^{June} = \alpha \Delta IO_{it} + \epsilon_{it}, \tag{9}$$

where Ret_{it}^{June} is stock i's return in June of year t, winsorized at 1%, and ΔIO_{it} is the change in institutional ownership measured from March until June of year t.

The problem with estimating equation (9) by OLS is that the change in institutional ownership ΔIO is an equilibrium object and hence is endogenous. We therefore expect the OLS estimate of α to be biased. To overcome this problem, we use an instrumental variable approach. Specifically, we use ΔBMI as an instrument for the change in effective supply of the stock. The main threat to this identification strategy is the presence of the index membership dummy in the expression for BMI (6), because index membership is potentially endogenous. However, there is a large literature that uses membership in the Russell 2000 index as an instrument for institutional ownership in a similar setting (e.g., Crane, Michenaud, and Weston (2016) and Glossner (2021)).[35] This literature argues that, after controlling for factors that determine index inclusion, most importantly for the ranking variable ($logMV$) that Russell uses for index assignment at the end of May, the index membership dummy is exogenous. In Section 3.2, we have also acknowledged our concern that a change in stocks' liquidity could be a potential source of endogeneity of ΔBMI (due to stocks' float factors entering the expression for BMI), and to address that concern we control for the Russell proprietary stock-level float factor as of May. Finally, Appel, Gormley, and Keim (2019) advocate including banding controls, and we do so in our specification.[36]

Armed with the instrument and a set of controls, we perform the following two-stage least squares estimation. The first-stage regression is

$$\Delta IO_{it} = \alpha_1 \Delta BMI_{it} + \zeta_1 logMV_{it} + \phi_1' BandingControls_{it} + \xi_1 Float_{it} + \delta_1' \bar{X}_{it} + \mu_{1t} + \varepsilon_{it}. \tag{10}$$

The second stage is

$$Ret_{it}^{June} = \alpha \widehat{\Delta IO}_{it} + \zeta logMV_{it} + \phi' BandingControls_{it} + \xi Float_{it} + \delta' \bar{X}_{it} + \mu_{2t} + \eta_{it}. \tag{11}$$

$logMV_{it}$ is the logarithm of total market value, the ranking variable as of May provided by Russell, $Float_{it}$ is the Russell float factor, μ_{1t} and μ_{2t} are year fixed effects, and $\bar{X}_{it}$

[35] The consensus in this literature is that Russell 2000 membership dummy is a weak instrument for institutional ownership, which we confirm below.

[36] There is one cutoff, at rank 1000, before 2007, and two cutoffs afterwards. We explain this in detail in Section 3.3 above.

and $BandingControls_{it}$ are the vectors of controls, as specified before. We perform the estimation in the neighborhood of 300 ranks around the cutoffs. By estimating this model, we aim to uncover the price impact of the actual change in institutional ownership, which is typically different from what is predicted based on ΔBMI_{it}. In reality, institutional investors do not hold all stocks in their benchmarks due to, for example, trading costs, from which our model abstracts.

The reason why we are reluctant to use mutual fund ownership instead of institutional ownership in (10) is that a change in BMI due to index reconstitution should affect all benchmarked institutional investors (e.g., pension funds), not only mutual funds, and therefore the exclusion restriction that ΔBMI affects the outcome variable only through changes in mutual fund ownership is potentially violated.

To further alleviate concerns about the possible endogeneity of ΔBMI, we conduct overidentifying restrictions tests. Specifically, we use two instruments in the first-stage regression (10): ΔBMI and D^{R2000}, with the latter being the index membership dummy used as an instrument for institutional ownership changes in the related literature cited above. Since with two instruments our model is overidentified, we can implement the Hansen J test. If the model with two instruments passes the J test, we can view this as statistical evidence that ΔBMI is (conditionally) exogenous.

Table 3 reports our results. First, it is clear that the OLS estimate of the effect of the change in institutional ownership on stock returns is biased. We therefore focus on the 2SLS estimates. The reported F-statistics indicate that the first stage specifications with one (ΔBMI) and two instruments (ΔBMI and D^{R2000}) are both strong. The reason for the higher t-statistic on ΔBMI relative to that on the dummy is that the former offers continuous treatment, while the dummy is a coarse binary variable. Consistent with this observation, the F-statistic of the first-stage regression, in which we include only the index membership dummy D^{R2000} and not ΔBMI, is lower than the conventional value of 10.[37] Although it is a coarse instrument, the index membership is conditionally exogenous and hence we are able to run the test of overidentifying restrictions to determine whether ΔBMI is a valid instrument. With a p-value of 52%, the Hansen J test cannot reject the null that that both of instruments are exogenous (conditional on $logMV$ and other controls).

The estimates of the price impact in the specifications with one and two instruments are essentially the same, given by 1.47.[38] It is instructive to compare our estimates to those in the related literature. Recent papers using the demand system approach to asset pricing, proposed in Koijen and Yogo (2019), estimate price impact at an investor group

[37] See Stock and Yogo (2002) for details.

[38] Our estimates are similar for a narrower band width. We report them in Table 15 in the Appendix.

level. Koijen and Yogo document that the aggregate price impact varies over the business cycle and ranges from 2 to 4. Our estimates, obtained via a different method, are within their confidence intervals. One potential argument for why the point estimate is lower is that we are performing our estimation in a small neighborhood around the Russell 1000/2000 cutoff, and stocks close to this cutoff are more substitutable in investor portfolios than large stocks like Apple and Microsoft. Another possible argument is that demand of the remaining investors in the market, primarily households and some hedge funds, which in our model are represented by direct investors, is quite elastic because they do not face institutional constraints or compensation contracts that introduce inelastic elements in their demand functions.[39]

Table 3: Change in BMI as an instrument for change in institutional ownership

	Return in June, %				**Return in April-June, %**
	OLS			2SLS	
	(1)	(2)	(3)	(4)	(5)
Panel A: Second-stage estimates					
ΔIO, %	0.09***	2.26	1.46**	1.47**	1.76***
	(3.84)	(1.43)	(2.55)	(2.57)	(2.86)
Panel B: First-stage estimates					
ΔBMI, %			0.20***	0.19***	0.23***
			(5.90)	(6.34)	(7.18)
D^{R2000}		0.84***	-0.15		
		(2.79)	(-0.54)		
F-Stat (excl. instruments)		7.81	20.07	40.20	51.56
Hansen J test, p-value			0.52		
Controls	Y	Y	Y	Y	N
Observations	12,833	12,833	12,862	12,862	13,749

This table reports α_1 and α from estimating (10) and (11), respectively, in the full sample period (1998-2018). Band width is 300 stocks around the cutoffs. The dependent variable is return in June. ΔIO the change in total institutional ownership of stock i from March to June in year t. Specifications in (1)-(4) include $logMV$ (the logarithm of proprietary total market value), $Float$ (proprietary float factor), $BandingControls$ (being in the band, being in the Russell 2000 and their interaction in May), $\bar{X}$ (β^{CAPM} and bid-ask spread), and year fixed effects. Specification in (5) includes year fixed effects only. In parenthesis are t-statistics based on standard errors double-clustered by stock and year. Significance levels are marked as: *p<0.10; **p<0.05; ***p<0.01.

[39] If we estimate specification (10)–(11) using changes in mutual fund ownership as opposed to changes in institutional ownership, we get a higher estimate of price impact, around 2.6. However, this estimate should be treated with caution because it attributes all of the price impact to mutual funds, while some of it may come from other benchmarked institutional investors, such as pension funds, etc.

The implied price elasticity of the residual demand—the demand of all remaining investors in the market (except institutional investors)—is the reciprocal of price impact, which is 0.7. This is significantly lower than our upper-bound estimate of 3.7 based on the price impact we estimate in Table 2, which reflects both that $\frac{b}{a+b}$ must be less than 1 and other considerations missing from our model, such as trading costs.

One drawback of the above approach to estimating price impact is that 13F institutional ownership is not observed at a monthly frequency, and so the periods over which we measure returns and changes in ownership are not perfectly aligned. An advantage is that this variable accounts for any rebalancing in anticipation of changes in BMI, but for the purposes of measuring price impact, we would have liked to use the change in ownership in June. For robustness, we also run a specification, in which as a dependent variable we use stock return from April to June, that is, for the same period as the change in ownership. In this specification, however, we cannot use our proprietary controls as they already reflect returns in April and May, and so we drop them. We report the estimated price impact in Table 3, column (5), and it is close to our main estimate in column (4).

Some of the discrepancy between the ownership predicted by BMI and the actual ownership is driven by so-called optimized sampling. Optimized sampling is a portfolio construction technique in which ex ante tracking error is balanced with expected transaction costs.[40] It directly interferes with the incentives to hold the benchmark portfolio. In the presence of transaction costs, funds no longer hold benchmark securities proportionally to benchmark weights. Rather, they typically hold the largest stocks with benchmark weights, completely omit the smallest and some mid-range stocks, and overweigh most of the mid-range stocks (see the illustrations in Figures 6 and 7 in the Appendix).

Optimized sampling might have implications for rebalancing around the Russell cutoff. With the introduction of banding in 2007, the incentives to hold stocks around the cutoffs might have changed. When a stock gets added to the Russell 1000 (and therefore to Russell Midcap), it has a rank of around 800, while the ranks of existing index constituents range up to 1300. This addition now contributes to funds' tracking errors significantly more than smaller stocks at the bottom of the index and it is not as expensive to trade. In other words, funds benchmarked to the Russell 1000 and Russell Midcap are now more likely to purchase this addition. At the same time, additions to the Russell 2000 obtain a rank of around 1300. Because the existing constituents now have ranks starting from 800, the contribution of these additions to funds' tracking errors is, on average, lower compared to the pre-banding period.

[40] In practice, transaction costs are an important consideration. Not buying an asset in the benchmark saves on transaction costs but increases the manager's tracking error relative to the benchmark. Optimized sampling addresses this trade-off.

Even though passive funds benchmarked to the Russell 2000 would still trade these stocks, active funds are less likely to do so. These different incentives correspond to a smaller change in the size of inelastic demand for additions and deletions compared to what BMI predicts and, therefore, could contribute to the performance of BMI in our tests after 2007.[41]

In the following section, we discuss the existing evidence of inelastic demand of active benchmarked managers and provide new results on our granular benchmark data.

4 Benchmarking Intensity and Mutual Fund Ownership

Starting from Gompers and Metrick (2001), empirical literature documented a range of effects of institutional trading and ownership on stock prices. A recent strand of literature looks into the effects of ownership on corporate outcomes. There has been little research, however, on benchmarking-induced ownership.

Benchmarking intensity reflects the incentives elicited by the contracts of asset managers, both active and passive. In this section, we show that both investor types have a considerable fraction of holdings concentrated in their benchmarks and that they rebalance stocks relevant for *their* benchmarks around the Russell cutoffs. That is, we document a heterogeneity of investor habitats dictated by their benchmarks, reflecting their inelastic demand for stocks in these benchmarks.

4.1 Net Purchases of Index Additions and Deletions

Earlier studies documented that ~~Russell~~ index funds and ETFs buy additions to and sell deletions from their benchmarks. We argue that this list is incomplete and that active managers engage in the same behavior but detecting it requires granular data on their benchmarks.

In order to see which funds rebalance additions and deletions, we estimate the fol-

[41] The change of benchmarking incentives after 2007 provides an alternative explanation to the reduction in the size of the index effect over time, documented in Chang, Hong, and Liskovich (2015). The authors hypothesize that the alleviation of limits to arbitrage over time made demand curves more elastic. We provide a different explanation: the introduction of banding made funds benchmarked to the Russell 1000 and Russell Midcap participate in index rebalancing almost at par with Russell 2000 funds. For example, the stocks that are being deleted from the Russell 2000 and experiencing selling pressure from Russell 2000 funds will also experience relatively higher buying pressure from Russell 1000/Midcap funds. In other words, the price pressure from buying and selling evens out. We provide evidence in support of our explanation in Section 4.

lowing equations at a stock level, which in changes is:

$$\Delta Own_{ijt} = \alpha_{1j} D_{it}^{R1000 \rightarrow R2000} + \alpha_{2j} D_{it}^{R2000 \rightarrow R1000} + \zeta_j logMV_{it} + \xi_j Float_{it} + \delta_j' \bar{X}_{it} + \mu_{jt} + \epsilon_{ijt}, \tag{12}$$

and in levels is:

$$Own_{ijt} = \alpha_j D_{it}^{R2000} + \psi_j Own_{ijt-1} + \zeta_j logMV_{it} + \phi_j' BandingControls_{it} + \xi_j Float_{it} + \delta_j' \bar{X}_{it} + \mu_{jt} + \epsilon_{ijt}. \tag{13}$$

In the above equations, $D_{it}^{R1000 \rightarrow R2000}$ is 1 when stock i is moved from the Russell 1000 to Russell 2000 on the reconstitution day in June of year t. Likewise, $D_{it}^{R2000 \rightarrow R1000}$ is 1 when the stock is moved from the Russell 2000 to Russell 1000. D_{it}^{R2000} is 1 when stock i belongs to the Russell 2000 on the reconstitution day in June of year t. ΔOwn_{ijt} is the change in the fraction of shares outstanding of stock i owned by all funds with benchmark j aggregated into a single portfolio from March to September of year t. We further split them by type (active/passive), e.g., active funds benchmarked to the Russell 1000 index. Own_{ijt} and Own_{ijt-1} are measured in September and March of year t, respectively. We perform our analysis on the changes in ownership from March to September because it is based on quarterly filings and it is in line with most of the previous studies (e.g., Appel, Gormley, and Keim (2016)). Because changes in the ownership share are more difficult to detect for fund groups with smaller AUM, we also report the results for extensive margin, with the trade dummy used as a dependent variable. Own_{ijt} is the same in levels: fraction of shares outstanding owned or a dummy for whether the aggregate fund portfolio benchmarked to index j owns it or not. All other variables are defined as earlier.

Conditional on $logMV$, dummies $D^{R2000 \rightarrow R1000}$ and $D^{R1000 \rightarrow R2000}$ represent an exogenous change in index membership.[42] We confirmed that the results are equivalent to using a 2SLS estimator, with index membership instrumented with a prediction as of the rank date in May.[43] Hence, our results identify the effect of addition to or deletion from an index without a concern that an omitted variable might be driving both membership in the index and the change in ownership of funds benchmarked to that index.

We estimate equations 12 and 13 at a stock level for each aggregate portfolio of funds with the same benchmark and distinguish between active and passive funds. For example, we run a separate regression for the change in the ownership share of the active Russell 1000

[42] As argued, for example, in Schmidt and Fahlenbrach (2017). Similarly, conditional on $logMV$ and $BandingControls_{it}$, index membership dummy D^{R2000} is exogenous.

[43] We report the results of the prediction step in Table 11 in the Appendix.

funds. In this example, the interpretation of α_1 is the change in their ownership share due to the stock's addition to the Russell 2000 index (and its deletion from the Russell 1000 index group – i.e., the Russell 1000 blend, Russell Midcap blend, and their value and growth counterparts).[44]

Table 4 documents that both passive and active funds rebalance additions and deletions. We report the most conservative results with double-clustered standard errors. Consistent with the literature, we find highly significant stock ownership changes for passive funds in line with their benchmarks. For example, passive funds benchmarked to the Russell 2000 purchase 77bps of shares of stocks added to the Russell 2000. These funds also sell deleted stocks in similar proportions (84bps). At the same time, we see that active funds benchmarked to the Russell 2000 also sell deletions, decreasing their ownership share by 55bps. Another example is that active funds benchmarked to the Russell Midcap sell, on average, 26bps of deleted shares (from Russell 1000 and Midcap) and buy 39bps of the added ones. These magnitudes are large given the average ownership levels of aggregate portfolios of funds with the same benchmark.

On the extensive margin, the benchmark-driven rebalancing is even easier to detect. As Panel B of Table 4 reveals, active funds are likely to sell deletions from their benchmarks and buy additions. Panel D shows that all aggregate fund portfolios in our sample are more likely to hold stocks added to their benchmarks and less likely to hold the deleted stocks.

Our results are robust to alternative specifications, varying band widths and controlling for the polynomials of the ranking variable, $logMV$.[45]

Because the composition of active funds holding the added stock changes significantly, the incentives active managers to monitor this stock may change too. The new literature on passive ownership and corporate governance relies on continuity of active ownership around the Russell cutoff.[46] In Table 22 in the Appendix, we use the approach of Appel, Gormley, and Keim (2019) on our data. One cannot detect a discontinuity in the *total* ownership of active mutual funds. However, the discontinuities are apparent when active funds are split by benchmark.[47] This may affect corporate governance, casting doubt on the plausibility of the exclusion restriction in the growing number of studies on the effects of passive ownership. Our results highlight the importance of considering active funds' benchmarks when studying

[44] We explore even more granular rebalancing by style in Section A.24 in the Appendix.

[45] We report the results for a narrower band in Table 18 in the Appendix. We add stock fixed effects in Table 19 in the Appendix. Furthermore, Table 20 in the Appendix reports how the estimates change from 1998-2006 to 2007-2018.

[46] The list of papers includes but is not limited to: Appel, Gormley, and Keim (2019), Schmidt and Fahlenbrach (2017), and Appel, Gormley, and Keim (2016).

[47] Our findings do not contradict Appel, Gormley, and Keim: because of the sheer size of the Russell 2000 passive funds, the total passive ownership is higher for stocks to the right of the cutoff.

the implications of ownership changes around the Russell cutoff.

Table 4: Rebalancing of additions and deletions, by benchmark and fund type

	Change in the aggregate ownership of funds with the same benchmark					
	Stocks ranked < 1000				Stocks ranked > 1000	
Benchmark	Russell 1000		Russell Midcap		Russell 2000	
Fund type	Active	Passive	Active	Passive	Active	Passive
Panel A: Change in ownership share						
$D^{R2000 \to R1000}$	0.122***	0.105***	0.394***	0.113***	-0.546***	-0.840***
	(2.97)	(3.60)	(4.41)	(3.16)	(-4.95)	(-4.18)
$D^{R1000 \to R2000}$	-0.101**	-0.100***	-0.264***	-0.103***	0.123	0.771***
	(-2.22)	(-3.29)	(-3.69)	(-2.90)	(1.47)	(3.61)
Panel B: Change in holding status						
$D^{R2000 \to R1000}$	0.356***	0.459***	0.288***	0.437***	-0.319***	-0.921***
	(7.05)	(7.93)	(5.02)	(5.20)	(-7.13)	(-11.47)
$D^{R1000 \to R2000}$	-0.298***	-0.828***	-0.237***	-0.694***	0.113**	0.829***
	(-4.68)	(-5.84)	(-5.62)	(-4.27)	(2.39)	(6.87)
Panel C: Ownership share						
D^{R2000}	-0.032	-0.067**	-0.136**	-0.065*	0.267**	0.653***
	(-1.05)	(-2.42)	(-2.24)	(-1.90)	(2.50)	(3.01)
Panel D: Holding status						
D^{R2000}	-0.177***	-0.351***	-0.057***	-0.651***	0.002	0.613***
	(-8.91)	(-6.72)	(-4.92)	(-4.72)	(0.45)	(13.06)

This table reports α_{1j} and α_{2j} from estimating (12) (Panels A and B) and α_j from estimating (13) in the full sample period (1998-2018). Estimation is performed at a stock level for an aggregate portfolio of funds benchmarked to index j (active or passive). Band width is 300 stocks around the cutoffs. The dependent variable in panel A is the change in fraction of shares owned by the respective aggregate portfolio in stock i from March to September in year t. In panel B, it is the direction of the trade of the group (1 for buy, 0 for no trade, and -1 – for sell). In panel C, it is the ownership share in September. In panel D, it is a dummy that equals 1 if the stock is held by the aggregate portfolio in September and 0 if it is not. Regressions in both panel C and D additionally control for the value of the dependent variable in March and include *BandingControls* (being in the band, being in the Russell 2000 and their interaction in May). All regressions include *logMV* (the logarithm of proprietary total market value), *Float* (proprietary float factor), $\bar{X}$ (β^{CAPM} and bid-ask spread), and year fixed effects. In parenthesis are t-statistics based on standard errors double-clustered by stock and year. Significance levels are marked as: *p<0.10; **p<0.05; ***p<0.01.

Overall, results in this section suggest that, in line with our theory, Russell benchmarks serve as both active and passive funds' preferred habitats. In the next section, we argue that the same holds true for all important equity indices in the United States.

4.2 External Validity

As Robert Stambaugh points out in his AFA Presidential Address (Stambaugh (2014)), U.S. mutual funds' tracking errors have been going down. In our dataset, this trend is drastic. A simple average tracking error of active funds went down from 7% per annum in the early 2000s to below 4% in the 2010s. For passive funds, these numbers have been below 2% and closer to 0.5%, respectively. Given that the share of passive funds grew significantly over the past two decades,[48] the overall industry tracking error is at its historical low.[49]

Exploiting the granularity of our dataset, we characterize how close mutual funds portfolios and returns are to their benchmarks. We aggregate assets of all funds with the same benchmark and of the same type (active or passive) into one portfolio. Table 5 reports characteristics of the most important aggregate fund portfolios in our sample. We compute the percentage of portfolio AUM invested in its benchmark stocks and the number of benchmark stocks held. In 2018, the average is high at 75% and 77%, respectively, for active funds. Both figures are close to 100% for passive funds.[50]

While there is some heterogeneity in portfolios of active funds benchmarked to the same index, Table 5 shows that, on aggregate, they resemble their benchmarks. From 1998 to 2018, the active shares and tracking errors went down across indices,[51] on average decreasing from 65 to 51% and from 4.8 to 2.3%, respectively.[52] It is also reassuring to see that value-weighted individual funds' tracking errors also decreased from 8.4 to 4%. In line with our discussion of optimized sampling in Section 3.3.4, we see that the aggregate portfolio of funds with the same benchmark is more likely to include the largest 25 stocks in the index compared to the smallest stocks. It is particularly pronounced for active funds that hold all top-25 stocks and only 17 out of 25 smallest stocks on average.

Results in this section suggest that benchmarks define funds' preferred habitats.[53] Importantly, active funds look like preferred habitat investors as well. In line with our model, they hold a significant fraction of assets in benchmark stocks and rebalance additions to and deletions from their benchmarks.

[48] The assets of stock index mutual funds and ETFs now match that of active funds, according to: https://www.bloomberg.com/news/articles/2019-09-11/passive-u-s-equity-funds-eclipse-active-in-epic-industry-shift.

[49] Another prominent measure of fund activeness is active share, proposed by Cremers and Petajisto (2009). Funds' active share is also decreasing over time in our sample.

[50] With the exception of the Russell 3000 Value portfolio which is represented by one fund and smallest in size.

[51] The only exception is the active share of the S$P 400 portfolio, for which we only have derived index weights after 2002.

[52] Related literature often uses S&P 500 as a benchmark for all U.S. mutual funds to compute tracking errors instead of the actual fund benchmark. In unreported analysis, we see that the resulting tracking errors are several times larger than those using prospectus benchmarks.

[53] All our analysis is conditional on the benchmark in the manager's contract. Our model does not take a stand on how end investors pick the benchmark or fund to invest in. Possible rational explanations include the need to hedge endowment shocks of a particular type or to hedge displacement risk. Behavioral explanations include psychological foundations for why investors prefer growth over value, over-reaction, and extrapolation of past returns.

Table 5: Characteristics of the aggregate portfolios of mutual funds with the same benchmark

Benchmark index	Fraction of index stocks held, %	% of portfolio in index stocks	AUM, $ billion		Number of funds		Active share, %		Tracking error (fund average), %		Aggregate TE, %		No. top 25/ bottom 25 index stocks held
			1998	2018	1998	2018	1998	2018	1998	2018	1998	2018	
Panel A: Active funds													
Russell 1000	95.1	97.6	12.5	82.9	14	31	58.8	47.7	9.3	4.0	7.9	2.9	25/24
Russell 1000 Growth	91.5	89.8	224.5	352.9	97	121	40.1	34.2	7.4	4.0	3.9	2.3	25/24
Russell 1000 Value	94.0	84.2	179.2	416.6	87	131	44.5	36.0	5.5	2.9	2.6	1.3	25/24
Russell 2000	96.4	66.2	29.0	135.4	86	126	61.9	51.9	9.7	4.6	4.4	2.2	25/25
Russell 2000 Growth	86.7	47.7	27.4	93.7	63	86	62.6	61.0	9.3	5.4	4.1	3.6	25/21
Russell 2000 Value	98.9	58.9	13.9	92.3	40	88	70.3	52.9	7.3	3.6	2.9	1.8	25/24
Russell 2500	86.1	78.7	9.5	30.7	10	37	81.7	68.1	7.2	4.4	3.4	2.9	25/14
Russell 2500 Growth	65.6	73.7	15.0	51.5	15	22	82.1	53.6	9.8	4.7	4.6	2.6	25/11
Russell 2500 Value	60.3	70.5		16.4		19		68.7		3.5		2.3	25/14
Russell 3000	57.2	95.7	9.8	63.0	15	40	75.9	38.8	8.0	2.6	5.7	1.2	25/0
Russell 3000 Growth	29.7	86.5	60.2	101.9	22	29	65.7	46.0	9.0	4.8	7.0	3.6	25/2
Russell 3000 Value	26.1	84.0	55.6	57.6	11	31	77.3	49.1	5.1	3.2	3.5	1.7	25/0
Russell Midcap	73.2	80.4	8.3	64.1	25	36	70.6	56.6	9.6	4.3	5.7	2.1	25/13
Russell Midcap Growth	92.8	67.5	50.7	159.3	60	63	68.8	52.8	10.3	4.0	5.1	2.1	25/24
Russell Midcap Value	91.4	69.6	17.9	140.7	22	54	77.0	48.9	8.5	3.3	5.2	1.7	25/23
S&P 400	67.4	30.4	7.9	32.1	16	15	69.0	77.4	10.6	4.6	7.0	3.1	21/16
S&P 500	99.4	87.0	651.9	1,574.5	340	362	34.7	30.1	7.5	4.7	4.0	1.7	25/25
Mean/total	77.2	74.6	1,373.4	3,465.5	923.0	1,291.0	65.1	51.4	8.4	4.0	4.8	2.3	25/17
Panel B: Passive funds													
CRSP US Large	98.9	99.9		20.1		1		1.2		0.1		0.1	25/25
CRSP US Large Growth	99.9	100.0		80.6		1		0.2		0.1		0.0	25/25
CRSP US Large Value	98.1	99.9		67.3		1		2.1		0.1		0.1	25/25
CRSP US Mid	98.8	99.7		97.9		1		1.3		0.1		0.1	25/25
CRSP US Mid Growth	100.0	100.0		12.4		1		0.0		0.1		0.1	25/25
CRSP US Mid Value	97.9	99.5		18.0		1		2.5		0.2		0.2	25/25
CRSP US Small	99.3	100.0		90.7		1		0.7		0.1		0.1	25/25
CRSP US Small Growth	99.4	100.0		23.5		1		0.5		0.1		0.1	25/25
CRSP US Small Value	99.2	99.9		30.9		1		0.9		0.1		0.1	25/25
CRSP US Total	98.7	100.0		744.5		2		2.0		0.1		0.0	25/21
Russell 1000	99.0	99.7	1.2	37.1	1	14	36.6	6.7	4.6	0.4	4.5	0.2	25/24
Russell 1000 Growth	99.8	97.9		62.0		11		4.9		0.9		0.7	25/25
Russell 1000 Value	98.9	99.3		50.1		13		3.4		0.3		0.2	25/24
Russell 2000	99.1	99.4	1.0	59.5	5	18	11.7	2.7	2.3	0.4	1.7	0.2	25/25
Russell 2000 Growth	98.9	99.8		11.1		4		1.1		0.1		0.1	25/25
Russell 2000 Value	99.2	99.6		11.1		6		1.1		0.1		0.1	25/25
Russell 3000	98.9	99.9		13.2		9		4.4		0.7		0.5	25/25
Russell 3000 Value	27.1	88.3		3.9		1		31.4		1.1		1.1	23/0
Russell Midcap	98.9	99.5		19.7		5		3.0		0.2		0.1	25/24
Russell Midcap Growth	99.8	100.0		8.9		1		0.2		0.1		0.1	25/25
Russell Midcap Value	98.5	99.6		10.8		1		1.6		0.1		0.1	25/24
S&P 400	99.7	97.2		65.1		16		2.9		0.2		0.1	25/25
S&P 500	99.6	99.6	146.3	1019.1	46	83	1.1	4.1	0.4	0.2	0.2	0.1	25/25
Mean/total	94.9	98.8	148.6	2,261.3	52.0	187.0	16.5	4.2	2.4	0.3	2.1	0.2	25/24

This table shows characteristics of the aggregate portfolios of active (Panel A) and passive (Panel B) mutual funds and ETFs. Each portfolio is a value-weighted sum of funds benchmarked to the respective index. Active share is for the aggregate portfolio. Tracking error is value-weighted across constituent funds, annualized. Aggregtate TE is for the aggregate portfolio. AUM and number of funds are as of June 1998 or June 2018. The last column is as of June 2018. The rest of the values are averages for the respective year. Only aggregate portfolios larger than $1 billion in assets are shown. Active share for S&P 400 in 1998 column is for 2002, from when we have the index weights.

5 Benchmarking Intensity and Stock Risk Premium

In this section, we explore the prediction of our theory that stocks with higher benchmarking intensities have lower expected returns. In particular, we find that a stock that experiences a conditionally exogenous increase (decrease) in its BMI due to the Russell reconstitution has a lower (higher) return for one to five years. We argue that this is not driven by a negative return momentum and future changes in cash flows or liquidity.

5.1 BMI and Long-Run Returns

In this section, we show that a higher benchmarking intensity leads to lower returns in the long run. Specifically, stocks with a larger increase in BMI in year t significantly underperform up to year $t+5$.

Our goal is to test the negative relationship between benchmarking intensity and stock returns predicted by our theory. As explained in Section 3.3, the Russell cutoff provides a convenient setup because the change in BMI is conditionally exogenous.

As earlier, we employ a stock-level specification to estimate α:

$$Y_{i\,t+h} = \alpha \Delta BMI_{it} + \zeta logMV_{it} + \phi' BandingControls_{it} + \xi Float_{it} + \delta' \bar{X}_{it} + \mu_i + \mu_t + \varepsilon_{it} \tag{14}$$

In the above specification, the dependent variable, $Y_{i\,t+h}$, is an average long-run return of stock i from September of year t over the investment horizon h. Specifically, we consider the 12-, 24-, 36-, 48-, and 60-month excess returns, which are not risk-adjusted. ΔBMI_{it} is the change in BMI from May to June in year t.[54] μ_i are stock fixed effects to remove any unobserved constant heterogeneity.[55] All other variables are defined as earlier. Our samples are again restricted to stocks around the cutoff, we report results with band widths of 300 and 150.

[54] As was shown earlier, it does not pick up the change in price in June.

[55] They are expected to be more important for the long-run returns compared to the short-run tests in the first part of the paper. We report results with and without stock fixed effects.

Table 6: Benchmarking intensity and long-run returns

	Excess returns, average over horizon				
Horizon (months)	12	24	36	48	60
Panel A: All baseline controls					
ΔBMI	-0.045**	-0.037***	-0.020***	-0.016**	-0.009**
	(-2.81)	(-3.63)	(-3.87)	(-2.75)	(-2.16)
Observations	13,813	12,318	10,928	9,731	8,633
Panel B: Baseline controls without stock fixed effects					
ΔBMI	-0.039*	-0.034**	-0.016**	-0.015**	-0.010
	(-1.86)	(-2.50)	(-2.31)	(-2.18)	(-1.58)
Observations	14,351	12,800	11,388	10,091	8,988
Panel C: $LogMV$, $Float$ and $BandingControls$ only					
ΔBMI	-0.039**	-0.034***	-0.020***	-0.016***	-0.011***
	(-2.69)	(-3.63)	(-4.52)	(-3.23)	(-3.15)
Observations	14,700	13,124	11,605	10,279	9,082
Panel D: All baseline controls and a narrower band					
ΔBMI	-0.033**	-0.029***	-0.016***	-0.014**	-0.010**
	(-2.38)	(-3.18)	(-3.54)	(-2.81)	(-2.91)
Observations	7,640	6,830	6,078	5,378	4,743
Panel E: All baseline controls and interaction with post-banding dummy					
ΔBMI	-0.044*	-0.046***	-0.020***	-0.015*	-0.009
	(-1.94)	(-3.35)	(-3.02)	(-1.84)	(-1.47)
$\Delta BMI \times D^{>2006}$	-0.001	0.017	0.001	-0.003	0.000
	(-0.07)	(1.46)	(0.09)	(-0.35)	(0.01)
Observations	13,813	12,318	10,928	9,731	8,633

This table reports the results of the regression of the long-run returns on change in BMI, ΔBMI, in the full sample (1998-2018). The dependent variable is an average monthly excess return from September in year t over the respective horizon. Panels A and B include all baseline controls, while Panel C – log total market value, the proprietary ranking variable, and the banding controls only. Panel E adds an interaction between ΔBMI and $D^{>2006}$, which equals 1 in years 2007-2018 and 0 otherwise. In Panels A, B, C, and E, we limit the sample to 300 stocks around the cutoffs (rectangular kernel). Panel D limits the sample to 150 stocks around the cutoffs. The baseline controls include $logMV$ (the logarithm of proprietary total market value), $Float$ (proprietary float factor), $BandingControls$ (being in the band, being in the Russell 2000 and their interaction in May), $\bar{X}$ (β^{CAPM} and bid-ask spread), and stock and year fixed effects. t-statistics based on standard errors double-clustered by stock and year are in parentheses. Significance levels are marked as: *p<0.10; **p<0.05; ***p<0.01.

Our dependent variable spans horizons from 12 months to 5 years. There is some ambiguity about what the long run is in the literature. The IPO performance literature (following Ritter (1991)) typically defines it as three years. The long-run reversal literature (started by De Bondt and Thaler (1985)) uses horizons from 18 months to five years. In our case, an additional problem is posed by flippers, i.e., stocks that switch from one benchmark to the other several times during the horizon that we are considering. Our model requires the stock's BMI to remain largely unchanged for the expected return result to play out as predicted.[56]

Results of estimating equation (14) are documented in Table 6. As the coefficient on ΔBMI is significantly negative, stocks with an increase in benchmarking intensities have lower returns in the future. The effect persists for up to 5 years after the reconstitution.[57]

The magnitude of this effect is economically significant. In order to interpret the magnitude for an average added or deleted stock in our sample, we need to take into account the average size of ΔBMI for added and deleted stocks, 5.22% and -4.40%, respectively. Our baseline estimates imply that addition to the Russell 2000 results in around 2.8% lower return in the following year while deletion from it leads to a 2.4% higher return. Magnitudes are roughly the same across specifications with different controls and for a narrower band width. Panel E of Table 6 shows that after 2007, the magnitudes are not significantly lower.

Consistent with the model, this analysis shows that an increase in the size of the preferred habitat has a long-lasting effect on stock returns.[58] In other words, inelastic demand from the benchmarked institutions does indeed lower the stock risk premium.

5.2 Robustness

5.2.1 Alternative Explanations

Recent literature has similarly exploited the Russell 1000/2000 cutoff to document a number of corporate implications of institutional ownership.[59] In this section, we explain why these findings are unlikely to explain our results.

It has been argued that the transition to the Russell 2000 increases passive ownership of a stock, which may have implications for corporate governance. The positive return in

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[56] Our theoretical predictions concern stocks that joined a set of indices and stayed in them until the end of the investment horizon. In unreported analysis, we see that our results are considerably stronger, both statistically and in magnitude, if we drop stocks that moved between the Russell 1000 and 2000 indices more than once in the relevant horizon. However, excluding flippers introduces a selection bias. A stock that was added to the Russell 2000 index has to appreciate to come back to the Russell 1000 the next year. Therefore, by excluding flippers, we naturally exclude stocks with the most positive return realizations, which biases the estimate of α in (14) downward.

[57] Even though it might seem from the table that most of the effect is concentrated in the first 12 months after index reconstitution, the negative relationship is long-term. To confirm this, we report Table 23 in the Appendix, which uses average returns over a future period as the dependent variable. It shows that the returns are lowest in the 1-12 months period, and they are significantly lower for the period between 13 and 24, and weakly lower between 25 and 36 as well as 37 and 48 months.

[58] Permanent, as long as the stock stays in the benchmark.

[59] See an overview in Appel, Gormley, and Keim (2019).

June could be a signal of an improvement in corporate governance that would take place in the future. The documented effects on corporate governance, however, seem to be mixed, with some metrics improving and some deteriorating.[60] Therefore, the expected cash flow or performance impact is not clear. Moreover, the majority of documented effects of Russell reconstitution on firm fundamentals are short-term: they are measured in the year following the reconstitution, while our main focus is on long-term returns.

Our model assumes that firms' cash flows are fixed and a change in BMI affects firm value through the discount rate, so we need to rule out the cash flow channel. We investigate whether the firms' cash flows change in response to the change in BMI. In particular, we regress the three-year change in fundamental characteristics associated with cash flows on ΔBMI and our standard controls. Table 24 in the Appendix describes the variables and Table 25 reports the estimates. We see that firms with a larger increase in BMI seem to have a weakly lower M/B ratio and weakly higher profitability. The latter is consistent with the literature (Appel, Gormley, and Keim (2016)), but both go against our finding that these firms underperform. In general, we find little evidence the change in BMI is related to future changes in accounting variables driving cash flows.

One may have a concern that stocks added to the Russell 2000 benefit from improved liquidity. Intuitively, if a stock has a higher BMI, it might be more subject to liquidity-based trading and, potentially, more available for lending. In Table 25, we also report whether turnover, short interest ratio, percentage bid-ask spread, and ILLIQ of Amihud (2002) change with BMI. We find that a change in short interest is positively related to the change in BMI. It is, in fact, consistent with our model: as stock price increases with BMI, direct investors are more likely to sell it (short). In practice, stocks with higher BMIs might have lower short-selling costs because of a larger securities lending supply by long-only funds. At the same time, turnover and liquidity measures are not related to BMI, and the loading on Pastor and Stambaugh (2003) liquidity factor does not change either.[61] Therefore, it is unlikely that a decrease in liquidity premium is driving our findings.

Another alternative explanation for our long-run results could be that returns of firms that have transitioned to the Russell 2000 are lower because these firms have fallen on hard times and their cash flows are deteriorating. If this momentum continues, it is not surprising

[60] See Heath, Macciocchi, Michaely, and Ringgenberg (2021), Appel, Gormley, and Keim (2021), Schmidt and Fahlenbrach (2017), and Appel, Gormley, and Keim (2016).

[61] Although our model does not suggest any changes in risk factor loadings, in unreported tests we check if they are affected by the change in BMI. We find no robust changes in either Fama-French-Carhart, Fama-French 5-factor, or Pastor and Stambaugh (2003) loadings. This analysis involves estimating a regression of the five-year change in loadings on change in BMI with our standard controls. All loadings are 5-year computed from monthly rolling regressions of stock excess returns on factor returns available from Ken French's website or WRDS, with a minimum of 2 years of data required for estimation.

to see that the firms added to the Russell 2000 have lower future returns relative to firms that stayed in the Russell 1000. In unreported tests, we see that controlling for past returns only slightly lowers the estimates. Nonetheless, we took further steps to ensure this explanation is ruled out. We have checked explicitly whether our results are driven by future financial distress. First, in our dataset, Altman Z-scores do not change upon index reconstitution (Table 25). Moreover, excluding firms classified by Altman Z-score as being 'in distress' or 'in the grey zone' does not change either the significance or magnitude of our results. Second, excluding firms that ever filed for bankruptcy or experienced credit rating downgrades does not affect the estimates.[62]

5.2.2 Further Remarks on Identification Approach

Our identification approach avoids several problems that have been highlighted in the literature (e.g. Wei and Young (2021)). Specifically, we do not use June weights for assignment or sample selection. Moreover, our proprietary ranking variable alleviates questions regarding the conditional exogeneity assumption.[63]

Furthermore, the variation in BMI does not conflict with the known discontinuities around the Russell cutoff. That is, the local variation in total institutional ownership (IO), passive IO, benchmarked IO, and ETF ownership are implicit in the construction of our measure. They are also assumed to be time-varying since the amount of capital linked to indices changes (shown in Table 10 in the Appendix) and new indices emerge. Therefore, BMI is a unifying measure that implies some variation in all aforementioned variables; whether it is more pronounced in a particular sample depends on the distribution of assets between benchmarks.

6 Conclusion

In this paper, we propose a measure that captures inelastic demand for a stock – benchmarking intensity. Exploiting a variation in the benchmarking intensity of stocks moving between the Russell 1000 and Russell 2000 indices, we document the effects of a change in BMI on stock prices, expected returns, ownership, and demand elasticities.

Our measure reflects the inelastic demand of both active and passive funds for stocks in their benchmarks. According to our preferred habitat view, active funds are not genuinely

[62] We have also experimented with excluding firms that had a rapid deterioration in their market value rank prior to reconstitution. While our baseline analysis excludes jumps of 500 ranks, we have tried excluding firms that lost even as little as 100 ranks. Our results remained qualitatively unchanged, albeit the magnitude of the effect was larger.

[63] As we discussed above, the assignment prediction quality is very high.

active investors. Rather, they simply deviate from their benchmarks to a larger extent than passive funds. In our sample, active funds own large fractions of shares outstanding, higher than passive funds, and that is why they contribute significantly to the aggregate inelastic demand for benchmark stocks. On average, a large part of active funds' holdings is in benchmark stocks, both in terms of the number of stocks and AUM share. We find evidence of the inelastic demand of active managers in the ownership data. Studying the rebalancing around the Russell cutoff, we document that both active and passive managers buy additions to their benchmarks and sell deletions. Because of this, our framework has important implications for measuring the price elasticity of demand for stocks. The demand elasticities differ from those in the previous research based on index inclusions because the literature has not accounted for the inelastic component in active managers' demand and for the heterogeneity of benchmarks.

Our model abstracts from transaction costs but, in practice, they are important. To save on transaction costs, fund managers often engage in the so-called optimized sampling, which leads to exclusion of some of the smallest stocks in the benchmark from the funds' portfolios. However, changes in BMI still represent a strong instrument for changes in institutional ownership and can be used for estimating demand elasticities. Our measure of BMI can be further refined by accounting for assets of benchmarked investors other than mutual funds. This is likely to make BMI stronger as an instrument.

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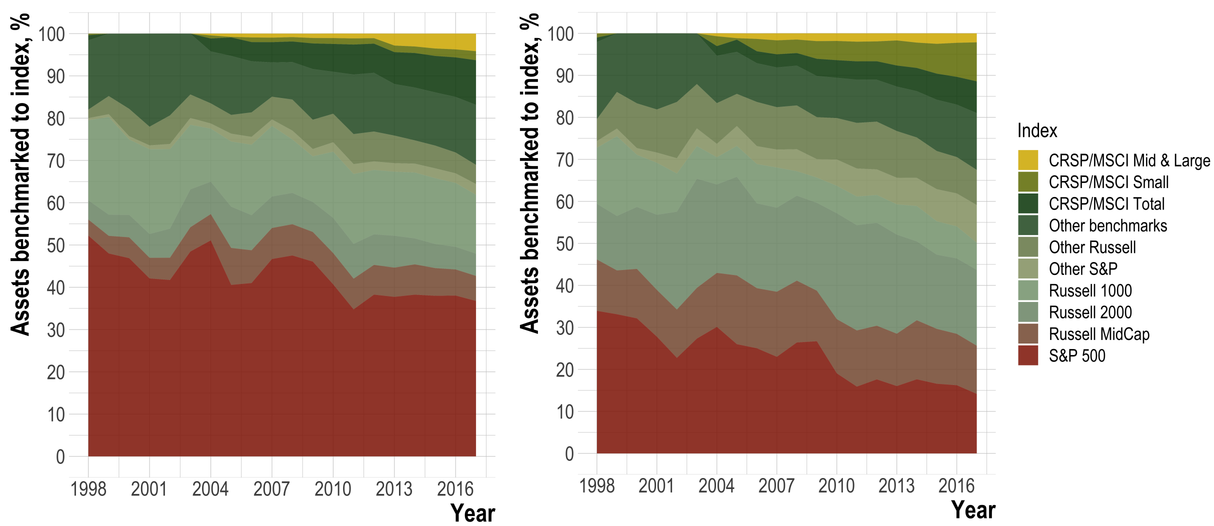
A Online Appendix

A.1 Assets Benchmarked to Indices

Figure 5: Assets benchmarked to indices

(a) All stocks (b) Mid- and small-cap stocks



This figure shows the evolution of the share of benchmark groups in the total assets under management of US domestic equity mutual funds. Mid- and small-cap stocks are in $75^{th} - 95^{th}$ percentile of market capitalization. All reported indices include blend, value and growth types, e.g. Russell 1000 above represents the sum of the Russell 1000, Russell 1000 Value, and Russell 1000 Growth. CRSP indices were launched in 2012 when Vanguard switched from MSCI indices. In the graphs, we show the share of CRSP after 2012 and corresponding MSCI indices before 2012. The group of 'other benchmarks' consists of such indices as Dow Jones, FTSE, and Wilshire as well as smaller benchmarks that we do not differentiate among.

A.2 Details on Data

Stock data comes from standard sources. We take daily returns, prices, adjustment factors, and bid and ask prices from CRSP.[64] Market, risk-free rate, and factor returns are from Ken French's Database. All fundamental accounting data comes from Compustat. We use CRSP-Compustat linking table and take into account release dates to make sure that the variables are available to the public by the rank date in May.

In fund rebalancing analyses, we use holdings available in the CRSP Mutual Fund Database (CRSP, June 2010 - December 2018) and Thomson Reuters S12 (TRS12, March 1980 - December 2018). Our main source after 2010 is CRSP and we use TRS12 to add funds

[64]Returns are adjusted for delisting in a standard way.

for which data is not available in CRSP. Moreover, CRSP is used to validate the net assets of the funds in TRS12 prior to 2010 and pull various fund-level characteristics, such as returns, expense ratios, equity percentage, and others. We merge the databases using MFLINKS following steps described in Section A.4 in the Appendix. We follow several data validation procedures and impose typical mutual fund filters, which are outlined in the Appendix as well (Section A.6). Mutual fund ownership share for any stock is computed as the percentage of shares held by funds of a certain type in the total number of shares outstanding for the stock. We exclude observations with the total mutual fund ownership over 100%.

We classify funds into active and passive based on the $index\_fund\_flag$ in CRSP and by screening fund names. All ETFs in our sample are classified as passive. A fund is classified as an ETF if its et_flag in CRSP is non-empty or it has *exchange-traded* or *etf* in its name. We manually resolve and exclude exceptions when the same portfolio has share classes of both active and passive funds. Detailed steps as well as the textual rules we deploy for the screening are listed in Section A.8 of the Appendix.

Total institutional ownership is from 13F filings.[65] We exclude observations with the total institutional ownership over 100%.

We use daily fund returns from CRSP and benchmark returns from Morningstar in order to compute tracking errors (net).

A.3 Construction of the Historical Benchmarks Data

We manually assemble a dataset of historical mutual funds benchmarks from the following sources:

1. Snapshot of benchmarks ($primary\_prospectus\_benchmark$ field) in Morningstar as of September 2018.

2. Database of historical fund prospectuses available on the website of the U.S. Securities and Exchange Commission (SEC)[66].

3. SEC Mutual Fund Prospectus Risk/Return Summary[67] data sets (MFRR). Benchmarks are mentioned in the annual return summary published in prospectuses.

We use the $crsp\_fundno$-CIK mapping from CRSP to link CIK, SEC identifiers, back to $crsp\_fundno$. To map CRSP and Morningstar, we mostly follow the procedure in

[65]We thank Luis Palacios, Rabih Moussawi, and Denys Glushkov for making their code for computing institutional ownership ratios publically available on WRDS.

[66]Follow SEC's mutual fund search page: https://www.sec.gov/edgar/searchedgar/mutualsearch.html

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

Pastor, Stambaugh, and Taylor (2015), details are below in Section A.5.

A.3.1 Scraping the EDGAR and Building Text-Based Series

Mutual funds are required to regularly submit filings to the SEC. The SEC's EDGAR system stores filings in electronic archives since 1994. Even though the SEC Rule S7-10-97[68] required funds to report their benchmark (or a 'reference broad market index') in prospectuses from December 1, 1999, some funds voluntarily did so prior to that (Sensoy (2009)). Reporting of manager compensation contracts was required by the SEC Rule S7-12-04[69] starting in the October of 2004. Therefore, the procedure discussed below will cover the history of filings for any particular fund back to 1998.

The filings that include information on fund benchmark and manager compensation are N-1A/485 (registration statement including a prospectus), 497K (summary prospectus), 497 (fund definitive materials), and 497J (certification of no change in definitive materials). All of these can be accessed via package 'edgarWebR' available in R.[70] Since the holdings data set is already linked to CRSP fund identifiers (*fundno*), we will use all CIK codes[71] available in the mapping file *crsp_cik_map*. For each CIK, we retrieve a list of all historical filings (485 and 497/497K/497J forms) using *company_filings()* function. Then we parse the filings into raw text format using *parse_filing()* function.

Having obtained the filings for each CIK and each filing date, we re-organize the data set into a panel: quarterly text files for each fund. To do so, we assign observations with a 497J form a 'no-change' tag. Moreover, after looking at the text data, we assign a 'no-change' tag to 497 forms with no reference to benchmark or manager compensation.[72]

Before extracting the data, each of the filings is tokenized (we work with both tokenized text and string formats) and de-capitalized, punctuation and certain stop words are removed.[73] All these steps are done using NLTK[74] module in Python. Afterwards, we classify all 485 and 497K documents as prospectuses, while we have to look into the content of 497 filings to classify them into prospectuses or statements of additional information (SAI).

[68] Available on: https://www.sec.gov/rules/final/33-7512r.htm.

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

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

[71] The Central Index Key (CIK) is used as the main identifier of the filing entities on the SEC's EDGAR and available per fund, fund series, and fund company. We first use series CIK as benchmarks differ at this level, then we use company CIK to fill in any missing observations.

[72] Since fund prospectus is a legal document and fund clientele supposedly depends on it, we see that prospectuses are relatively 'sticky' and hence the time series for most of the funds looks like 'prospectus' definition at an early date and then at most 1-2 changes for the fund history.

[73] Numerical data and special characters cannot be removed though as they are included in benchmark names. Moreover, we retain negation.

[74] Official page is: http://www.nltk.org/.

Typically, funds specify the type of the document in the header, we therefore search for the exact match ('prospectus' or 'statement of additional information') in the first 100 characters of the filing.

There are a few challenges we face when extracting the fund benchmark from prospectus text. Even though all funds are required to disclose the benchmark, they tend to do it in a very different manner. Some funds explicitly say that the performance can be evaluated against a particular market index, some only report the index performance below the required performance tables (as an implicit benchmark). If referring to the benchmark in the text, funds do not use standardized language: some may say 'benchmark', some 'market index' or 'reference index' and some may omit the term and only use a phrase similar to 'performance is measured against'. Moreover, some funds may define a mixture of indices as their benchmark, e.g., '60% Russell 1000, 40% Russell 2000'. Therefore, we are faced with the task of extracting information from unstructured text.

Finally, in some cases, we need to first isolate the text to extract the benchmark name from. Fund families may choose to submit one prospectus for many funds. Within one prospectus document, many funds can either share the same section or each fund can have a separate section. We therefore extract the fund-relevant part of prospectus whenever possible (typically in the second case only). To do so, we search for the fund name and the fund ticker in the text. Most commonly, the relevant section starts with a ticker/name and has it repeated on each page throughout the section. We hence extract the part of the text with the highest density of tickers/fund names.

When extracting benchmarks from the (isolated) text, we use a set of rules that maximizes the chance of the algorithm picking up the benchmark correctly. The set of rules includes but is not limited to:

- Search for a benchmark provider name from the list (de-capitalized already): {*s&p, russell, crsp, msci, dj, dow jones, nasdaq, ftse, schwab, barclays, wilshire, bridgeway, guggenheim, calvert, kaizen, lipper, redwood, w.e. donoghue, essential treuters, barra, ice bofaml, bbgbarc, cboe*}.[75] If a benchmark from the list is found, retrieve the subsequent 40 characters to extract the full benchmark name. Match the full names using the list from Morningstar (for example, *russell 1000 value tr usd*).

- If several matches are established, we record the number of matches and each benchmark name (with subsequent characters, as above).

[75] This list has been compiled using the Morningstar benchmark snapshot. It is survivorship-bias free. According to Morningstar, the first three providers take over 90% of the market and the first five - around 98%.

- We also search for words from the list (*context words*): {*index, benchmark, reference, performance, relative, return, measure, evaluate, assess, calculate*}. We use these words in two ways. Firstly, if a benchmark name match is established, we check if any of these *context words* is present within 100 characters around the name. Secondly, if no match is established, we record pairwise distance in letters between benchmark names and *context words* and return the pair with minimum distance. This second approach is based on the string format of the text and required if the match was not established due to imprecision in tokenization.

We manually clean the extracted data to remove typos and map it to full benchmark names. In the resulting sample of quarter-fund-benchmarks, we manually verify all funds that got matched with several benchmarks or that had a benchmark change. Subsequently, we validate a random sample of funds through manual analysis of the prospectus text. We also compare the benchmarks as of September 2018 with a snapshot we obtained from the Morningstar database and manually resolve any mismatch. Furthermore, we compare a time series we get with a series available for a small sample of funds in MFRR.

As expected, prospectuses are relatively sticky. In the entire sample over 1998-2018, we observe 1,208 changes at a share class level (around 300 at master fund level). The largest benchmark change in terms of tracking assets for passive funds in Vanguard's move from MSCI to CRSP indices in 2012 and 2013. For active funds, it is T. Rowe Price's change from the S&P 500 to Russell 1000 Value and Growth indices in 2018.

A.4 CRSP and Thomson Reuters S12 Merge Procedure

We use Mutual Fund Links (MFLINKS) to merge CRSP and TRS12 similar to the procedure described in Doshi, Elkamhi, and Simutin (2015).

Firstly, we prepare TRS12 holdings:

- keep last holdings report for each fund in a given month,
- match WFICN number from MFLINKS to fundno, rdate, and fdate in TRS12 file,
- when there are duplicate reports for the same date, keep the fund with the largest assets,
- pull CRSP stock files and adjust reported number of shares by the correct adjustment factor - as of rdate.

Then, we prepare CRSP holdings:

- clean the data based on portnomap to ensure that only one portno is valid for a particular date for any fund (remove overlaps in the data due to mergers),
- match WFICN number from MFlinks to crsp_fundno,
- clean overlaps in wficn-portno mapping,

- keep the last report for every month.

Finally, we stack the two parts and remove duplicate entries from CRSP (at a fund level).

A.5 CRSP and Morningstar Merge Procedure

The merge procedure is a slight modification of Pastor, Stambaugh, and Taylor (2015).[76]

A.6 Asset Validation

TNA and holdings data are generally validated by MFLINKS (only funds with sufficient match quality are linked). However, we additionally validate the TNA in order to ensure a better match with the holdings. In the case of CRSP, we use the sum of assets across share classes and weigh share class level data such as equity percentage by the fraction of total assets this share class represents. Because TRS12 reports only equity and CRSP reports all assets, we multiply the most recent equity percentage by CRSP assets. We use the following for validation:
- compare the total dollar sum of holdings in the merged file with the assets reported by TRS12 and CRSP and call the difference 'unexplained',
- if the difference between TRS12 and CRSP is smaller than 1%, we use CRSP,
- if CRSP has lower unexplained or TRS12 does not report assets, we use CRSP and otherwise TRS12.

A.7 Filtering

In the final sample, we keep only funds that:
- have fund-quarter entries where I validated the assets at 20% precision;
- are either active or passive domestic equity funds that did not change its style or objective over their history (see details below in Section A.8);
- have an average common equity percentage between 50 and 120%;
- have more than USD 1 million in assets.

A.8 Active and Passive Domestic Equity Funds

We follow the major steps of the procedure described in Doshi, Elkamhi, and Simutin (2015) to filter out active domestic equity funds and augment it to identify passive funds

[76] Details are available upon request.

better.

We use $crsp\_obj\_cd$ (CRSP objective code) to identify ‘equity’, ‘domestic’, ‘cap-based or style’ and exclude ‘hedged’ and ‘short’ and remove those funds that changed their objectives. I also only keep funds with ’ioc’ variable in TRS12 file (investment objective) not in (1,5,6,7). Active funds are identified as those without ‘$Index\_fund\_flag'$ or with ‘B' (index-based funds) and without ‘et_flag'. I also exclude funds that have a range of words in their names, as per the list below.

List of n-grams to exclude from active funds names (all in lower case).

1. Generic and index provider names: index, indx, ‘ idx ‘, s&p, ‘ sp ‘ (with spaces), nasdaq, msci, crsp, ftse, barclays, ‘ dj ‘, ‘ dow ‘, jones, russell, ‘ nyse ‘, wilshire, 400, 500, 600, 1000, 1500, 2000, 2500, 3000, 5000

2. Passive management names: ishares, spdr, trackers, holdrs, powershares, streettracks, ‘ dfa ‘, ‘program’, etf, exchange traded, exchange-traded

3. Target fund names: target, retirement, pension, 2005, 2010, 2015, 2020, 2025, 2030, 2035, 2040, 2045, 2050, 2055, 2060, 2065, 2070, 2075

Our sample of passive funds consists of index funds and ETFs available on CRSP. Index funds are those with ‘$index\_fund\_flag'$ of ‘D' or ‘E' and those that include a range of words in their name:

1. Generic and index provider names: index, indx, ‘ idx ‘, s&p, ‘ sp ‘ (with spaces), nasdaq, msci, crsp, ftse, barclays, ‘ dj ‘, ‘ dow ‘, jones, russell, ‘ nyse ‘, wilshire, 400, 500, 600, 1000, 1500, 2000, 2500, 3000, 5000

2. Passive management names: ishares, ‘ dfa ‘, ‘program’

ETFs are those with not missing ‘et_flag' or having $'etf'$, ‘$exchange - traded'$, ‘$exchangetraded'$ in their name:

1. Passive management names: spdr, trackers, holdrs, powershares, streettracks, etf, exchange traded, exchange-traded

Target funds are those with target years in the name, e.g., ‘2015’ and ‘2075’, or ‘retirement’, ‘target’. Creating a clean sample of target funds potentially requires different treatment of objective codes (see CRSP Style Guide). Since we only aim to exclude them, we remove fund with the following n-grams in their names:

1. Target fund names: target, retirement, pension, 2005, 2010, 2015, 2020, 2025, 2030, 2035, 2040, 2045, 2050, 2055, 2060, 2065, 2070, 2075

We exclude all leverage and inverse funds by identifying the following n-grams in the names: $'leverage'$, $'inverse'$, $'2x'$, $'1.5x'$, $'1.25x'$, $'2.5x'$, $'3x'$, $'4x'$.

If we apply the rules above, some of the funds in the sample will include both active and passive share classes. We clean the resulting sample of funds with share classes of different types as per the rule: (a) Put ETF shares of index funds as ETFs (passive type maintained). (b) When missing the flag for otherwise index funds and portno is the same, set to index. (c) If *portno*/*cl_grp* are different, exclude.

The remaining funds are further filtered based on the common equity percentage as discussed in A.7.

A.9 Russell Reconstitution

Russell indices undergo a yearly reconstitution at the end of June. The reconstitution is a two-step process: assigning a stock to an index and determining the weight of the stock in that index.

The first step is solely based on the ranking of all eligible securities by their total market capitalization on the rank day in May. For most of the years in our sample, the rank day falls on the last trading day in May.[77] Russell uses its broadest Russell 3000E index as the universe of eligible securities together with newly admitted stocks.[78] Ranks are computed based on the proprietary measure of the total market capitalization of eligible securities. This proprietary measure has been made available to us by Russell[79][80] and hence we are able to replicate the assignment rule very closely.

In the second step, each stock in the index is assigned a weight based on its float-adjusted market capitalization in June. To define the adjustment, Russell uses proprietary float factors, which we can infer from total and float-adjusted market capitalization. These factors do not affect index assignment but they explain some variation in the benchmarking intensity due to their direct relationship with index weights: all else equal, stocks will have lower index weight if the float adjustment is larger, and hence lower BMI.

Before 2007, a firm would be assigned to the Russell 2000 index if and only if its total market value rank falls between 1000 and 3000. Since the assignment is based on ranks, firms cannot manipulate it.[81] Moreover, an idiosyncratic shock to the market value on the rank date can bring the stock to the other side of the cutoff. Hence, the assignment is as good as random.

In order to reduce the turnover between indices, FTSE Russell introduced a 'banding' policy in 2007. According to the new rule, a stock is assigned to the Russell 2000 index if and only if:

- it was in the Russell 2000 in the previous year and its total market value rank in May falls between the left cutoff $(1000 - c_1)$ and 3000[82]

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

[78] See the details on the methodology in the official and publicly available guide.

[79] We match this measure to the May Russell 3000E constituent lists as well as the preliminary constituent lists from June in order to arrive at the universe of eligible securities. The preliminary lists have also been provided by Russell.

[80] We performed our analysis with the market value measure constructed from CRSP and Compustat as in Chang, Hong, and Liskovich (2015) as well. This measure delivers qualitatively identical main results.

[81] Typically, bunching is formally tested for with McCrary (2008) test but since the assignment variable is a rank, which is relative to other stocks, bunching is not possible.

[82] The rule is similar for stocks moving to the Russell 2000 from below, i.e., around rank 3000. We are omitting it here for brevity.

- it was in the Russell 1000 and its total market value rank in May falls between the right cutoff ($1000 + c_2$) and 3000.

The band, that is, the range of ranks between ($1000 - c_1$) and ($1000 + c_2$), is still based on a mechanical rule but it changes each year with the distribution of firm sizes around the cutoff.[83] Because of banding, the turnover between indices went down significantly, as intended.[84] We list the number of additions and deletions per year in Table 7.

Table 7: Historical Details on Russell 2000 Reconstitution

Year	Additions	Deletions	Russell 1000 Smallest	Russell 1000 Smallest w/banding	Russell 2000 Largest w/banding	Russell 2000 Largest
1998	57	54	1.4			1.4
1999	59	70	1.4			1.4
2000	50	48	1.6			1.5
2001	86	104	1.4			1.4
2002	78	73	1.3			1.3
2003	43	56	1.2			1.2
2004	49	38	1.6			1.6
2005	61	58	1.8			1.7
2006	49	68	2.0			1.9
2007	5	15	2.5	1.8	3.1	2.5
2008	31	38	2.0	1.4	2.7	2.0
2009	36	39	1.2	0.8	1.7	1.2
2010	14	25	1.7	1.3	2.2	1.7
2011	23	35	2.2	1.6	3.0	2.2
2012	27	32	2.0	1.4	2.6	1.9
2013	27	30	2.5	1.8	3.3	2.5
2014	28	24	3.1	2.2	4.1	3.1
2015	48	20	3.4	2.4	4.3	3.4
2016	48	34	2.9	2.0	3.9	2.9
2017	40	31	3.4	2.3	4.5	3.4
2018	35	48	3.7	2.5	5.0	3.7

This table reports the number of additions to and deletions from the Russell 2000. We only report deletions which moved to the Russell 1000, not those that moved down in the ranking. The last for columns report the market value (in billions USD) of smallest and largest stocks in the indices.

[83] Specifically, it is a 5% band around the cumulated market cap of the stock ranked 1000 in Russell 3000E universe on the rank date.

[84] Russell's analysis is available online: https://www.ftserussell.com/blogs/russell-2000-recon-banding-results-lower-turnover.

A.10 Descriptive Statistics

Table 8: Descriptive statistics

	Obs.	Mean	St.Dev.	Min	Max
BMI, %	16,359	18.74	7.42	0.49	68.57
ΔBMI, %	16,359	0.24	3.27	-52.34	31.77
Return in June, % (winsorized at 1%)	16,674	0.05	10.15	-33.56	47.97
Average long-run excess return, % (winsorized at 1%):					
12-month	15,625	0.98	2.70	-11.18	12.27
24-month	13,928	0.97	1.89	-7.11	8.35
36-month	12,376	0.99	1.50	-4.86	6.34
48-month	10,936	1.00	1.27	-3.86	5.37
60-month	9,682	1.04	1.12	-3.04	4.83
Average periodic excess return, % (winsorized at 1%):					
0-12 months	15,625	0.49	2.84	-15.04	9.27
13-24 months	13,930	0.25	3.02	-14.26	8.84
25-36 months	12,385	0.33	2.96	-13.39	8.73
37-48 months	10,950	0.37	2.89	-12.73	8.51
49-60 months	9,700	0.42	2.83	-11.98	8.30
Bid-ask spread, % of close price	16,492	13.80	14.30	0.00	492.91
β^{CAPM}, winsorized at 1%	15,400	1.18	0.68	-0.08	3.56
MV, $ million	16,675	2442.93	1485.22	525.09	9675.00
$Float$	16,438	0.15	0.22	0.00	0.97
$ValueRatio$	16,314	0.53	0.45	0.00	1.00
M/B ratio, winsorized at 1%	16,636	2.02	1.50	0.54	10.28
1(In the band in May)	16,675	0.29	0.45	0.00	1.00
1(In Russell 2000 in May)	16,675	0.53	0.50	0.00	1.00

This table reports the descriptive statistics of the main stock-level variables used in the analysis. These statistics are calculated on the annual panel of 300 stocks around both cutoffs in 1998-2018. All returns are monthly. Bid-ask spread is a 1-year average bid-ask percentage spread. β^{CAPM} is a 5-year monthly rolling CAPM beta. MV is the proprietary Russell total market value, logarithm of which we use as one of controls. $Float$ is the proprietary Russell float factor which approximates the fraction of shares outstanding in free float. $ValueRatio$ is the proprietary Russell value ratio which reflects the fraction of floated shares assigned to value style. 1(In the band in May) equals 1 if the stock belongs to the band in May. 1(In Russell 2000 in May) equals 1 if the stock belongs to the Russell 2000 in May. The latter two variables and their interaction form $BandingControls$.

A.11 Descriptive Statistics for Ownership Ratios

Table 9: Descriptive statistics for ownership

	Obs.	Mean	St.Dev.	Min	Max
Total institutional ownership	14,483	70.27	25.37	0.00	99.99
Total mutual fund ownership	16,675	17.88	11.37	0.00	60.43
Russell 1000 active ownership	16,675	0.50	1.03	-2.55	16.37
Russell Midcap active ownership	16,675	1.85	2.59	0.00	34.00
Russell 2000 active ownership	16,675	4.86	5.13	0.00	34.80
Russell 1000 passive ownership	16,675	0.11	0.16	-0.38	1.17
Russell Midcap passive ownership	16,675	0.12	0.18	0.00	0.84
Russell 2000 passive ownership	16,675	0.89	1.20	0.00	4.75

This table reports the descriptive statistics of the main ownership variables used in the analysis. These statistics are calculated on the annual panel of 300 stocks around both cutoffs in 1998-2018. Ownership is defined as the fraction of total shares outstanding held by investor group in September (in %). Total institutional ownership is truncated at 100%. Negative values are from short positions available in CRSP.

A.12 Benchmarked Assets

Table 10: Benchmarked assets and market capitalization of the Russell indices

	Assets under management, billion US dollars											**Index market value, billion US dollars**		
	Russell 1000			Russell Midcap			Russell 2000			Russell 1000	Russell 2000	Russell	Russell	Russell
	Blend	Value	Growth	Blend	Value	Growth	Blend	Value	Growth	Group, total	Group, total	1000	Midcap	2000
1998	13.7	179.3	224.7	8.3	17.9	50.7	30.0	13.9	27.4	494.6	71.4	10,093.0	2,958.0	1,271.7
1999	20.7	195.8	340.7	7.8	15.5	56.7	28.9	12.4	28.1	637.2	69.5	12,469.2	3,052.5	1,101.8
2000	22.4	154.2	472.7	11.0	12.8	113.8	35.2	12.2	53.4	786.9	100.9	14,476.4	3,459.3	1,271.3
2001	19.4	171.8	333.5	11.3	18.1	84.7	41.5	19.3	42.9	638.8	103.7	12,229.6	3,045.5	1,082.2
2002	14.3	155.8	228.6	13.1	25.8	60.3	50.4	28.5	35.5	497.9	114.4	10,115.7	2,602.6	921.4
2003	15.8	155.5	215.9	14.4	25.1	63.3	51.4	26.8	37.1	490.0	115.3	10,071.1	2,585.9	894.5
2004	19.7	206.2	232.7	22.3	51.5	88.5	79.0	41.6	51.3	620.8	171.9	12,026.9	3,348.9	1,237.5
2005	24.0	244.5	211.5	26.6	76.1	106.1	92.5	50.8	53.6	688.9	197.0	12,740.1	3,787.9	1,362.1
2006	39.1	277.1	203.9	30.9	91.5	120.2	111.8	60.8	61.0	762.7	233.6	13,517.3	4,093.3	1,486.2
2007	53.9	354.4	219.0	37.2	121.0	130.6	131.2	72.5	66.1	916.1	269.7	16,151.5	4,967.5	1,696.1
2008	39.6	281.1	202.6	32.6	93.9	120.1	106.5	57.6	54.7	769.8	218.8	13,610.7	4,083.0	1,240.9
2009	33.2	197.3	135.9	23.7	60.4	78.7	82.2	45.1	39.8	529.3	167.2	9,532.5	2,598.3	886.4
2010	40.7	228.8	147.4	29.7	78.1	91.0	103.2	56.1	46.4	615.8	205.8	11,155.6	3,352.8	1,098.7
2011	50.6	280.6	196.5	41.2	103.0	122.6	142.2	72.0	68.0	794.4	282.2	14,475.4	4,548.3	1,466.9
2012	61.3	269.9	218.6	39.2	95.2	109.5	129.3	63.2	62.5	793.7	255.0	14,570.7	4,383.6	1,351.7
2013	64.9	342.1	257.9	41.0	107.7	118.0	147.3	73.5	76.9	931.5	297.7	17,061.7	5,291.1	1,669.5
2014	91.5	443.0	317.3	66.8	150.3	147.0	180.4	88.2	92.6	1,215.9	361.2	21,077.4	6,804.8	2,045.1
2015	99.4	440.8	345.8	72.2	148.1	155.0	163.4	88.3	95.2	1,261.3	346.8	22,033.5	6,930.4	2,174.9
2016	115.3	422.4	322.1	67.7	136.8	135.0	145.7	79.6	74.8	1,199.3	300.1	21,551.1	6,345.9	1,895.6
2017	121.3	458.2	352.0	80.2	152.0	152.7	177.1	96.7	85.6	1,316.4	359.4	24,589.0	7,157.4	2,253.1
2018	120.0	466.7	415.0	83.8	151.5	168.2	194.9	103.3	104.7	1,405.1	403.0	27,241.1	7,930.4	2,556.7
Mean	51.5	282.2	266.4	36.2	82.5	108.2	105.9	55.4	59.9	827.0	221.2	15,275.7	4,444.2	1,474.5

This table reports the mutual fund assets benchmarked to Russell indices by year. Russell 1000 Group represents the total for Russell 1000 and Russell Midcap indices of all styles; Russell 2000 Group – for Russell 2000 indices of all styles. The last three columns report total CRSP market value of all stocks in the indices. The last row shows the mean of 1998-2018. All data is as of June.

A.13 Instrumenting Index Membership

Table 11: Predicting Russell 2000 membership

	D^{R2000}: **stock in Russell 2000 index in June**					
	1998-2018	1998-2006	2007-2018	1998-2018	1998-2006	2007-2018
1(Rank > cutoff in May)	0.941***	0.930***	0.898***	0.919***	0.875***	0.857***
	(110.32)	(62.33)	(62.91)	(78.76)	(33.81)	(45.47)
Band width		300			150	
Observations	16,675	4,966	11,709	9,456	2,487	6,969
Adjusted R^2, %	96.4	96.1	96.6	94.9	92.9	95.8

This table reports the results of regressing actual index membership dummy in June, D^{R2000}, on its predicted value based on total market value rank. All regressions include $logMV$ (the logarithm of proprietary total market value), $BandingControls$ (being in the Russell 2000, being in the band, and their interaction in May, the latter two are for 2007-2018 only), and year fixed effects. Band width is 300 or 150 stocks around the cutoffs (rectangular kernel). t-statistics based on standard errors double-clustered by stock and year are in parentheses. Significance levels are marked as: *p<0.10; **p<0.05; ***p<0.01.

A.14 Index Effect in Our Sample

We estimate the following specification:

$$Ret_{it}^{June} = \alpha D_{it}^{R2000} + \zeta logMV_{it} + \phi' BandingControls_{it} + \xi Float_{it} + \delta' \bar{X}_{it} + \mu_t + \varepsilon_{it} \quad (15)$$

In the above specification, D_{it}^{R2000} is 1 when stock i is in the Russell 2000 on the reconstitution day in June of year t. Ret_{it}^{June} is the return of stock i in June of year t, winsorized at 1%. Other variables are defined as in the main text.

Table 12: The average index effect

	Return in June					
	(1)	(2)	(3)	(4)	(5)	(6)
D^{R2000}	0.017*	0.017	0.020**	0.018*	0.022**	0.022*
	(2.06)	(1.69)	(2.19)	(1.82)	(2.24)	(1.96)
$D^{R2000} \times trend$					-0.001	-0.001*
					(-1.64)	(-1.96)
Band width	300		150		300	
Observations	16,640	15,135	9,432	8,616	16,640	15,135
Adjusted R^2, %	15	16	15	16	15	16

This table reports the results of estimating equation (15) for stocks in the full sample (1998-2018).[a] The dependent variable is the winsorized stock return in June. The key independent variable (D^{R2000}) is the Russell 2000 index membership dummy, measured in June. *trend* is a linear trend. All regressions include $logMV$ (the logarithm of proprietary total market value), $Float$ (proprietary float factor), $BandingControls$ (being in the band, being in the Russell 2000 and their interaction in May), $\bar{X}$ (β^{CAPM} and bid-ask spread), and year fixed effects. Band width is 300 or 150 stocks around the cutoffs (rectangular kernel). t-statistics based on standard errors double-clustered by stock and year are in parentheses. Significance levels are marked as: *p<0.10; **p<0.05; ***p<0.01.

[a] Using the RDD specification in Chang, Hong, and Liskovich (2015) on our data delivers estimates close to those reported in this table.

A.15 Price Pressure and BMI in Narrower Bands

Table 13: BMI change and return in June

	Return in June				
	(1)	(2)	(3)	(4)	(5)
ΔBMI	0.244***	0.286**	0.254***		
	(2.94)	(2.73)	(2.87)		
1(ΔBMI quartile 1)				-0.011***	-0.012***
				(-3.29)	(-3.43)
1(ΔBMI quartile 2)				-0.001	-0.004***
				(-0.93)	(-2.63)
1(ΔBMI quartile 3)				0.004*	0.003*
				(1.69)	(1.78)
1(ΔBMI quartile 4)				0.009**	0.009**
				(2.46)	(2.37)
Fixed effect	Year	Year	Stock & Year	N	N
Controls	N	Y	Y	N	Y
Observations	9,432	8,616	8,037	9,432	8,616
Adj. R^2, %	15.3	16.6	20.6	1.1	1.6

This table reports the results of estimating equation (7) for stocks in the full sample (1998-2018). The dependent variable is the winsorized return of stock i in June in year t (in columns (1)-(3) and demeaned by year in (4)-(5)). The independent variable is ΔBMI_{it}, the change in the BMI of stock i between June and May of year t, or the dummies for its quartiles. All regressions include $logMV$ (the logarithm of proprietary total market value), $Float$ (proprietary float factor), $BandingControls$ (being in the band, being in the Russell 2000 and their interaction in May). Columns (2), (3) and (5) include controls in $\bar{X}$ (β^{CAPM} and bid-ask spread). All controls are demeaned by year in columns (4)-(5). The constant is excluded. Band width is 150 around both cutoffs. t-statistics based on standard errors double-clustered by stock and year are in parentheses. Significance levels are marked as: *p<0.10; **p<0.05; ***p<0.01.

A.16 Price Pressure and Deflated BMI

Table 14: Deflated BMI change and return in June

	Return in June				
	(1)	(2)	(3)	(4)	(5)
ΔBMI	0.193**	0.265**	0.271**		
	(2.80)	(2.54)	(2.61)		
1(ΔBMI quartile 1)				-0.010***	-0.012***
				(-3.58)	(-3.67)
1(ΔBMI quartile 2)				-0.002	-0.006***
				(-1.45)	(-3.92)
1(ΔBMI quartile 3)				0.005***	0.004***
				(2.59)	(2.66)
1(ΔBMI quartile 4)				0.008***	0.008***
				(2.96)	(2.79)
Fixed effect	Year	Year	Stock & Year	N	N
Controls	N	Y	Y	N	Y
Observations	16,640	15,135	14,549	16,640	15,135
Adj. R^2, %	15.4	16.7	19.3	1.0	1.6

This table reports the results of estimating equation (7) for stocks in the full sample (1998-2018). The dependent variable is the winsorized return of stock i in June in year t (in columns (1)-(3) and demeaned by year in (4)-(5)). The independent variable is deflated ΔBMI_{it}, the change in the BMI of stock i between June and May of year t deflated to May prices, or the dummies for its quartiles. All regressions include *logMV* (the logarithm of proprietary total market value), *Float* (proprietary float factor), *BandingControls* (being in the band, being in the Russell 2000 and their interaction in May). Columns (2), (3) and (5) include controls in $\bar{X}$ (β^{CAPM} and bid-ask spread). All controls are demeaned by year in columns (4)-(5). The constant is excluded. Band width is 150 around both cutoffs. t-statistics based on standard errors double-clustered by stock and year are in parentheses. Significance levels are marked as: *p<0.10; **p<0.05; ***p<0.01.

A.17 Change in BMI as an Instrument in Narrower Bands

Table 15: Change in BMI as an instrument for change in institutional ownership, with a narrower band

	Return in June, %				**Return in April-June, %**
	OLS			2SLS	
	(1)	(2)	(3)	(4)	(5)
Panel A: Second-stage estimates					
ΔIO, %	0.09***	3.39	1.44**	1.54**	1.48**
	(4.47)	(1.16)	(2.32)	(2.40)	(2.20)
Panel B: First-stage estimates					
ΔBMI, %			0.20***	0.19***	0.21***
			(5.90)	(6.21)	(6.49)
D^{R2000}		0.58	-0.40		
		(1.59)	(-1.12)		
F-Stat (excl. instruments)		2.54	18.94	38.62	42.06
Hansen J test, p-value			0.31		
Controls	Y	Y	Y	Y	N
Observations	7,256	7,256	7,244	7,244	7,720

This table reports α_1 and α from estimating (10) and (11), respectively, in the full sample period (1998-2018). Band width is 150 stocks around the cutoffs. The dependent variable is return in June. ΔIO the change in total institutional ownership of stock i from March to June in year t. Specifications in (1)-(4) include $logMV$ (the logarithm of proprietary total market value), $Float$ (proprietary float factor), $BandingControls$ (being in the band, being in the Russell 2000 and their interaction in May), $\bar{X}$ (β^{CAPM} and bid-ask spread), and year fixed effects. Specification in (5) includes year fixed effects only. In parenthesis are t-statistics based on standard errors double-clustered by stock and year. Significance levels are marked as: *p<0.10; **p<0.05; ***p<0.01.

A.18 Demand Change Computed Using Benchmarked Assets

In this section, we show that using the BMI change is, in concept, analogous to using the change in benchmarked assets used by Chang, Hong, and Liskovich (2015) but BMI change is continuous and accounts for heterogeneous benchmarks, which has quantitative implications for the estimate of elasticity.

To evaluate the percentage change in demand, Chang, Hong, and Liskovich use:

$$\Delta Demand_{i,t} = \omega_{i,R2000,t} BA_{R2000,t} - \omega_{i,R1000,t} BA_{R1000,t}$$
$$\%\Delta Demand_{i,t} = \Delta Demand_{i,t}/MV_{i,t} = \left(\frac{BA_{R2000,t}}{\sum_{R2000} MV_{k,t}} - \frac{BA_{R1000,t}}{\sum_{R1000} MV_{k,t}} \right)$$

where $BA_{j,t}$ corresponds to the assets benchmarked to index j in year t (AUM of funds benchmarked to index j), $\omega_{i,j,t}$ to the weight of stock i in index j, and $\sum_j MV_{k,t}$ to the total market value of stocks in index j. Notice that if only Russell 1000 and 2000 weights were changing and float factors were 1, the change in BMI would be exactly that.

However, when a stock moves across the Russell cutoff, not only does it leave the Russell 1000 and join the Russell 2000, but it also leaves the Russell 1000 Value and/or Growth. It is important to account for the latter. Table 10 shows that Russell Value and Growth indices are even larger than blend indices in terms of the assets benchmarked to them. Moreover, since the Russell Midcap represents the smallest 800 stocks in the Russell 1000, the stock exits it too. The size of the investor base of the Russell Midcap is just as large as that for the Russell 2000. It is therefore surprising that most of the literature studying the Russell cutoff has not taken all these indices into account.

The change in our BMI measure provides the most accurate change in inelastic demand for the stock available in the literature. To illustrate the importance of heterogeneous benchmarks, we will use the detailed assets of Russell indices (we assume membership in S&P and CRSP indices is held constant). A change in demand of a stock moving across the Russell cutoff can be formalized using the weight of the stock in the indices and the assets benchmarked to them:

$$\begin{aligned}\Delta Demand_{i,t} = {} & \omega_{i,R2000,t} BA_{R2000,t} + \omega_{i,R2000V,t} BA_{R2000V,t} + \omega_{i,R2000G,t} BA_{R2000G,t} \\ & - \omega_{i,R1000,t} BA_{R1000,t} - \omega_{i,R1000V,t} BA_{R1000V,t} - \omega_{i,R1000G,t} BA_{R1000G,t} \\ & - \omega_{i,RMid,t} BA_{RMid,t} - \omega_{i,RMidV,t} BA_{RMidV,t} - \omega_{i,RMidG,t} BA_{RMidG,t}\end{aligned}$$

The percentage change in demand is:

$$
\begin{aligned}
\%\Delta Demand_{i,t} &= \Delta Demand_{i,t}/MV_{i,t} \\
&= \frac{BA_{R2000,t}}{\sum_{R2000} MV_{jt}} + \frac{Shares^G_{i,t}/Shares_{i,t} \times BA_{R2000G,t}}{\sum_{R2000G} MV_{j,t}} + \frac{Shares^V_{i,t}/Shares_{i,t} \times BA_{R2000V,t}}{\sum_{R2000V} MV_{j,t}} \\
&- \frac{BA_{R1000,t}}{\sum_{R1000} MV_{j,t}} + \frac{Shares^G_{i,t}/Shares_{i,t} \times BA_{R1000G,t}}{\sum_{R1000G} MV_{j,t}} + \frac{Shares^V_{i,t}/Shares_{i,t} \times BA_{R1000V,t}}{\sum_{R1000V} MV_{j,t}} \\
&- \frac{BA_{RMid,t}}{\sum_{RMid} MV_{j,t}} + \frac{Shares^G_{i,t}/Shares_{i,t} \times BA_{RMidG,t}}{\sum_{RMidG} MV_{j,t}} + \frac{Shares^V_{i,t}/Shares_{i,t} \times BA_{RMidV,t}}{\sum_{RMidV} MV_{j,t}}
\end{aligned}
$$

where in the second equality we used the definition of market value weights in Russell indices and where $Shares^G_{i,t}/Shares_{i,t}$ is the fraction of floated shares of stock i assigned to the growth style by Russell, and $Shares^V_{i,t}/Shares_{i,t}$ to value. We assume that the float factors are, on average, the same and hence they cancel out.

Assuming that on average a half of stock shares are assigned to value style,[85] we can write the percentage change in demand as:

$$
\begin{aligned}
\%\Delta Demand_{i,t} =& \frac{BA_{R2000,t} + BA_{R2000G,t} + BA_{R2000V,t}}{\sum_{R2000} MV_{j,t}} - \frac{BA_{R1000,t} + BA_{R1000G,t} + BA_{R1000V,t}}{\sum_{R1000} MV_{j,t}} \\
&- \frac{BA_{RMid,t} + BA_{RMidG,t} + BA_{RMidV,t}}{\sum_{RMid} MV_{j,t}}
\end{aligned}
$$

As Table 16 shows, this percentage change in demand for a stock moving across the cutoff is substantial and time-varying. For the Russell indices only, it ranges between -1.12% to 9.73%. It implies that up to 10% of the shares of a stock might be demanded in an index reconstitution event due to benchmarking.

Finally, the full change in demand, accounting for the Russell and the remaining indices, as implied by the change in BMI is higher, 6.46% on average. It is evident though that the two comove. This allows us to evaluate the quantitative implications of the heterogeneity of benchmarks. As Table 17 shows, averaged Russell-implied demand change of 5.72% results in elasticity of -1.14 for 5% index effect. Also, if we were to omit the Russell Midcap from the calculation, the average % demand change would be 10.68%. This would imply a significantly higher estimate of price elasticity of demand of -2.14. For comparison, our

[85] Russell uses proprietary stock fundamentals and a proprietary algorithm to assign stocks to value and growth indices. This assignment is performed within the Russell 1000 and Russell 2000 universes separately. In our data, we observe the resulting split: some shares of a stock are assigned to value and the rest to growth. On average, the split is at 50%, even though we observe pure value or pure growth stocks. Naturally, it mirrors that approximately half of the Russell 1000 or 2000 market value is in value, e.g., $\sum_{R2000V} MV_{j,t} \approx 0.5 \sum_{R2000} MV_{j,t}$. Therefore, our simplifying assumptions are realistic. We have also computed the percentage demand change on the actual value-growth splits and got identical implications.

BMI-based demand change of 6.46% delivers elasticity estimate of -1.29 if 5% index effect is assumed.

To compare with the BMI-based upper-bound value of elasticity in the main text, we need to use our estimate of index effect provided in Table 12: 1.9%. This results in elasticity of -6.46/1.9 = -3.4 which is close to the reported value of -3.7. It is important to keep in mind that the calculation based on % Demand change averaged over years is necessarily coarser than our regression-based approach in the main text.

Table 16: Demand change for additions to the Russell 2000

	Percentage demand change, %				
	Full (BMI)	All Russell	Russell 1000	Russell Midcap	Russell 2000
1998	-0.46	-1.12	-4.14	-2.60	5.62
1999	-0.33	-0.78	-4.47	-2.62	6.31
2000	0.99	-0.53	-4.49	-3.98	7.93
2001	0.64	1.54	-4.29	-3.75	9.58
2002	3.29	4.66	-3.94	-3.81	12.42
2003	7.27	5.07	-3.84	-3.98	12.89
2004	6.85	5.24	-3.81	-4.85	13.89
2005	5.99	5.18	-3.77	-5.51	14.46
2006	7.21	5.95	-3.85	-5.93	15.72
2007	6.14	6.20	-3.88	-5.81	15.90
2008	8.32	7.75	-3.84	-6.04	17.63
2009	10.55	8.75	-3.84	-6.27	18.86
2010	9.92	9.06	-3.74	-5.93	18.73
2011	10.83	9.73	-3.64	-5.87	19.24
2012	9.25	9.52	-3.77	-5.57	18.86
2013	10.64	8.90	-3.90	-5.04	17.83
2014	8.58	8.27	-4.04	-5.35	17.66
2015	6.02	6.51	-4.02	-5.42	15.95
2016	7.98	6.49	-3.99	-5.35	15.83
2017	8.29	6.78	-3.79	-5.38	15.95
2018	7.81	7.00	-3.68	-5.09	15.76
Mean	6.46	5.72	-3.94	-4.96	14.62

This table reports the demand change for a stock moving from the Russell 1000 to Russell 2000 Index, both total, i.e., implied by BMI, and driven by the Russell indices only. To get the demand change implied by BMI, ΔBMI is averaged for all additions to the Russell 2000 in year t. Russell 1000, Russell Midcap, and Russell 2000 columns represent the percentage change in demand corresponding to the assets benchmarked to the respective indices. Computational details are in Appendix A.18, all data is as of June for the respective year. The last row shows the mean of 1998-2018.

Table 17: Sensitivity of Elasticity Estimates

Sample	Demand change, %	Elasticity estimates for index effect of:			
		2%	3%	4%	5%
Panel A: Based on Russell indices					
1998-2018	5.72	-2.86	-1.91	-1.43	-1.14
1998-2012	5.08	-2.54	-1.69	-1.27	-1.02
Panel B: Based on BMI					
1998-2018	6.46	-3.23	-2.15	-1.62	-1.29
1998-2012	5.76	-2.88	-1.92	-1.44	-1.15

This table reports the sensitivity of the estimates of price elasticity of demand to the size of index effect. Elasticities are computed based on the approach of Chang, Hong, and Liskovich (2015), i.e., as *-% Demand change / Index effect %*. The average demand change values come from Table 16. Panel A uses % Demand change based on Russell indices, Panel B uses change in BMI. Second row in each panel reports the estimates for 1998-2012, sample closest to Chang, Hong, and Liskovich, who find that the price pressure amounts to 5%.

A.19 Optimized Sampling in Prospectus

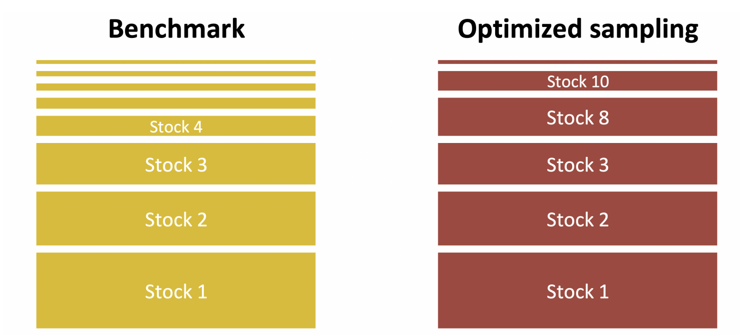
Figure 6: An extract from the prospectus of Fidelity's ZERO Large Cap index fund.

Principal Investment Strategies

- Normally investing at least 80% of assets in common stocks of large capitalization companies included in the Fidelity U.S. Large Cap Index℠, which is a float-adjusted market capitalization-weighted index designed to reflect the performance of U.S. large capitalization stocks. Large capitalization stocks are considered to be stocks of the largest 500 U.S. companies based on float-adjusted market capitalization.
- Using statistical sampling techniques based on such factors as capitalization, industry exposures, dividend yield, price/earnings (P/E) ratio, price/book (P/B) ratio, and earnings growth to attempt to replicate the returns of the Fidelity U.S. Large Cap Index℠ using a smaller number of securities.
- Lending securities to earn income for the fund.

A.20 Implications of Optimized Sampling for Portfolio Weights

Figure 7: Benchmark portfolio weights vs. optimized sampling weights



This figure illustrates the differences between a pure benchmark portfolio (left) and a portfolio constructed using optimized sampling (right). Horizontal bars represent stocks and their heights represent weights of these stocks in the respective portfolios.

A.21 Rebalancing Regressions Using a Narrower Band

Table 18: Rebalancing of additions and deletions, by benchmark and fund type

	Change in the aggregate ownership of funds with the same benchmark					
	Stocks ranked < 1000				Stocks ranked > 1000	
Benchmark	Russell 1000		Russell Midcap		Russell 2000	
Fund type	Active	Passive	Active	Passive	Active	Passive
Panel A: Change in ownership share						
$D^{R2000 \to R1000}$	0.117***	0.114***	0.353***	0.122***	-0.493***	-0.882***
	(3.09)	(3.89)	(3.88)	(3.36)	(-3.77)	(-4.30)
$D^{R1000 \to R2000}$	-0.095	-0.100***	-0.277***	-0.102**	0.073	0.778***
	(-1.69)	(-3.25)	(-3.83)	(-2.84)	(0.85)	(3.63)
Panel B: Change in holding status						
$D^{R2000 \to R1000}$	0.391***	0.467***	0.276***	0.469***	-0.335***	-0.929***
	(6.96)	(8.25)	(4.47)	(5.17)	(-6.55)	(-11.38)
$D^{R1000 \to R2000}$	-0.326***	-0.886***	-0.247***	-0.703***	0.087	0.804***
	(-5.98)	(-6.55)	(-5.52)	(-4.40)	(1.70)	(6.86)
Panel C: Ownership share						
D^{R2000}	-0.054	-0.076**	-0.068	-0.078**	0.166	0.733***
	(-1.57)	(-2.79)	(-1.11)	(-2.32)	(1.63)	(3.47)
Panel D: Holding status						
D^{R2000}	-0.169***	-0.306***	-0.048***	-0.635***	0.015*	0.605***
	(-7.96)	(-6.49)	(-3.48)	(-4.92)	(1.79)	(12.66)

This table reports α_{1j} and α_{2j} from estimating (12) (Panels A and B) and α_j from estimating (13) in the full sample period (1998-2018). Estimation is performed at a stock level for an aggregate portfolio of funds benchmarked to index j (active or passive). Band width is 150 stocks around the cutoffs. The dependent variable in panel A is the change in fraction of shares owned by the respective aggregate portfolio in stock i from March to September in year t. In panel B, it is the direction of the trade of the group (1 for buy, 0 for no trade, and -1 – for sell). In panel C, it is the ownership share in September. In panel D, it is a dummy that equals 1 if the stock is held by the aggregate portfolio in September and 0 if it is not. Regressions in both panel C and D additionally control for the dependent variable in March and include $BandingControls$ (being in the band, being in the Russell 2000 and their interaction in May). All regressions include $logMV$ (the logarithm of proprietary total market value), $Float$ (proprietary float factor), $\bar{X}$ (β^{CAPM} and bid-ask spread), and year fixed effects. In parenthesis are t-statistics based on standard errors double-clustered by stock and year. Significance levels are marked as: *p<0.10; **p<0.05; ***p<0.01.

A.22 Rebalancing Regressions Using Stock Fixed Effects

Table 19: Rebalancing of additions and deletions, by benchmark and fund type

	Change in the ownership by investor group					
	Stocks ranked < 1000				Stocks ranked > 1000	
Benchmark	Russell 1000		Russell Midcap		Russell 2000	
Fund type	Active	Passive	Active	Passive	Active	Passive
Panel A: Change in ownership share						
$D^{R2000\rightarrow R1000}$	0.115***	0.100***	0.327***	0.107***	-0.579***	-0.850***
	(3.82)	(3.69)	(3.55)	(3.25)	(-6.45)	(-4.41)
$D^{R1000\rightarrow R2000}$	-0.074	-0.098***	-0.271***	-0.103***	0.069	0.813***
	(-1.47)	(-3.50)	(-4.24)	(-3.08)	(0.84)	(4.04)
Panel B: Change in holding status						
$D^{R2000\rightarrow R1000}$	0.327***	0.436***	0.225***	0.445***	-0.298***	-0.924***
	(7.48)	(7.81)	(4.95)	(6.62)	(-7.87)	(-11.59)
$D^{R1000\rightarrow R2000}$	-0.279***	-0.882***	-0.208***	-0.730***	0.060	0.863***
	(-4.94)	(-7.10)	(-5.35)	(-5.02)	(1.43)	(9.24)
Panel C: Ownership share						
D^{R2000}	-0.025	-0.075***	-0.127	-0.072**	0.224*	0.706***
	(-0.82)	(-2.88)	(-1.69)	(-2.26)	(2.08)	(3.57)
Panel D: Holding status						
D^{R2000}	-0.170***	-0.360***	-0.064***	-0.667***	0.007	0.605***
	(-10.24)	(-7.43)	(-5.60)	(-5.88)	(0.94)	(14.37)

This table reports α_{1j} and α_{2j} from estimating (12) (Panels A and B) and α_j from estimating (13) in the full sample period (1998-2018). Estimation is performed at group j level (by benchmark and fund type). Band width is 300 stocks around the cutoffs. The dependent variable in panel A is the change in fraction of shares owned by the respective investor group of stock i from March to September in year t. In panel B, it is the direction of the trade of the group (1 for buy, 0 for no trade, and -1 – for sell). In panel C, it is the ownership share in September. In panel D, it is a dummy that equals 1 if the stock is held by the group in September and 0 if it is not. Regressions in both panel C and D additionally control for the dependent variable in March and include banding controls. All regressions include log total market value ($logMV$), controls in $\bar{X}$, and stock and year fixed effects. In parenthesis are t-statistics based on standard errors double-clustered by stock and year. Significance levels are marked as: *p<0.10; **p<0.05; ***p<0.01.

A.23 Rebalancing in Subsamples

Table 20: Rebalancing of additions and deletions, by benchmark and fund type

	Change in the aggregate ownership of funds with the same benchmark					
	Stocks ranked < 1000				Stocks ranked > 1000	
Benchmark	Russell 1000		Russell Midcap		Russell 2000	
Fund type	Active	Passive	Active	Passive	Active	Passive
Panel A: Change in ownership share						
$D^{R2000 \rightarrow R1000}$	0.047	0.024**	0.183**	0.013	-0.335***	-0.318**
	(1.27)	(2.14)	(2.20)	(1.20)	(-3.45)	(-2.66)
$D^{R1000 \rightarrow R2000}$	-0.053	-0.026**	-0.246**	-0.016	0.076	0.311**
	(-0.88)	(-2.15)	(-2.58)	(-1.32)	(1.08)	(2.23)
$D^{R2000 \rightarrow R1000} \times D^{>2006}$	0.219***	0.245***	0.595***	0.300***	-0.605***	-1.562***
	(3.33)	(7.53)	(3.99)	(7.26)	(-3.36)	(-6.23)
$D^{R1000 \rightarrow R2000} \times D^{>2006}$	-0.173**	-0.256***	-0.129	-0.302***	0.216	1.598***
	(-2.51)	(-6.70)	(-1.07)	(-7.19)	(1.04)	(6.10)
Panel B: Change in holding status						
$D^{R2000 \rightarrow R1000}$	0.261***	0.413***	0.171***	0.362***	-0.255***	-0.801***
	(5.12)	(6.56)	(2.97)	(4.25)	(-6.35)	(-6.72)
$D^{R1000 \rightarrow R2000}$	-0.245***	-0.742***	-0.172***	-0.618**	0.064	0.935***
	(-2.94)	(-3.68)	(-4.38)	(-2.65)	(1.38)	(7.15)
$D^{R2000 \rightarrow R1000} \times D^{>2006}$	0.276***	0.147	0.343***	0.226	-0.189**	-0.316*
	(3.49)	(1.66)	(3.66)	(1.49)	(-2.23)	(-1.99)
$D^{R1000 \rightarrow R2000} \times D^{>2006}$	-0.196**	-0.280	-0.242***	-0.262	0.175	-0.284
	(-2.17)	(-1.33)	(-3.48)	(-1.05)	(1.70)	(-1.40)
Panel C: Ownership share						
D^{R2000}	-0.028	-0.056***	-0.123**	-0.049***	0.262**	0.577***
	(-1.03)	(-3.84)	(-2.58)	(-2.93)	(2.48)	(4.03)
$D^{R2000} \times D^{>2006}$	-0.074*	-0.163***	-0.240***	-0.218***	0.091	1.246***
	(-1.96)	(-6.03)	(-3.13)	(-8.67)	(0.49)	(7.19)
Panel D: Holding status						
D^{R2000}	-0.175***	-0.357***	-0.057***	-0.655***	0.002	0.619***
	(-8.86)	(-6.84)	(-4.98)	(-4.59)	(0.37)	(13.74)
$D^{R2000} \times D^{>2006}$	-0.041	0.121**	-0.018	0.087	0.008	-0.121**
	(-1.55)	(2.57)	(-1.26)	(0.66)	(0.97)	(-2.68)

This table reports α_{1j} and α_{2j} from estimating (12) (Panels A and B) and α_j from estimating (13) as well as the coefficients on interaction with $D^{>2006}$ dummy that equals 1 in 2007-2018 and zero otherwise. Estimation is performed at a stock level for an aggregate portfolio of funds benchmarked to index j (active or passive). Band width is 300 stocks around the cutoffs. The dependent variable in panel A is the change in fraction of shares owned by the respective aggregate portfolio in stock i from March to September in year t. In panel B, it is the direction of the trade of the group (1 for buy, 0 for no trade, and -1 – for sell). In panel C, it is the ownership share in September. In panel D, it is a dummy that equals 1 if the stock is held by the aggregate portfolio in September and 0 if it is not. Regressions in both panel C and D additionally control for the dependent variable in March and include *BandingControls* (being in the band, being in the Russell 2000 and their interaction in May). All regressions include *logMV* (the logarithm of proprietary total market value), *Float* (proprietary float factor), $\bar{X}$ (β^{CAPM} and bid-ask spread), and year fixed effects. In parenthesis are t-statistics based on standard errors double-clustered by stock and year. Significance levels are marked as: *p<0.10; **p<0.05; ***p<0.01.

A.24 Value and Growth Indices

We document additional rebalancing patterns disaggregating ownership by benchmark style (value or growth). When a stock moves from the Russell 1000 to Russell 2000, it also enters the Russell 2000 Value and Growth indices.[86] In an analysis similar to the previous section, we show that active value funds rebalance value stocks and growth funds rebalance growth stocks.

In order to perform a well-specified test as in the main text, we would need to control for variables that define assignment to value and growth indices. This assignment is not as easy to predict compared to market cap indices. Using a proprietary database of I/B/E/S forecasts, B/P, and sales growth, Russell runs a custom probability algorithm to define a share of stock's market cap as value or growth. Therefore, we cannot ensure the exogeneity of style dummies, e.g., $D^{R2000\,Value}$ and $D^{R2000\,Growth}$. The best we can do with our data is to control for the Russell value ratio as of May (fraction of shares assigned to Value style) and the average M/B ratio in the year prior to the reconstitution.

Because a stock can simultaneously belong to value and growth indices, we estimate the following specification in levels, similar to (13) in the main text:

$$\begin{aligned} Own_{ijt} = {} & \alpha_j D^{Index}_{i,t} + \psi_j Own_{ijt-1} + \zeta_j logMV_{it} + \phi_j' BandingControls_{it} + \xi_j Float_{it} \\ & + \pi_j ValueRatio_{it} + \kappa_j M/B_{it} + \delta_j' \bar{X}_{it} + \mu_{jt} + \epsilon_{ijt} \end{aligned}$$

In the above specifications, D^{Index}_{it} is 1 when stock i belongs to Index (Russell 1000, Russell 2000, Russell 1000 Value, Russell 1000 Growth, Russell 2000 Value, or Russell 2000 Growth) on the reconstitution day in June of year t. Own_{ijt} is the fraction of shares outstanding owned or a dummy for whether aggregate portfolio of funds with benchmark j owns it or not. The funds are aggregated by benchmark and type (active/passive), e.g., active funds benchmarked to the Russell 1000 Value index. $ValueRatio_{it}$ is fraction of shares outstanding assigned to Value style by Russell. M/B_{it} is market-to-book ratio of the stock, averaged over the year prior to the reconstitution. All other variables are as defined in the main text.

As Table 21 reports, both active and passive funds hold portfolios in line with their benchmarks. For example, passive Russell Midcap Growth funds hold a larger fraction of shares of stocks in the Russell 1000 Growth universe and a smaller one of stocks in the Russell 2000 Growth universe.

[86] Russell methodology is such that most of the stocks belong to both indices, i.e., some part of market value is assigned to value and some – to growth. In other words, a stock is rarely a pure value or growth. Russell has special indices for pure style stocks that are rather small in AUM.

Table 21: Rebalancing of additions and deletions, by benchmark, style and fund type

Change in the aggregate ownership of funds with the same benchmark

Type	Active									Passive								
Benchmark	Russell 1000			Russell MidCap			Russell 2000			Russell 1000			Russell Midcap			Russell 2000		
Style	Blend	Value	Growth	Blend	Value	Growth	Blend	Value	Growth	Blend	Value	Growth	Blend	Value	Growth	Blend	Value	Growth
Panel A: Intensive margin																		
D^{R1000}	0.005			0.048**			-0.281***			0.013*			0.042**			-0.581***		
	(0.82)			(2.54)			(-2.94)			(1.92)			(2.17)			(-3.51)		
$D^{R1000Value}$		0.080***			0.204***			-0.100**			0.073***			0.058***			-0.100***	
		(3.94)			(4.82)			(-2.86)			(5.12)			(4.81)			(-5.50)	
$D^{R1000Growth}$			0.099***			0.294***			-0.102***			0.078***			0.056***			-0.083***
			(6.60)			(7.15)			(-3.81)			(6.55)			(6.10)			(-6.43)
D^{R2000}	-0.005			-0.048**			0.281***			-0.013*			-0.042**			0.581***		
	(-0.82)			(-2.54)			(2.94)			(-1.92)			(-2.17)			(3.51)		
$D^{R2000Value}$		-0.025*			-0.010			0.403***			-0.021***			-0.017***			0.243***	
		(-2.06)			(-0.33)			(6.61)			(-3.95)			(-3.06)			(7.14)	
$D^{R2000Growth}$			-0.037***			-0.122***			0.306***			-0.022***			-0.019***			0.235***
			(-3.27)			(-3.14)			(7.89)			(-4.56)			(-4.38)			(7.25)
Panel B: Extensive margin																		
D^{R1000}	0.234***			0.129***			-0.023**			0.376***			0.722***			-0.779***		
	(4.76)			(6.98)			(-2.85)			(6.55)			(5.85)			(-19.75)		
$D^{R1000Value}$		0.245***			0.098***			0.004			0.579***			0.742***			-0.289***	
		(7.10)			(6.22)			(0.36)			(8.18)			(9.91)			(-6.46)	
$D^{R1000Growth}$			0.324***			0.171***			0.070***			0.471***			0.854***			-0.196***
			(13.58)			(9.12)			(7.75)			(6.92)			(15.34)			(-6.60)
D^{R2000}	-0.234***			-0.129***			0.023**			-0.376***			-0.722***			0.779***		
	(-4.76)			(-6.98)			(2.85)			(-6.55)			(-5.85)			(19.75)		
$D^{R2000Value}$		-0.087***			-0.015			0.017			-0.196***			-0.256***			0.685***	
		(-3.99)			(-1.21)			(1.10)			(-3.56)			(-4.86)			(13.11)	
$D^{R2000Growth}$			-0.041*			0.036**			0.109***			-0.148***			-0.253***			0.663***
			(-1.80)			(2.82)			(7.75)			(-3.72)			(-7.43)			(11.56)

This table reports the differences in rebalancing of stocks assigned to different style indices. Estimation is performed at a stock level separately for each aggregate fund portfolio with the same benchmark, style, and type. Band width is 300 stocks around the cutoffs. The dependent variables represent ownership of stock i in September in year t by the respective aggregate fund portfolio. All regressions include $logMV$ (the logarithm of proprietary total market value), $Float$ (proprietary float factor), $\bar{X}$ (β^{CAPM} and bid-ask spread), $ValueRatio$ (proprietary value ratio), M/B (1-year monthly average M/B ratio), lagged dependent variable, and year fixed effects. t-statistics in parentheses are based on standard errors double-clustered by stock and year. Significance levels are marked as: *p<0.05; **p<0.01; ***p<0.001.

A.25 Alternative Identification on Ownership Data

Table 22: Active and Passive Ownership

	Percentage of firm's common shares held by							
	All active	All passive	Active funds benchmarked to:			Passive funds benchmarked to:		
			Russell 1000	Russell Midcap	Russell 2000	Russell 1000	Russell Midcap	Russell 2000
Panel A: Approach of Appel, Gormley, and Keim (2008-2014)								
D^{R2000}	-0.67	1.82***	-0.11	-0.91**	0.20	-0.23***	-0.29***	2.05***
	(-1.09)	(17.34)	(-1.40)	(-3.14)	(0.39)	(-12.19)	(-21.64)	(12.72)
Panel B: Approach of Appel, Gormley, and Keim and our sample (1998-2018)								
D^{R2000}	0.18	0.78***	-0.04	-0.33***	0.42**	-0.11***	-0.11***	0.92***
	(0.80)	(4.61)	(-1.22)	(-3.93)	(2.60)	(-3.70)	(-3.30)	(4.39)

This table replicates and extends the findings of Appel, Gormley, and Keim (2021). Panel A reports the results for the original sample, and panel B - for the extended one. The dependent variable is the fraction of shares in stock i owned by the respective investor group in September of year t. All regressions include year fixed effects, log total market value ($logMV$) and its square, float and banding controls as in Appel, Gormley, and Keim (2021). Band width is 500. In parenthesis are t-statistics based on standard errors two-way clustered by stock and year. Significance levels are marked as: *p<0.10; **p<0.05; ***p<0.01.

A.26 Results for Long-Run Periodic Returns

Table 23: Benchmarking intensity and long-run returns

	Excess returns, average over horizon				
Horizon (months)	1-12	13-24	25-36	37-48	49-60
Panel A: All baseline controls					
ΔBMI	-0.047**	-0.032*	-0.000	-0.007	0.006
	(-2.68)	(-1.79)	(-0.03)	(-0.58)	(0.50)
Observations	13,813	12,319	10,931	9,739	8,645
Panel B: Baseline controls without stock fixed effects					
ΔBMI	-0.045*	-0.033*	-0.002	-0.012	-0.003
	(-1.93)	(-1.82)	(-0.14)	(-1.29)	(-0.31)
Observations	14,351	12,801	11,393	10,100	9,001
Panel C: $LogMV$**,** $Float$ **and** $BandingControls$ **only**					
ΔBMI	-0.041**	-0.031*	-0.006	-0.008	0.002
	(-2.44)	(-1.87)	(-0.52)	(-0.70)	(0.14)
Observations	14,700	13,126	11,609	10,288	9,095
Panel D: All baseline controls and a narrower band					
ΔBMI	-0.049***	-0.015	-0.002	-0.010	0.012
	(-3.10)	(-0.90)	(-0.18)	(-0.67)	(0.70)
Observations	7,640	6,832	6,082	5,383	4,750
Panel E: All baseline controls and interaction with post-banding dummy					
ΔBMI	-0.047*	-0.051*	0.009	-0.002	0.009
	(-1.94)	(-2.07)	(0.57)	(-0.11)	(0.50)
$\Delta BMI \times D^{>2006}$	0.001	0.036	-0.018	-0.010	-0.006
	(0.06)	(1.52)	(-0.98)	(-0.60)	(-0.32)
Observations	13,813	12,318	10,928	9,731	8,633

This table reports the results of the regression of the long-run returns on change in BMI, ΔBMI, in the full sample (1998-2018). The dependent variable is an average monthly excess return from September in year t over the respective horizon. Panels A and B include all baseline controls, while Panel C – log total market value, the proprietary ranking variable, and the banding controls only. Panel E adds an interaction between ΔBMI and $D^{>2006}$, which equals 1 in years 2007-2018 and 0 otherwise. In Panels A, B, C, and E, we limit the sample to 300 stocks around the cutoffs (rectangular kernel). Panel D limits the sample to 150 stocks around the cutoffs. The baseline controls include $logMV$ (the logarithm of proprietary total market value), $Float$ (proprietary float factor), $BandingControls$ (being in the band, being in the Russell 2000 and their interaction in May), $\bar{X}$ (β^{CAPM} and bid-ask spread), and stock and year fixed effects. t-statistics based on standard errors double-clustered by stock and year are in parentheses. Significance levels are marked as: *p<0.10; **p<0.05; ***p<0.01.

A.27 Tests on Additional Stock Characteristics

Table 24: Description of additional stock characteristics

Variable	Definition	Obs.	Mean	St.Dev.	Min	Max
Leverage	(Long-Term Debt + Debt in Current Liabilities) / (Long-Term Debt + Debt in Current Liabilities + ME)	16,570	0.26	0.23	0.00	1.00
ROA	Net Income (Loss) / Assets	16,594	0.03	0.10	-0.93	0.28
Repurchase	Purchase of Common and Preferred Stock / ME	15,000	0.02	0.04	0.00	0.22
Div.yield	(Dividends Common/Ordinary + Dividends - Preferred/Preference) / ME	16,367	0.02	0.03	0.00	0.15
Sales growth	(Sales year 1 - sales year 0) / sales year 0	15,456	0.33	0.84	-0.74	7.28
Capex/Assets	Capital Expenditures / Assets	16,602	0.04	0.06	0.00	0.33
R&D/Sales	R&D / Sales	16,556	0.08	0.48	0.00	7.15
1(Acquisition)	1 if Acquisition expenditures are positive and 0 otherwise	16,641	0.43	0.49	0.00	1.00
Asset growth	log(Assets year 1) - log(Assets year 0)	15,514	0.22	0.38	-0.71	1.99
Altman Z-score	Altman (1968)	16,602	4.11	5.99	-9.10	46.33
SUE	Surprise to I/B/E/S reported analyst forecast	15,716	-0.01	0.02	-0.10	0.09
Turnover	Volume / Shares outstanding, annualized	16,641	2.62	1.96	0.08	10.09
ILLIQ	Amihud (2002), cross-sectionally scaled	16,538	0.01	0.03	0.00	2.15
Short interest ratio	Short interest / Shares outstanding	15,461	0.05	0.05	0.00	0.25

This table reports the descriptive statistics of the additional stock characteristics. These statistics are calculated on the annual panel of 300 stocks around both cutoffs in 1998-2018 using Compustat and CRSP. For accounting variables, the last publicly available value prior to May is used. For SUE, ILLIQ, and short interest ratio, an average value over the year is used (June-May). All variables are winsorized at 1%.

Table 25: Tests on additional stock characteristics

	Leverage	ROA	Repurchase	Div.yield
ΔBMI	-0.090	0.102*	-0.001	-0.013
	(-1.39)	(1.97)	(-0.06)	(-1.28)
Observations	11,426	11,426	10,159	11,417
	Capex/Assets	M/B	R&D/Sales	Asset growth
ΔBMI	0.009	-1.400*	0.135	0.530
	(0.55)	(-2.03)	(1.11)	(1.64)
Observations	11,427	11,427	11,407	11,422
	Sales growth	1(Acquisition)	Altman Z-score	SUE
ΔBMI	0.299	0.104	-1.887	-0.010
	(0.52)	(0.76)	(-0.77)	(-1.10)
Observations	11,387	11,434	11,427	10,797
	Turnover	ILLIQ	Bid-ask spread	Short interest ratio
ΔBMI	0.718	-0.026	-0.016	0.110***
	(1.22)	(-1.14)	(-0.41)	(5.78)
Observations	11,434	11,375	11,329	10,642

This table reports how the change in stock characteristics is related to the change in BMI . Dependent variable is the 3-year change in the respective variable compared to the value prior to the reconstitution. The main independent variable is the change in BMI, ΔBMI. We limit the sample to 300 stocks around the cutoffs (rectangular kernel). All regressions include *logMV* (the logarithm of proprietary total market value), *Float* (proprietary float factor), *BandingControls* (being in the band, being in the Russell 2000 and their interaction in May), $\bar{X}$ (β^{CAPM} and bid-ask spread), and year fixed effects. t-statistics based on standard errors double-clustered by stock and year are in parentheses. Significance levels are marked as: *p<0.10; **p<0.05; ***p<0.01.