The Hidden Cost of Stock Market Concentration: When Funds Hit Regulatory Limits

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Abstract

As stock market concentration has risen, regulatory limits on fund portfolio concentration have become increasingly binding, especially for large-cap growth funds. When funds approach these limits, they trim their largest holdings and reduce equity exposure. Funds perform worse when constrained. A constraint-based ownership measure predicts stock returns, particularly among the largest firms. These findings suggest that high market concentration can distort stock prices by limiting the ability of optimistic investors to scale their positions. Just like short-sale constraints can produce overpricing by limiting pessimistic investors' views, constraints on long positions can generate underpricing by suppressing optimists' views.

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1. Introduction

The U.S. stock market has become highly concentrated. Figure 1 shows that between 2015 and 2024, the share of the 10 largest stocks in total market capitalization rose from 13% to 31%. Within the large-cap growth style, the top 10 stocks' share rose even higher, from 30% to 48%. In fact, just seven companies—the "Magnificent 7"—account for roughly one-third of the total market capitalization of the S&P 500 Index, and over 55% of the Russell 1000 Growth Index, at the end of 2024.[1] As a result, many investors' portfolios have become highly concentrated, raising concerns about exposure to a handful of dominant firms.

Rising market concentration also makes it increasingly difficult for investment firms to satisfy regulatory limits on portfolio concentration. Virtually all U.S. mutual funds and exchange-traded funds (ETFs) elect to be treated as Regulated Investment Companies under the Internal Revenue Code, which allows them to pass income through to investors without paying entity-level taxes. To qualify for this treatment, a fund must satisfy a diversification test commonly referred to as the "50/5/10 rule." This statutory rule requires that at least 50% of the fund's total assets consist of securities for which no single issuer represents more than 5% of total assets and no more than 10% of the issuer's voting securities. In other words, less than half of a fund's portfolio can be invested in large positions, as defined above. Because most funds seek to avoid large tracking errors relative to capitalization-weighted benchmarks, their largest positions tend to occur in the largest-capitalization stocks. The 50/5/10 rule therefore effectively constrains funds' long positions in the largest firms.

Can long-position constraints affect stock prices? We hypothesize they can: in a concentrated market, the largest stocks may become temporarily underpriced if some investors are unwilling or unable to hold them to the desired extent. For example, an active large-cap growth fund manager optimistic about Nvidia may be reluctant to overweight it relative to its already large benchmark weight, to reduce the risk of violating portfolio-concentration limits. If such optimistic investors are underrepresented in aggregate demand, the stock will be underpriced in equilibrium. We formalize this intuition in a simple model. The pricing pressure can be even stronger if the benchmark itself is so highly concentrated that the 50/5/10 limit constrains even passive index funds.

We analyze how the 50/5/10 regulatory constraint affects fund behavior and stock prices in a concentrated market. After documenting that this constraint has tightened in recent years, we show that funds adjust their portfolios to avoid breaching it, with adverse effects

[1] These seven companies include Alphabet, Amazon, Apple, Meta, Microsoft, Nvidia, and Tesla. See, for example, Fidelity Investments (2025) and American Century Investments (2025).

on performance. A constraint-based ownership measure positively predicts stock returns, consistent with the correction of temporary underpricing among the largest firms.

We examine a sample of 4,745 U.S. domestic equity funds, whose quarterly portfolio holdings we obtain from regulatory filings. For each fund and quarter in 2019 through 2024, we measure proximity to breaching the 50/5/10 rule by computing the fund's *buffer* as 50% minus the sum of its large positions. A negative buffer indicates a breach, which is rare, while a small positive buffer implies proximity to the constraint. We classify a fund as *constrained* if its buffer is small–between 0 and 5%, as we explain later.

We find that the 50/5/10 constraint, historically a formality, has become increasingly binding. Constrained fund assets rise from negligible levels in 2019Q3 to 6% of total fund assets in 2024Q4. At the peak in 2024Q3, 171 funds are constrained, managing almost $1.4 trillion, or 8% of total assets. Most of the increase occurs in the large-cap growth category: in 2024Q3, about one-third of these funds are constrained, managing over $1.1 trillion–half of the category's assets. This pattern reflects rising stock market concentration, as the largest firms in 2024 are predominantly large-cap growth stocks.[2]

We apply the same buffer concept to funds' benchmark indexes to see whether rising concentration has pushed the indexes themselves toward the 50/5/10 limit. Index buffers have declined across the board, especially for large-cap growth indexes, whose buffers approached zero in 2024. The Nasdaq-100 index even implemented a special rebalance in 2023, reducing the weights of its largest constituents to avoid breaching the 50/5/10 limit. Benchmark concentration translates directly into fund-level constraints. For passive funds, the connection is mechanical: a fund tracking a concentrated benchmark inherits the benchmark's small buffer. Active funds are affected as well, despite their greater flexibility, because index buffers explain a large share of the variation in active fund buffers. Thus, rising stock market concentration has pushed both active and passive funds toward the 50/5/10 constraint.

Do funds alter their portfolios after becoming constrained? We find they do, in two ways. First, they rebalance away from their largest positions and toward stocks with smaller market capitalizations. This rebalancing is stronger when the large positions are close to the 5% threshold and exhibit higher return volatility, consistent with such positions posing greater compliance risk. Second, constrained funds reduce their overall equity exposure, substituting non-equity assets such as cash for large equity holdings.

[2]Examples of funds that actually breached the 50/5/10 constraint (i.e., had negative buffers) temporarily in 2024 include Fidelity's $67 billion Blue Chip Growth Fund, T Rowe Price's $63 billion Blue Chip Growth Fund, and BlackRock's Long-Term US Equity ETF (Financial Times, 2024). Funds that breached the constraint have a grace period within which they must restore compliance.

Does being constrained impair fund performance? We find it does. In regressions with fund fixed effects, large-cap growth funds perform worse when constrained. Over the full 2019-2024 sample, these funds earn significantly lower risk-adjusted returns in the six months following the constrained quarter. In the first three months alone, the average large-cap growth fund's four-factor-adjusted return is 57 basis points (bps) lower. This underperformance deepens to 1.31% when estimated over the 2023-2024 period, when the constraint was especially binding. Across all funds, the corresponding effect is 83 bps, smaller but still significant. Funds with negative buffers underperform even more, by 1.15% (all funds) or 2.11% (large-cap growth funds) over three months in 2023-2024. The underperformance reflects both rebalancing away from large positions and reduced equity exposure.

These results suggest that after rebalancing away from large positions, constrained funds forgo the high subsequent returns of those positions. We hypothesize that these returns reflect the correction of temporary underpricing. A stock may become underpriced when enough funds underweight it to comply with the 50/5/10 rule, and the mispricing is later corrected as unconstrained investors step in with a delay. This hypothesis predicts that stocks held disproportionately by constrained funds should subsequently outperform.

To test this prediction, we compute for each stock and month a *constrained ownership share,* C, defined as the fraction of the stock's outstanding shares held as large positions by funds with buffers below 5% (i.e., constrained and negative-buffer funds). Our prior evidence indicates that stocks with $C > 0$ are likely underweighted in some of these funds' portfolios. The total market capitalization of $C > 0$ stocks grows from \$11 trillion in 2019Q3 to \$41 trillion in 2024Q4—more than 60% of aggregate market capitalization. Many large-cap growth stocks have $C > 0$; for example, Nvidia and Microsoft have C values around 5%.

We find that C positively predicts risk-adjusted returns in the cross section of large stocks. This predictability is marginally significant over the full sample but highly significant in the 2023–2024 period, when the 50/5/10 constraint was especially tight. During that period, stocks with $C > 0$ significantly outperform $C = 0$ stocks at all horizons from 1 to 12 months. At the 6-month horizon, for example, positive-C stocks earn cumulative abnormal returns 2.3% higher than $C = 0$ stocks. The return differential is significantly larger for high-volatility stocks. These findings are consistent with temporary underpricing of positive-C stocks, particularly those with greater compliance risk.

These return predictability results are based on panel regressions with time fixed effects. To complement them, we design two trading strategies. First, we sort stocks into high-C ($C > 0$) and low-C ($C = 0$) groups. The value-weighted high-C portfolio earns annualized four-factor alphas of 1.7% in 2019–2024 and 2.3% in 2023–2024. Second, we double-sort stocks on C and return volatility. The value-weighted portfolio of high-C, high-volatility stocks earns even larger alphas, 7.9% in 2019–2024 and 11.8% in 2023–2024. These alphas are only marginally statistically significant, given the short samples, so they must be interpreted with caution. They are notable, however, because many high-C stocks are among the largest and most liquid equities, for which cross-sectional anomalies are rare. Any evidence of return predictability among such firms warrants attention and further scrutiny, especially when they account for a historically high share of total market capitalization.

When we separate funds into active and passive, we find that both types trim their large positions as they approach or violate the 50/5/10 limit, and that higher volatility amplifies the trimming. Both types also underperform when constrained, to similar degrees, but active funds' constrained ownership has more power to predict stock returns. This finding supports the interpretation that portfolio concentration limits can distort stock prices by capping the positions of active investors who are optimistic about the largest stocks.

While our main focus is the 50/5/10 rule, we also analyze a separate 75/5/10 rule that applies to funds classified as diversified under the 1940 Investment Company Act. Although this constraint is widely viewed as softer than the 50/5/10 rule, we show it still affects portfolio choices. Diversified funds near the 75/5/10 limit trim large positions more aggressively than non-diversified funds, experience modest performance drag, and generate marginally significant return predictability. These findings suggest that even a softer diversification rule can influence fund behavior and asset prices when market concentration is high.

We contribute to several strands of research, including work on corporate concentration. Prior studies show that economic activity has become increasingly dominated by a small set of "superstar" firms (Autor, Dorn, Katz, Patterson, and Van Reenen, 2020), and that corporate concentration has risen persistently over the past century (Kwon, Ma, and Zimmermann, 2024). Yet the implications of this trend for asset prices and investment management remain understudied. A notable exception is Jiang, Vayanos, and Zheng (2025), who examine how market concentration interacts with the rise of passive investing. They show that flows into passive funds disproportionately boost the valuations of the largest firms. We also study the interplay between concentration and fund management but emphasize a different mechanism: rising market concentration pushes both active and passive funds toward statutory portfolio-concentration limits, restraining the valuations of the largest firms.

This paper also relates to the literature on the effects of fund regulation. Investment companies operate under extensive statutory requirements and adjust their portfolios when these rules change. Prior work studies fund responses to a variety of regulations.[3] We examine previously unexplored statutory requirements: the 50/5/10 and 75/5/10 constraints. To our knowledge, we are the first to document how binding these constraints have become and to trace their effects on fund behavior and stock prices.

A long-standing question in finance is whether restrictions on short positions affect equilibrium asset prices. In the presence of disagreement or asymmetric information, short-sale constraints limit the market representation of pessimistic views, leading to overpricing (Miller, 1977). This mechanism has received substantial empirical support.[4] In contrast, we seem to be the first to study restrictions on long positions. We argue that these restrictions prevent optimistic investors from holding sufficiently large positions, precluding their bullish views from being fully reflected in stock prices, leading to underpricing. We show that these long-position limits bind for some of the largest stocks, whereas short-sale constraints primarily affect small and illiquid stocks (e.g., D'Avolio (2002)).

Besides regulatory limits and short-sale constraints, mutual funds face a variety of other investment restrictions (Almazan, Brown, Carlson, and Chapman, 2004). A prominent example is the investment mandate. Prior studies analyze how such mandates arise endogenously (He and Xiong, 2013) and how they affect equilibrium asset prices (e.g., Brennan (1993), Cuoco and Kaniel (2011), Basak and Pavlova (2013), and Buffa, Vayanos, and Woolley (2022)). However, this literature does not examine how investment restrictions interact with market concentration or large fund positions, which are the focus of our study.

Prior studies of large fund positions include Blume and Keim (2017), who show that the largest stocks tend to be underweighted in institutional portfolios, and Chen (2025), who examines changes in mutual funds' largest portfolio weights. Consistent with some of our findings, Chen (2025) shows that active equity funds predictably trim their largest positions, especially those approaching 5% of portfolio value, and that such trading contributes to predictable patterns in stock returns. The main difference between Chen's work and ours is the statutory 50/5/10 regulatory constraint, which is absent from his analysis. A fund's

[3]For example, Golec and Starks (2004) show that when asymmetric performance-fee schedules were banned in 1971, affected funds altered their risk exposures. An, Huang, Lou, and Shi (2021) argue that when leverage and short-selling limits were relaxed in the 1990s, mutual funds entered those strategy spaces. Chakraborty, Ferracuti, Heater, and Phillips (2025) show that the SEC's adoption of the Liquidity Rule (Rule 22e-4) led U.S. funds to increase their holdings of liquid assets. Joenväärä and Kosowski (2020) find that hedge funds subject to European UCITS regulations underperform less-regulated peers.

[4]For example, Diether, Malloy, and Scherbina (2002) show that stocks with greater disagreement—proxied by dispersion in analysts' earnings forecasts—earn lower future returns. Chen, Hong, and Stein (2002) measure disagreement by the breadth of mutual fund ownership and reach similar conclusions. Jones and Lamont (2002) find that expensive-to-short stocks have high valuations and low subsequent returns, consistent with overpricing. Daniel, Klos, and Rottke (2024) review related evidence.

proximity to this constraint—the fund's buffer—is central to our empirical design. Chen's sample also ends in 2022, before the constraint became meaningfully binding. There are also other differences; for example, we examine constrained funds' performance and study the role of stock return volatility in both fund trading and return predictability.

Existing literature generally interprets portfolio concentration as the outcome of active choice. For example, Kacperczyk, Sialm, and Zheng (2005) and Choi, Fedenia, Skiba, and Sokolyk (2017) argue that fund managers choose to hold concentrated portfolios to exploit expertise or information advantages, and Van Nieuwerburgh and Veldkamp (2010) show that concentration emerges endogenously in a model with costly information acquisition. We emphasize that portfolio concentration can also arise mechanically rather than by choice, simply by tracking an index that itself becomes concentrated. When funds approach regulatory portfolio concentration limits, even informed managers may be forced to trade away from their best ideas, sacrificing performance and muting price discovery.

Finally, we contribute to the voluminous literature on stock return predictability by constructing an effective predictor based on a previously unexplored regulatory constraint. Whereas prior literature finds predictability to be concentrated primarily in small and illiquid stocks (e.g., Green, Hand, and Zhang (2017) and Hou, Xue, and Zhang (2020)), we find predictability among some of the largest and most liquid stocks in the market.

This paper is organized as follows. Section 2 provides the institutional background. Section 3 assesses how binding the 50/5/10 constraint has become. Sections 4 and 5 analyze the response and performance of constrained funds, respectively. Section 6 examines stock return predictability motivated by the constraint. Section 7 separates active and passive funds. Section 8 conducts a parallel analysis for the 75/5/10 rule. Section 9 concludes.

2. Institutional background

In this section, we first review the regulatory setting that is central to our analysis. We then use recently introduced regulatory filings to demonstrate that rising stock market concentration has made compliance increasingly difficult for funds.

2.1. Regulated Investment Companies

Regulated Investment Companies (RICs) are investment vehicles that elect pass-through tax treatment under Subchapter M of the Internal Revenue Code, allowing them to distribute income to investors without incurring entity-level taxation. RIC status was introduced by the Revenue Act of 1936. To qualify, a firm must derive most of its income from securities, distribute the bulk of this income to shareholders, and maintain a sufficiently diversified portfolio. In practice, RIC status is adopted by the vast majority of mutual funds, ETFs, and closed-end funds, but not by hedge funds, private equity funds, venture capital funds, pension funds, insurance companies, or separately managed accounts.

RICs play an increasingly important role in U.S. equity markets. Figure 2 shows that the share of U.S. corporate equities held by RICs rose by a factor of ten, from 2.5% to 25%, between 1952 and 2024. This growth reflects several forces, including the shift from direct stockholding by households to delegated portfolio management, the expansion of tax-advantaged retirement accounts, and the rapid adoption of low-cost index funds. As a result, RICs now account for a substantial fraction of total equity ownership.

Figure 2 also plots quarterly stock market concentration from 1952 to 2024, extending the solid line in Figure 1 (the share of the 10 largest stocks in total market capitalization) further back in time. Market concentration in 2024 is high relative to its levels over the previous half-century. It has not been this high since the early 1960s, when RICs' share of total equity ownership was much smaller—about one fifth of its 2024 level. The 2020s are thus the first decade in which high stock market concentration coincides with high equity ownership by RICs, creating scope for RICs' diversification requirements to affect stock prices.

2.2. The 50/5/10 rule

The primary diversification requirement for RICs, codified in Section 851(b)(3) of the Internal Revenue Code, is commonly known as the "50/5/10 rule." This rule requires that at least 50% of a fund's total assets be invested in securities such that no single issuer represents more than 5% of total assets and the fund holds no more than 10% of the issuer's voting securities. The remaining assets are largely unrestricted, except that no more than 25% of total assets may be invested in any single issuer. The 50/5/10 rule effectively caps large positions, particularly for funds whose benchmarks are dominated by just a few firms.

Compliance is evaluated at the end of each fund's taxable quarter, based on market values.

The law recognizes that valuation changes can temporarily push a fund out of compliance. Two forms of relief apply. First, under the *fluctuation-in-value* exception, a fund that was compliant at the previous testing date retains its RIC status if a breach arises solely from price movements, provided it rebalances by the next quarter end. Second, for breaches caused by active trading, a fund has thirty days after quarter end to cure the failure. The RIC Modernization Act of 2010 added a further six-month backstop for inadvertent violations, subject to remedial taxes and an IRS filing. In practice, most managers rebalance within thirty days to avoid these costs.

In the 2019–2024 period, this hierarchy of rules implies the following: (i) valuation drifts must be corrected by the next quarter end; (ii) small, trading-induced breaches may be cured within six months; and (iii) material breaches are typically corrected within thirty days. Because large breaches usually involve sizable positions in a few dominant issuers, funds manage those exposures actively around quarter ends. Portfolio managers, compliance officers, and tax specialists coordinate these adjustments to maintain compliance.

The 50/5/10 rule is not the only regulatory limit that governs portfolio concentration. Under the Investment Company Act of 1940, a fund can be marketed as "diversified" only if it satisfies a separate 75/5/10 rule: at least 75% of a fund's total assets consist of securities for which no single issuer represents more than 5% of total assets and the fund holds no more than 10% of the issuer's voting securities. In structure, this rule resembles the 50/5/10 rule but applies to a larger share of the portfolio (75% rather than 50%). In practice, however, it is far softer, which is why our primary focus is on the 50/5/10 rule. In Section 8, we describe the 75/5/10 rule in more detail and examine funds' responses to it.

2.3. Data

Our main data source is the SEC's NPORT-P filings, which report the complete portfolio holdings and total assets of each registered fund at the end of every fiscal quarter. These filings coincide with funds' taxable quarters and provide the appropriate accounting basis for evaluating compliance with the 50/5/10 rule, as they include total assets rather than total net assets as in CRSP. We complement these data with information from the CRSP mutual fund and stock databases, which include fund-level characteristics such as returns, expense ratios, and Lipper classifications, as well as stock-level variables such as returns, shares outstanding, and industry classifications. We obtain accounting data from Compustat to construct book-to-market ratios used in classifying firms as growth or value, and we use the Fama–French factors from Ken French's data library at Dartmouth.

Our sample period begins in September 2019, when NPORT-P data first become available, and ends in December 2024. The sample includes 4,745 domestic equity funds—both mutual funds and ETFs, both active and passive funds, and only funds whose equity holdings are between 50% and 150% of their total assets.[5] The sample also includes 6,807 U.S.-listed common stocks that are ever held by these funds during the sample period; 4,440 of these appear at the end of 2024. When we refer to a stock, we mean a firm identified by the CRSP permanent company identifier (PERMCO); when we refer to a fund, we mean a unique SEC series rather than a share class. We aggregate CRSP data from the security (PERMNO) to the firm (PERMCO) level using market-capitalization weights, and we aggregate fund share classes to the series level using CRSP-reported total net assets as weights.

3. Is the constraint binding?

In this section, we examine the extent to which the 50/5/10 constraint has become binding. We study the tightness of the constraint at both the fund level (Section 3.1) and the index level (Section 3.2) and find a close link between the two (Section 3.3).

3.1. Fund buffers

We follow the regulatory definitions in Section 2.2 to assess how close funds are to the 50/5/10 rule limit and how often the constraint binds in practice. For each fund f and quarter t, we compute the portfolio weight of stock s as

$$\text{Weight}_{f,s,t} = \frac{\text{Value}_{f,s,t}}{\text{TotalAssets}_{f,t}} \times 100\,, \tag{1}$$

where $\text{Value}_{f,s,t}$ is the value of fund f's holdings in stock s in quarter t, and $\text{TotalAssets}_{f,t}$ is the fund's total assets in that quarter. Both variables come from NPORT-P filings. We classify a holding as a *large position* if it exceeds 5% of the fund's total assets or 10% of the issuer's voting securities. For simplicity, we assume that each common share carries one vote. We then measure the fund's distance from the diversification limit as

$$\text{Buffer}_{f,t} = 50\% - \sum_{s \in \text{LargePos}_{f,t}} \text{Weight}_{f,s,t}\,, \tag{2}$$

[5] In addition to the mentioned filters, we excluded four funds from our sample—Parnassus Mid Cap Growth, Mid Cap, Endeavor, and Core Equity (SEC series: S000000852, S000000853, S000000855, and S000000856)—as their reported held shares before September 2021 contained significant errors (e.g., held shares exceeding twice the total shares outstanding).

where $\text{LargePos}_{f,t}$ denotes the set of the fund's large positions.[6] A negative buffer indicates that the fund's portfolio would breach the 50/5/10 rule if tested at that quarter end, while a small positive buffer signals proximity to the constraint. Throughout the analysis, we refer to funds with buffers below 0 as *negative-buffer funds* and funds with buffers between 0 and 5% as *constrained funds*. We set the upper bound at 5% to match the regulatory threshold for large positions. Funds with buffers below 5% face an elevated risk of violating the 50/5/10 rule because a small increase in a single holding—from 4.99% to 5.01%, for example—can reclassify it as a large position and make the fund non-compliant.

Figure 3 presents the cross-sectional distributions of fund buffers at year-ends of 2019 and 2024, based on the number of funds and total fund assets. The histograms show a visible discontinuity at zero, with very few funds ever reporting $\text{Buffer}_{f,t} < 0$. This discontinuity is more pronounced in 2024, when many more funds are pushed close to the limit. For example, in 2024, 4% of funds, accounting for 6% of total fund assets, have positive buffers smaller than 5%. We thus see that funds generally comply with the 50/5/10 rule, but the compliance is considerably more challenging in 2024 than in 2019. There is also a visible discontinuity at the buffer level of 25%, highlighting the relevance of the 75/5/10 rule discussed in Section 8. The latter discontinuity is also more pronounced in 2024.

Figure 4 plots the time series of the number of constrained funds and their total assets. The prevalence of the constraint rises gradually over the sample period, with a sharp jump in 2024. At the peak, in 2024Q3, 171 funds are constrained, representing 4.5% of all domestic equity funds. These funds manage 8% of total fund assets, almost $1.4 trillion.

Figure 5 examines the role of the investment style, plotting the number of constrained funds and their assets within each fund category of the 3×3 Lipper classification. We see that the upward trend observed in Figure 4 is driven almost entirely by large-cap growth funds. By 2024Q3, about one-third of these funds are constrained, managing more than $1.1 trillion, about half of the category's assets. It is not a coincidence that much of the recent rise in stock market concentration comes from the large-cap growth segment.

Figure 6 shows that large-cap growth funds account for about 80% of constrained fund assets at the end of 2024, up from less than 5% in 2019. In contrast, sector funds account for 80% of constrained fund assets in 2019 but only 20% in 2024. For many years, the 50/5/10 rule used to be of concern primarily to niche sector funds, and very few funds were affected. Recently, however, the rule has come to affect more funds, especially large-cap growth, which

[6] Strictly speaking, the regulatory definition evaluates the fraction of the fund's portfolio invested in non-large positions. We perform a mirror-image symmetric calculation, adding up large positions, because it is simpler to process equity holdings than the holdings of bonds, cash equivalents, and derivatives.

are much larger in both numbers and assets. Summing up, the patterns in Figures 3 through 6 indicate that the 50/5/10 rule, historically a formality, has become a binding constraint for a significant share of the fund industry.

3.2. Index buffers

Next, we assess the tightness of the constraint for market indexes. We approximate index weights using daily ETF holdings data from ETF Global. We consider two broad-market indexes, the CRSP Total Market (corresponding ETF: VTI) and the S&P 500 (SPY); two large-cap growth indexes, the Russell 1000 Growth (IWF) and the S&P 500 Growth (SPYG); the technology-heavy Nasdaq-100 (QQQ); and ten sector indexes. For each index, we compute its daily buffer as in equation (2), subtracting from 50% the sum of all index weights exceeding 5% (we disregard the 50/5/10 rule's 10% voting-securities provision, which is irrelevant for the index itself, though it could matter for a large index fund).

Figure 15 displays index buffers from 2012 to 2024. Panel A shows month-end values for the broad-market indexes and large-cap growth indexes. Panel B shows daily values for the Nasdaq-100; the daily frequency is needed to capture the jump on the special-rebalance date of July 24, 2023. Buffers differ markedly across indexes, at four levels.

First, both broad-market indexes maintain comfortable buffers. Until 2020, these indexes were completely unconstrained, with buffers at the maximum value of 50% (implying that no stock exceeded 5% of total market cap). Since then, their buffers have fallen to about 30% in 2024, consistent with the rise in market concentration shown in Figure 1. Even so, a 30% buffer is far from binding, indicating that broad-market index funds remain effectively unconstrained by the 50/5/10 rule.

Second, both large-cap growth indexes have much tighter buffers, falling from above 40% in the mid-2010s to near zero in 2024, again consistent with Figure 1. At these levels, even funds that fully replicate the two large-cap growth indexes could be constrained. Funds tracking narrower, more concentrated large-cap growth indexes could be heavily constrained, as could many active large-cap growth funds.

Third, for narrower indexes, the diversification constraint can become so binding that the indexes themselves must take action to comply. The best example is the Nasdaq-100, tracked by QQQ, one of the largest ETFs in the world. The Nasdaq-100 methodology triggers a special rebalance when the combined weight of stocks with individual weights exceeding 4.5% rises above 48%, slightly below the statutory 5% and 50% limits. For example, on

July 24, 2023, the index reduced the weights of its seven largest companies—the Magnificent 7—and redistributed the excess weight across the remaining 93 constituents.

Fourth, sector indexes are even more constrained. Their buffers are typically below 20% and frequently approach zero, especially for Communication Services and Technology, where mega-cap stocks such as the Magnificent 7 carry heavy weights (Figure A.3). This pattern aligns with our earlier observation that sector funds have historically been the most constrained group under the 50/5/10 rule (see Figure 6). Sector funds tend to be smaller than large-cap growth funds, making their constraints less price-relevant, but they can still matter, given how tight their buffers are.

The index buffers plotted in Figures 15 and A.3 may underestimate the severity of the 50/5/10 constraint because we approximate unobserved index weights using the holdings of index-tracking ETFs. While this approximation is typically reasonable, it may become less accurate when the buffer computed from the underlying index weights turns negative. In such (rare) cases, the ETF may tolerate a larger-than-usual tracking error to keep its reported portfolio compliant with the 50/5/10 rule. Our ETF-based index buffer will then remain non-negative even though the underlying index buffer is negative. Thus, when ETF-based buffers are close to zero, the 50/5/10 constraint could be even tighter for index funds than our figures suggest.

To summarize, the 50/5/10 constraint has become binding even for some major benchmark indexes. As a result, even some passive funds have become constrained. Rising index concentration has tightened buffers for both active and passive funds, as we show next.

3.3. Drivers of fund buffers

Section 3.1 shows that a growing share of fund assets sits close to the 50/5/10 constraint. In this section, we show that this proximity is primarily driven by the rising concentration of funds' benchmark indexes.

To assess to what extent index buffers explain fund buffers, we estimate panel regressions of fund buffers on their corresponding benchmark index buffers,

$$\text{Buffer}_{f,t} = \alpha + \beta \cdot \text{IndexBuffer}_{b(f),t} + \gamma' X_{f,t} + \mu_f + \tau_t + \varepsilon_{f,t}\,, \tag{3}$$

where $b(f)$ is fund f's benchmark index, t denotes fiscal quarters, and $X_{f,t}$ is a vector of fund-level controls.[7] We identify each fund's benchmark $b(f)$ using the prospectus benchmark

[7]These controls include fund size, age, expense ratio, turnover ratio, flows, returns, return volatility,

reported in the Morningstar database. For each benchmark, we use the buffer of the passive fund (ETF or index fund) with the lowest 2019–2024 tracking error as $\text{IndexBuffer}_{b(f),t}$. We estimate equation (3) separately for passive and active funds.

Table 1 reports the estimates. For passive funds, $\hat{\beta}$ ranges from 0.93 to 0.99 across specifications, and the adjusted R^2 in the specification with *IndexBuffer* alone exceeds 0.97. This is consistent with passive funds closely tracking their benchmarks: as the index buffer shrinks by one percentage point, the fund buffer shrinks by nearly the same amount. For active funds, $\hat{\beta}$ ranges from 0.33 to 0.75 and remains highly statistically significant, reflecting these funds' flexibility to deviate from their benchmarks while still bearing meaningful exposure to index concentration. Importantly, *IndexBuffer* accounts for about 60% of the explained variation in active fund buffers, and even in specifications with fund and time fixed effects, it has greater predictive power than all other fund-level controls combined.

These results indicate that fund-level buffer tightness is largely inherited from rising benchmark index concentration. As index concentration rises, maintaining compliance with the 50/5/10 rule increasingly requires rebalancing away from the largest index constituents. Next, we examine whether and how funds adjust their portfolios to ensure compliance.

4. How do funds respond?

We now analyze whether the 50/5/10 rule affects fund behavior. Section 4.1 studies portfolio rebalancing across individual holdings, while Section 4.2 analyzes adjustments in overall equity exposure. Together, the evidence shows that funds with near-zero buffers tend to limit the weights of their largest positions and reduce their aggregate equity exposure.

4.1. Stock substitution

To examine whether funds adjust their portfolios in response to the 50/5/10 constraints, we begin by studying rebalancing at the level of individual holdings. The rule treats positions above 5% as "large" and the regulatory buffer is determined by their aggregate weight (equation (2)). Constrained funds therefore have strong incentives to trim large positions, especially those near the 5% threshold, to remain in compliance.

Carhart four-factor loadings, number of equity holdings, a diversified-fund dummy, Morningstar rating, fund family size, and the volatility of the benchmark index. The vector of controls is intentionally broad, so that we get a conservative estimate of *IndexBuffer*'s explanatory power.

We start with nonparametric evidence. Figure 7 plots three distributions of fund-level portfolio weights around the 5% cutoff, pooled across all quarters in our sample. We also report kernel density estimates on either side of the 5% cutoff (McCrary, 2008). The distributions correspond to negative-buffer funds (Panel A), constrained funds (Panel B), and unconstrained funds (Panel C). The weight pattern for unconstrained funds is smooth, reflecting the underlying firm-size distribution, with only a small discontinuity around 5%, likely due to compliance with the 75/5/10 rule (Section 8). In contrast, constrained funds display pronounced bunching just below 5%, consistent with active management of position sizes around the regulatory threshold. The weight density begins to decline already around the 4.9% mark, suggesting preemptive rebalancing.[8] Negative-buffer funds exhibit a different pattern, with an elevated frequency of positions just above 5%, reflecting how these funds have obtained negative buffers. Overall, these results suggest that the 50/5/10 rule incentivizes funds to keep their positions below the 5% threshold.

Funds tend to rebalance away from large positions. Figure 8 plots the directional changes in large positions from one quarter to the next for the same three categories of funds. All funds are more likely to decrease than increase their large positions. While 59% of constrained funds reduce their portfolio weights in large positions, only 41% increase them. The proportions are very similar for negative-buffer funds, but the wedge is smaller for unconstrained funds, 55% of which reduce large-position weights while 45% increase them.

To test whether near-zero-buffer funds reduce their large positions more aggressively than unconstrained funds, we estimate the following regression in the fund–stock–quarter panel:

$$\begin{aligned}\Delta\text{Weight}_{f,s,t+1} = \beta_0 + \beta_1 D^{W>5}_{f,s,t} + \beta_2 D^{B<0}_{f,t} + \beta_3 D^{0\leq B<5}_{f,t} + \beta_4 (D^{W>5}_{f,s,t} \times D^{B<0}_{f,t}) \\ + \beta_5 (D^{W>5}_{f,s,t} \times D^{0\leq B<5}_{f,t}) + \epsilon_{f,s,t+1}, \qquad (4)\end{aligned}$$

where $\Delta\text{Weight}_{f,s,t+1}$ is the change in fund f's weight in stock s from fiscal quarter t to $t+1$. The D variables are all 0/1 dummies: $D^{W>5}_{f,s,t} = 1$ if fund f holds more than 5% in stock s in quarter t, $D^{B<0}_{f,t} = 1$ if fund f's buffer from equation (2) is negative in quarter t, and the remaining indicators are defined analogously. The interaction coefficient β_4 captures the incremental reduction in large positions by negative-buffer funds relative to unconstrained funds, and β_5 similarly compares constrained to unconstrained funds.

When estimating regression (4), and throughout Section 4.1, we restrict the sample to stocks in the top 50% of the market-capitalization distribution each quarter. Large positions are observed almost exclusively among these stocks: 98.4% of observations with $D^{W>5}_{f,s,t} = 1$

[8]The McCrary (2008) density test indicates a statistically significant discontinuity in the distribution of portfolio weights around the 4.9% threshold (Figure A.1).

correspond to stocks with above-median market caps. Including smaller stocks would therefore add many observations with no variation in the key indicators, increasing unnecessary noise in the estimates. We also exclude stocks with prices below $5.

Table 2 reports the estimates. The coefficient β_1 is negative and significant, indicating that funds reduce large positions, on average. More importantly, both interaction terms, β_4 and β_5, are negative and significant, implying that constrained and negative-buffer funds trim large positions more aggressively than unconstrained funds. The average reduction for large positions is about 12 bps per quarter, rising to more than 20 bps when a fund is near the 50/5/10 limit. These patterns appear both in the full sample and in the more concentrated 2023–2024 subperiod.

Fund buffers may be correlated with unobserved fund characteristics, such as investment style or the propensity to hold concentrated industry positions (Kacperczyk, Sialm, and Zheng, 2005). Furthermore, stock-level dynamics could affect both funds' buffers and their rebalancing decisions. To mitigate the concern that our results could reflect latent heterogeneity rather than regulatory pressure, we estimate specifications of equation (4) increasingly saturated with fixed effects. For example, fund-by-quarter fixed effects absorb all time-varying fund characteristics, including flows, style shifts, and overall risk exposure, while stock-by-quarter fixed effects absorb all stock-level shocks. Including these fixed effects leaves the estimates largely unchanged (see Table 2), indicating that it is the proximity to the 50/5/10 limit that drives the observed trimming of large positions.

Accordingly, we identify the effect of the tightness of the 50/5/10 constraint on fund rebalancing by exploiting within-fund, within-stock variation. Our identifying assumption is that, conditional on stock-by-quarter and fund-by-quarter fixed effects, changes in the large positions of funds with different buffers reflect only regulatory pressure. This assumption seems plausible because, after absorbing fund- and stock-level shocks, it is unclear what forces other than regulatory pressure would lead these funds to rebalance differently.

Because funds may window-dress around quarter-ends, reported buffers may reflect not only the tightness of the 50/5/10 constraint but also trading intended to improve reported positions. This is relevant for the interpretation of Table 2 because our baseline design uses the observed quarter-end buffer to proxy for regulatory pressure. If a fund actively trades to improve its reported buffers before quarter-ends, those buffers partly reflect the fund's response to the constraint. To address this concern, we instrument observed buffers with "no-trade buffers" constructed from lagged holdings and passive returns. Even though the IV estimates are somewhat less precise, they remain very similar to the baseline results, suggesting that our findings are not substantially affected by window-dressing. We report this analysis in Appendix A.3.[9]

To shed more light on the outcomes implied by the estimates in Table 2, Figure 9 plots the predicted change in weight across initial weight buckets for all fund groups, using the specification with stock-by-quarter and fund fixed effects. Two patterns emerge: (i) rebalancing intensifies sharply with initial position size, and (ii) constrained and negative-buffer funds reduce positions above 5% more aggressively than unconstrained funds, while trimming less in the 4%–5% bucket, in line with the evidence from Figure 7.

The negative β_1 estimates suggest that even unconstrained fund managers dislike concentrated holdings, consistent with an incentive to limit exposure to idiosyncratic risk. If this motive matters, trimming should be stronger for more volatile stocks. To test this hypothesis, we define $\text{Volatility}_{s,t}$ as the standard deviation of daily returns for stock s in the corresponding fiscal quarter t and estimate the panel regression

$$\begin{aligned}\Delta\text{Weight}_{f,s,t+1} = \gamma_0 + \gamma_1 \text{Weight}_{f,s,t} + \gamma_2 \text{Volatility}_{s,t} \\ + \gamma_3(\text{Weight}_{f,s,t} \times \text{Volatility}_{s,t}) + \varphi_{f,s,t+1}\,. \end{aligned} \tag{5}$$

Table 3 shows that volatility amplifies trimming: a one-percentage-point larger position in a zero-volatility stock predicts a 2-3 bps weight reduction next quarter, and moving from the 25th to the 75th percentile of volatility increases this reduction by roughly 1 bp. These results are consistent with funds choosing to limit exposure to idiosyncratic risk.

As noted in the introduction, Chen (2025) examines changes in funds' largest portfolio weights, and some of our findings overlap with his. His evidence aligns with our Figures 7 and 8, although he compares diversified and non-diversified funds, whereas we compare funds with different buffers relative to the 50/5/10 rule. In Table 2, the negative estimates of β_1 from equation (4) are unsurprising given his results showing that funds tend to reduce their largest positions. By contrast, the negative estimates of β_4 and β_5, which capture interactions with fund buffers and represent the core of our analysis, are new. Likewise, in Table 3, the negative estimates of γ_1 from equation (5) are consistent with his findings, but the negative γ_3 estimates, which capture interactions with volatility, are novel. The results in our remaining tables and figures are also complementary to Chen (2025).

[9] We also construct a leave-one-out version of the no-trade buffer that excludes stock s when measuring fund f's distance to the 50/5/10 threshold. The concern is that a rise in stock s's price can tighten the fund's no-trade buffer and at the same time make the stock more likely to be trimmed for reasons unrelated to the regulation. The leave-one-out construction removes this link by excluding the focal stock from the instrument, so that the identifying variation comes from the rest of the portfolio. The resulting estimates are very similar to those reported in Appendix A.3.

Our results show that funds close to the 50/5/10 limit tend to rebalance their large positions more aggressively. However, individual large positions differ in how much they contribute to the limit. This heterogeneity is driven primarily by two factors.

First, positions right above the 5% regulatory threshold have the highest marginal contribution to the buffer: a small trim can remove them from the set of large positions entirely. For example, consider a fund holding 20% in Nvidia and 5.1% in Meta. Reducing the Meta position by only 0.2 percentage points—bringing it to 4.9%—eliminates Meta from the large-position set, increasing the fund's buffer by 5.1 percentage points. Achieving the same buffer improvement via Nvidia would require reducing that position by more than a quarter, to 14.9%. Thus, positions just above the 5% threshold, which we refer to as *marginal large positions*, have outsized importance for funds managing regulatory compliance.

Second, volatility amplifies the importance of marginal large positions. For a volatile stock, the end-of-quarter weight is more uncertain, raising the risk that it drifts above 5% and pushes the fund (further) into non-compliance. This uncertainty strengthens the incentive to trim volatile marginal large positions preemptively.

To examine the effects of volatility and marginality of large positions, we estimate the following regression separately for constrained and negative-buffer funds:

$$
\begin{aligned}
\Delta \text{Weight}_{f,s,t+1} = {} & \delta_0 + \delta_1 (D^{W>6}_{f,s,t} \times \text{Volatility}_{s,t}) + \delta_2 (D^{5<W\leq 6}_{f,s,t} \times \text{Volatility}_{s,t}) \\
& + \delta_3 (D^{4<W\leq 5}_{f,s,t} \times \text{Volatility}_{s,t}) + \delta_4 D^{W>6}_{f,s,t} + \delta_5 D^{5<W\leq 6}_{f,s,t} + \delta_6 D^{4<W\leq 5}_{f,s,t} \\
& + \delta_7 \text{Volatility}_{s,t} + \eta_{f,s,t+1}.
\end{aligned}
\tag{6}
$$

The dummy variables are defined analogously to those in equation (4); for example, $D^{5<W\leq 6}_{f,s,t} = 1$ if fund f's weight in stock s is between 5% and 6% in quarter t. The intercept δ_0 captures the average rebalancing of zero-volatility positions with weight below 4%.

Table 4 shows that volatility matters most precisely where our argument suggests: for constrained funds, the interaction terms are largest for marginal large positions with weights between 5% and 6% ($\delta_2 < 0$), indicating that these funds disproportionately trim volatile positions just above the regulatory threshold. We find similar results for funds with negative buffers, especially in the 2023-2024 sample which includes more funds of this type. Volatility has a weaker but still noticeable effect for positions in the 4%–5% bucket ($\delta_3 < 0$), consistent with funds preemptively limiting positions that could drift above 5%.

Figure 10 illustrates the predicted rebalancing behavior across initial position sizes and volatility percentiles for funds with different regulatory buffers. The predicted values are constructed from specification (6) augmented with the same buffer interactions as in specification (4) and estimated in the full sample of funds. The figure shows that return volatility steepens rebalancing just above the 5% threshold for constrained funds (Panels C and D), as well as for negative-buffer funds, although the latter effect appears only in 2023-2024 (Panel B), when negative-buffer funds are more prevalent. For unconstrained funds, no comparable change in rebalancing behavior is visible around the 5% threshold (Panels E and F). Consistent with Table 3, unconstrained funds disproportionately trim large volatile positions, presumably to limit idiosyncratic risk.

Results thus far indicate that constrained funds tend to reduce weights in their large positions, more so for volatile stocks. In the absence of flows, a fund could reduce its weight in large positions by selling shares held or by using cash to purchase other securities. With inflows, the same reduction may be achieved via a relatively larger investment in other securities, so the large positions may increase in size as long as the rest of the portfolio grows even more. Funds may be reluctant to sell shares outright to avoid triggering capital gains tax liabilities as well as short-term negative price pressure.

To understand how funds achieve lower weights on large positions, we study changes in share holdings. First, we consider trade direction, which we define as

$$\text{TradeDirection}_{f,s,t+1} = \begin{cases} 1, & \text{if } \Delta\text{Shares}_{f,s,t+1} > 0, \\ 0, & \text{if } \Delta\text{Shares}_{f,s,t+1} = 0, \\ -1, & \text{if } \Delta\text{Shares}_{f,s,t+1} < 0, \end{cases} \tag{7}$$

where the percentage change in shares held is computed as

$$\Delta\text{Shares}_{f,s,t+1}\,(\%) = 2 \times \frac{\text{Shares}_{f,s,t+1} - \text{Shares}_{f,s,t}}{\text{Shares}_{f,s,t+1} + \text{Shares}_{f,s,t}} \times 100\,, \tag{8}$$

picking up both trade direction and trade size. $\text{Shares}_{f,s,t}$ denotes the number of shares held by fund f in stock s in fiscal quarter t, adjusted for stock splits and dividends (using CFACSHR from CRSP). We compute the change in shares following the approach of Davis and Haltiwanger (1992), which avoids asymmetry and outlier issues caused by small bases.

TradeDirection seems well suited for studying the effects of the 50/5/10 rule on fund rebalancing for the following reasons. First, the required amount of rebalancing (size of ΔWeight) depends on the actual portfolio composition, and funds may be able to restore compliance by using even smaller weight changes than observed in rebalancing of unconstrained funds. Second, detecting those small changes in a sample dominated by unconstrained funds is statistically challenging. Since TradeDirection picks up propensity to trade in a certain direction rather than the size of adjustments, it alleviates both of these concerns.

Using TradeDirection as a dependent variable in regressions (4) and (6), we find that constrained and negative-buffer funds are less likely to increase, and more likely to decrease, large positions compared to unconstrained funds: the interaction coefficients between the buffer dummies and the weight-above-5% dummy are negative and significant. For funds close to the 50/5/10 limit, interaction with volatility has a negative sign but is often insignificant, suggesting that these funds tend to limit all large positions. See Appendix A.4.2.

We also use ΔShares as the dependent variable to study the intensive margin of position adjustments. With the largest set of fixed effects, funds sell large positions on average, reducing them by about 1%. The additional reduction for negative-buffer funds is larger in magnitude but only marginally significant, and the evidence is mixed overall. This makes sense: we expect the results to be weaker for ΔShares than for ΔWeight because the regulations constrain weights, not shares. Funds experiencing inflows can reduce large weights without selling. Furthermore, funds can delay trading to see whether noncompliant weights adjust through price movements alone. For example, if a fund must reduce a 5.1% weight below 5% and price movements alone could move the weight to either 5.3% or 4.9%, the fund will sell only in the former case, while no trade is needed in the latter.

When funds reduce their weight on large positions to stay compliant with the 50/5/10 rule, what do they put more weight on? To explore such portfolio substitution, we assess the market capitalization of increased positions. For each constrained fund and quarter, we calculate the average market cap of the fund's large positions whose portfolio weights decrease in quarter $t + 1$, as well as that of stocks whose weights increase. The results, plotted in Figure 11, show that when constrained funds decrease weights in large positions, they tend to increase weights in smaller stocks. The substitution patterns are very similar for value-weighted rather than equal-weighted averages of market capitalization, for negative-buffer funds rather than constrained funds, and for changes in shares rather than weights (see Appendix A.2).

In summary, constrained funds tend to reduce portfolio weights in large positions to stay compliant with the 50/5/10 rule. They also reduce weights in marginal large positions with larger return volatility, which are more likely to bring the fund into non-compliance. Weight reductions do not necessarily come from sales, as funds with inflows may choose to invest in other securities. Indeed, weight reductions for large positions tend to be accompanied by weight increases for smaller-cap stocks. Next, we explore an alternative compliance margin: changes in the overall equity exposure of constrained funds.

4.2. Equity exposure changes

Because compliance with the 50/5/10 rule is assessed using total fund assets, funds can restore compliance not only by reallocating within equities but also by adjusting their overall equity exposure. This channel is particularly relevant when funds experience net inflows, as is the case on average in our sample. To study how funds near the 50/5/10 limit adjust equity exposure, we estimate the regression

$$\Delta Y_{f,t\to t+1} = \beta_0 + \beta_1 \, D^{B<0}_{f,t} + \beta_2 \, D^{0\leq B<5}_{f,t} + \varepsilon_{f,t} \,, \tag{9}$$

where $\Delta Y_{f,t\to t+1}$ is the change in fund f's equity exposure from quarter t to $t{+}1$. We consider two types of changes in equity exposure. The observed change, $\Delta \text{EE}_{f,t\to t+1}$, captures the total change in the fraction of fund assets allocated to stocks, including both rebalancing and valuation effects. The implied active change, Active-$\Delta\text{EE}_{f,t\to t+1}$, removes the valuation effects and captures the implied active rebalancing from stocks to other assets such as cash and its equivalents. We define both variables in more detail in Appendix A.5. Finally, the two dummy variables are equal to one if $\text{Buffer}_{f,t}$ is in the corresponding range and zero otherwise. We estimate specifications with and without fund and quarter fixed effects to assess whether the results are driven by market conditions or funds' styles or mandates.[10] We also include controls for time-varying fund characteristics, namely, fund size, net fund flows, gross fund return, and fund return volatility, all measured over the previous quarter.

Table 5 reports the results. Funds with small positive buffers reduce equity exposure significantly, and those with negative buffers do so even more. Relative to other funds in the same quarter, funds with negative buffers lower their equity exposure by 78 bps, while those with small positive buffers reduce it by 30 bps. When we include both fund and quarter fixed effects, the magnitudes increase substantially: negative buffers correspond to a 1.7 percentage point reduction in equity exposure, and small positive buffers to a 0.7 percentage point reduction. These effects are economically meaningful given that the median equity fund in our sample invests about 93% of its total assets in equities and that the cross-sectional standard deviation of equity-exposure changes is only 3.5%. Including fund and quarter fixed effects strengthens the estimates, while controlling for fund characteristics has little effect. These results suggest that it is the proximity to the 50/5/10 limit that drives the observed changes in equity exposure, rather than broad market conditions or fund characteristics.

Since the reported quarter-end buffers may reflect window-dressing in addition to the tightness of the 50/5/10 constraint, we again instrument observed buffers with no-trade

[10] Recall that in the prior tables we include fund-by-quarter fixed effects. These are not suitable here because the observations in equation (9) are at fund-quarter level, not fund-stock-quarter level as before.

buffers, as in Section 4.1. As we report in Appendix A.3, the second-stage estimates are less precise, but their magnitudes are similar to those in Table 5.

Table 5 also shows that more than 80% of the observed change in equity exposure is due to active rebalancing rather than valuation drift.[11] Funds whose buffers tighten or turn negative seem to manage compliance with the 50/5/10 rule not only by stock rebalancing but also by lowering their aggregate stock holdings. While this strategy helps funds meet regulatory limits, it may affect subsequent performance, a possibility we examine next.

5. Fund performance

In this section, we examine whether proximity to the 50/5/10 constraint affects fund performance. In Section 5.1, we assess the performance impact using realized fund returns. We find that funds underperform after approaching or breaching the constraint. In Section 5.2, we use counterfactual portfolio returns to examine the sources of the performance drag. We find that both "cure" strategies used to restore compliance, rebalancing away from large positions and reductions in total equity exposure, contribute to the underperformance.

5.1. Realized returns

To compute funds' risk-adjusted returns, we adjust funds' gross returns for their four-factor (Carhart, 1997) loadings estimated over rolling 252-day windows. For each month t, we construct the cumulative risk-adjusted return $\text{Ret(FF4)}_{f,t+h}$ for fund f over the horizon $[t+1, t+h]$, for h up to 12 months. Appendix A.7 provides the calculation details.

We then estimate the following panel regression:

$$\text{Ret(FF4)}_{f,t+h} = \delta_0 + \delta_1 D^{B<0}_{f,t} + \delta_2 D^{0\leq B<5}_{f,t} + \gamma_f + \varphi_{f,t+h}\,, \tag{10}$$

where γ_f denotes fund fixed effects, which absorb time-invariant differences in performance across funds. The estimates of δ_1 and δ_2 reveal how a given fund performs when its buffer is close to zero relative to its own performance when its buffer exceeds 5%. We run this regression for all funds as well as for large-cap growth funds, for which the concentration limits became the most binding during our sample period, as discussed earlier.

[11] Our conclusions are robust to an alternative measure of Active-$\Delta\text{EE}_{f,t\to t+1}$, which assumes that funds rebalance to the end-of-quarter holdings at the start, rather than the end, of quarter $t+1$. We also find that accounting for equity exposure through derivative and ETF positions does not meaningfully move our estimates. Appendix A.6 describes these alternative approaches and reports the corresponding results.

Table 6 reports the results for large-cap growth funds. Constrained funds deliver significantly lower risk-adjusted returns following the quarter when they hit the constraint. For example, in the three months after a fund becomes constrained, its FF4-adjusted return falls by 57 bps. The performance drag is even more pronounced—1.31%—in 2023–2024, when concentration levels surged and more funds approached the regulatory limit. Negative-buffer funds underperform even more in 2023–2024—by 2.11%. The underperformance is significant for at least 6 months in the full sample and at least 12 months in 2023–2024.

The effect of constraints on fund performance is quite robust. Using CAPM-adjusted returns yields even larger underperformance. The underperformance is not driven by small funds because its magnitude remains similar when we reestimate regression (10) with weighted least squares using funds' lagged total assets. When we expand the sample to include all funds (not only large-cap growth), the underperformance of constrained and negative-buffer funds remains strong and statistically significant in 2023–2024, though it is largely insignificant in the full sample (Appendix A.8). The underperformance also survives controlling for AI-stock appreciation, which may not be fully captured by the four-factor risk adjustment. Specifically, the estimates are only slightly smaller when we augment the four-factor model with the return on an AI-technology sector ETF (see Table A.18).

Overall, funds underperform after reaching the 50/5/10 constraints. These results suggest that the actions managers take to preserve compliance, such as reducing large positions and equity exposure, generate a measurable performance drag.

5.2. Counterfactual portfolio returns

We next explore the sources of underperformance for constrained and negative-buffer funds. Lacking performance-attribution data, we rely on a counterfactual exercise based on reported holdings and portfolio adjustments documented in Section 4. To assess how these adjustments affect returns, we construct counterfactual portfolios that do not rebalance large positions or equity exposure. Specifically, we create three portfolios that approximate what fund holdings would have been absent the 50/5/10 rule. We then compare their realized performance with that of the implied fund portfolio, which reflects the actual post-adjustment holdings. Across specifications, the counterfactual portfolios outperform the implied portfolios, indicating a measurable performance drag from compliance-driven rebalancing.

The *implied fund portfolio* is constructed by deflating reported holdings to remove the effects of realized returns between t and $t+1$. The implied weight of stock s in fund f at time t is

$$w_{f,s,t}^{\text{implied}} = \frac{\text{ImpliedValue}_{f,s,t}}{\text{ImpliedTA}_{f,t}}, \tag{11}$$

where

$$\text{ImpliedValue}_{f,s,t} = \frac{\text{Value}_{f,s,t+1}}{1 + hpr_s^{t\to t+1}} \tag{12}$$

$$\text{ImpliedTA}_{f,t} = \frac{\text{TotalAssets}_{f,t+1}}{1 + R_{f,t\to t+1}^{\text{fund}}}, \tag{13}$$

$hpr_s^{t\to t+1}$ is a holding period return on stock s over quarter $t+1$, and $R_{f,t\to t+1}^{\text{fund}}$ is a gross return on fund f over quarter $t+1$. This setup assumes that the fund rebalances immediately after fiscal quarter t and then holds its portfolio constant until $t+1$, so that passive growth from stock returns matches the fund's reported holdings at $t+1$.

The first counterfactual is the *constant-exposure portfolio*, which isolates the contribution of changes in total equity exposure. Within each fund, we keep the relative weights across stocks fixed and rescale the overall equity exposure to match the fund's actual exposure at time t:

$$w_{f,s,t}^{\text{constant-exposure}} = \frac{w_{f,s,t}^{\text{implied}}}{\sum_{j\in\mathcal{S}_{f,t}(implied)} w_{f,j,t}^{\text{implied}}} \cdot \text{EquityExposure}_{f,t}, \tag{14}$$

where $\mathcal{S}_{f,t}(implied)$ is the set of stocks in the implied portfolio and $\text{EquityExposure}_{f,t} = \frac{\sum_{s\in\mathcal{S}_{f,t}} \text{Value}_{f,s,t}}{\text{TotalAssets}_{f,t}}$, as defined in Appendix A.5. The difference in returns between the implied and constant-exposure portfolios captures the performance effect of adjusting total equity exposure while keeping the within-equity portfolio weights unchanged.

The second counterfactual is the *large-rebalanced portfolio*, which isolates the effect of rebalancing large positions across stocks. While funds may alter both their equity exposure and specific holdings, this portfolio holds equity exposure and non–large positions fixed:

$$w_{f,s,t}^{\text{large-rebalanced}} = \begin{cases} w_{f,s,t}^{\text{implied}}, & \text{if } s \text{ is not a large position,} \\ \tilde{w}_{f,s,t}, & \text{if } s \text{ is a large position,} \end{cases} \tag{15}$$

where $\tilde{w}_{f,s,t}$ equals the previously reported $\text{Weight}_{f,s,t}$ reweighted across large positions (i.e., portfolio weights above 5%) so that the total equity exposure of the large-rebalanced portfolio matches that of the implied portfolio. The return difference between the implied and large-rebalanced portfolios isolates the effect of rebalancing large positions.

For each fund f and quarter t, the return of any portfolio is computed as

$$R_{f,t\to t+1}^{\text{portfolio}} = \sum_{s\in\mathcal{S}_f^{\text{portfolio}}(t)} w_{f,s,t}^{\text{portfolio}} \cdot hpr_s^{t\to t+1} + \left(1 - \sum_{s\in\mathcal{S}_f^{\text{portfolio}}(t)} w_{f,s,t}^{\text{portfolio}}\right) \cdot r_f, \tag{16}$$

where $w_{f,s,t}^{\text{portfolio}}$ is the stock's portfolio weight, $\mathcal{S}_f^{\text{portfolio}}(t)$ is the set of held stocks, and r_f is the risk-free rate over the same period.

To further assess economic significance, we translate return differences into dollar impacts. For any two portfolios A and B, the dollar impact of their return differential is

$$\text{Impact}_{f,t\to t+1} = \left(R^A_{f,t\to t+1} - R^B_{f,t\to t+1}\right) \times \text{TotalAssets}_{f,t}. \tag{17}$$

Table 7 reports the estimated average performance drag associated with equity-exposure and large-position adjustments. The implied portfolios of constrained funds underperform the counterfactual portfolios, indicating that compliance-induced rebalancing contributes negatively to fund returns. Had they maintained constant equity exposure, constrained funds would have earned 8.2 bps higher annualized returns, worth $411 million in aggregate, in 2023–2024. Adjustments within large positions impose an even larger cost: by not rebalancing positions with portfolio weights above 5%, funds would have saved 26 bps, or $1.51 billion. For negative-buffer funds, the patterns are similar, but the aggregate dollar impact is smaller given the small number of actual breaches.

These are counterfactuals, so they can only suggest that the "cure" strategies documented in Section 4 put downward pressure on fund returns. Funds' actual returns reflect also trading costs, intra-quarter rebalancing, and any countermeasures that fund managers may take. We therefore do not expect our estimates in this section to match the magnitudes of the constrained fund realized underperformance from Section 5.1.[12]

In sum, the counterfactual portfolio analysis suggests that constrained funds' compliance actions, reductions of weights in large positions and equity exposure, can lower subsequent fund returns. These effects are economically significant, concentrated in 2023–2024, and consistent with the patterns observed in realized fund performance.

6. Stock return predictability

In this section, we explore whether funds' rebalancing away from large positions, documented in Section 4.1, has any pricing effects. We hypothesize that this rebalancing temporarily depresses the prices of stocks commonly held in large positions, and that these stocks earn high future returns as this underpricing corrects. In Section 6.1, we design a metric that

[12] In Table 7, we consider funds of all investment styles rather than only large-cap growth. Results for large-cap growth funds are weaker statistically but otherwise similar, except that equity-exposure adjustment contributes more than large-position adjustment to the performance drag. See Appendix A.8.

measures the fraction of a stock's outstanding shares held in large positions by low-buffer funds. Section 6.2 demonstrates that this metric positively predicts risk-adjusted returns in the cross-section of stocks, consistent with our hypothesis. Section 6.3 constructs a trading strategy that exploits this predictability and earns abnormal returns. Section 6.4 describes a theoretical model that helps us interpret the evidence.

6.1. Constrained ownership share

To evaluate the stock-level pricing implications of the 50/5/10 rule, we construct a measure of *constrained ownership share*, $C_{s,t}$, for each stock s and month t:

$$C_{s,t}(\%) = \frac{\sum_f \sum_{\tau=t-2}^{t} \text{Shares}_{f,s,\tau} \cdot D_{f,s,\tau}}{\text{Shares Outstanding}_{s,t}} \times 100, \tag{18}$$

where $\text{D}_{f,s,t} = D^{5<W}_{f,s,t} \times D^{B<5}_{f,t}$ and $\text{Shares}_{f,s,\tau}$ are defined right after equation (8). We use the C values from each of the three most recent months (t, $t-1$, and $t-2$) to account for differences in fiscal quarter-ends across funds. For each fund, we use only the latest holdings report available within this three-month window.

The value of C measures the fraction of a stock's outstanding shares held by funds with sub-5% buffers (i.e., constrained and negative-buffer funds) that hold large positions in this stock. A higher C indicates that a larger portion of the stock is owned by funds that are likely to reduce those positions or to have done so recently (Section 4.1). Consequently, C may proxy for the degree to which the stock is underpriced due to the aggregate underweight of the funds whose portfolios are close to the 50/5/10 limit.

Figure 12 plots the time series of the number and aggregate market capitalization of stocks with positive constrained ownership shares. The vast majority of stocks have $C = 0$. For a stock to have $C > 0$, the stock must comprise more than 5% of the portfolio of at least one constrained or negative-buffer fund, which is rare. Nonetheless, the prevalence of stocks with $C > 0$ has increased over time. The number of $C > 0$ stocks has grown from 93 in 2019Q3 to 269 in 2024Q4. While these 269 stocks represent only 8% of all stocks, their total market capitalization is $41 trillion—over 60% of the entire U.S. equity market.

The positive values of C tend to be relatively small: most of them are below 1%, according to Figure 12. Nevertheless, stocks with $C > 1\%$ account for almost 30% of total U.S. market capitalization at the end of our sample, and some stocks' C values are as high as 5.3% (Nvidia) and 4.7% (Microsoft). Moreover, C is essentially a lower bound for constrained ownership, for three reasons. First, we use all shares outstanding in the denominator of equation (18), but any limits to float make the effective constrained ownership share higher. Second, stocks whose weights are below the regulatory threshold but close to it, such as 4.9%, must be on the fund manager's radar, as they can quickly make the fund non-compliant. Third, we define C based on funds with sub-5% buffers, yet some funds with buffers above 5% can be constrained as well (e.g., by the 75/5/10 rule). These margins are non-trivial: if we redefine large positions as weights above 4% and treat funds with buffers below 10% as constrained, the market share of stocks with $C > 0$ rises to 78% in 2024Q4 and over 36% of the market have $C > 1\%$. For all these reasons, C understates the true size of ownership constrained by the 50/5/10 rule.

Figure 13 shows which stocks are most affected by rising constrained ownership. For each quarter and across the 3×3 style classifications, we report the number and total market cap of stocks with $C > 0$. The concentration of constrained ownership is highest among large-cap growth stocks, followed by large-cap neutral and large-cap value. Within large-cap growth, constrained ownership expanded rapidly in 2023–2024, reaching \$30 trillion—more than three quarters of the segment's total market cap—by year-end 2024. Figure 14 presents the quarterly distribution of constrained stocks across styles and isolates the "Magnificent 7." This figure confirms that large-cap growth stocks, and primarily these seven, account for the largest share of the market cap within the constrained segment.

These patterns indicate that the 50/5/10 rule constrains the ownership of a growing share of market capitalization, including some of the largest companies. Do these constraints affect stock prices? That is the question we turn to next.

6.2. Predicting individual stock returns

In this section, we examine whether constrained ownership share predicts cross-sectional differences in stock returns. The underlying mechanism is intuitive: when constrained funds must avoid expanding their large positions, they collectively underweight the corresponding stocks relative to their desired positions. This underweight is likely to be larger for more volatile stocks, which pose greater compliance risk and exhibit more idiosyncratic risk.

We estimate two panel regressions:

$$Ret(FF4)_{s,t+h} = \beta \, High\, C_{s,t} + \gamma_{t+h} + \epsilon_{s,t+h} \tag{19}$$

$$\begin{aligned} Ret(FF4)_{s,t+h} &= \eta_1 \, High\, C_{s,t} + \eta_2 \, High\, Vol_{s,t} + \eta_3 \, High\, C_{s,t} \times High\, Vol_{s,t} \\ &\quad + \lambda_{t+h} + \varphi_{s,t+h} \, . \end{aligned} \tag{20}$$

For stock s and horizon $t+h$, $Ret(FF4)_{s,t+h}$ denotes the cumulative return adjusted for market, size, value, and momentum factors (Carhart (1997)). We consider horizons up to 12 months, with calculation details reported in Appendix A.7. $High\,C_{s,t}$ is an indicator for stocks with positive constrained ownership shares; stocks with $C_{s,t} = 0$ form the omitted low-C group. We compute volatility as the standard deviation of daily stock returns over months $t-2$, $t-1$, and t, and $High\,Vol_{s,t}$ as an indicator for stocks with above-median volatility in month t. Therefore, coefficients η_1 through η_3 in equation (20) compare the returns of the corresponding portfolios with the return of a low-C, below-median-volatility portfolio.

When estimating regressions (19) and (20), and also in the rest of Section 6, we again remove low-priced stocks and restrict the sample to stocks with above-median market capitalization in each month. The purpose of the latter restriction is to reduce the noise in the estimation. It is very rare for a stock with below-median market cap to have $C > 0$, and sample stocks with $C = 0$ are simply adding noise. For example, among all stocks with $C > 0$, 95% have above-median market caps. Moreover, stocks with above-median market caps account for 97.6% of the total market cap. We cluster standard errors by stock to allow for serial correlation in our panel setting, but not by time, because factor adjustment and time fixed effects already remove most cross-sectional dependence in the residuals. In Appendix A.9, we show that results are similar under Driscoll-Kraay standard errors with $h-1$ lags, which account for both serial and cross-sectional correlation.

Table 8 reports the results. Stocks with positive constrained ownership exhibit higher risk-adjusted returns. The coefficient on $High\,C$ is positive and significant, especially in 2023–2024: stocks with $C > 0$ earn three-month cumulative abnormal returns 1.1% higher than those of stocks with $C = 0$. The return differential persists up to 12 months and is stronger among high-volatility stocks, consistent with their larger underweighting.

Both constrained and negative-buffer funds contribute to the constrained ownership share, and we find that even their individual ownership shares (i.e., $C_{s,t}$'s computed based on $D_{f,t}^{0<B<5}$ and $D_{f,t}^{B<0}$ rather than $D_{f,t}^{B<5}$) predict stock returns. The only difference is that return volatility matters less for the predictive ability of negative-buffer fund ownership shares, consistent with our results in Section 4.1.

Our findings are consistent with the mechanism discussed in Section 4.1, whereby funds with low buffers tend to underweight large positions—especially in stocks with high volatility—leading to undervaluation and subsequent high returns on those stocks. Given the short sample period, these results are only suggestive, yet they are striking in that the stocks affected by the constraints are among the largest stocks in the market, for which traditional cross-sectional anomalies are rarely observed. For example, the "Magnificent 7" stocks are frequently sorted into the group with $High\,C = 1$ and $High\,Vol = 1$, as Nvidia, Tesla, Meta, and Amazon all appear in it over multiple quarters.

We also rerun our predictability regressions after excluding the Magnificent 7 stocks from the sample. The results are slightly weaker than in Table 8 but remain mostly significant in the 2023–2024 period, indicating that the predictability is not confined to these seven stocks. See Table A.16. Our results are thus not driven solely by the largest stocks.

Many large-cap stocks, not just the Magnificent 7, performed well during our sample period. We account for this performance by adjusting stock returns for their exposure to the size factor (and three other factors), as noted earlier. In addition, large-cap stocks are more likely to represent large positions in funds' portfolios, and such positions tend to be trimmed by all funds, constrained or not (see Table 2 as well as Blume and Keim (2017) and Chen (2025)). However, we show that the predictive ability of C does not simply reflect funds' propensity to trim large positions: our results are robust to controlling for a large-weight indicator (see Appendix A.9). Instead, predictability depends on whether the fund holding the stock in a large position is constrained. This finding is consistent with our model, in which predictability arises from the cap on constrained funds' long positions rather than from diversification-driven demand.

Given that stocks with large C values overlap heavily with leading firms developing the AI technology, one might wonder whether the documented predictability reflects unexpected appreciation in AI stocks rather than the correction of constraint-induced underpricing. We address this concern by augmenting the Carhart four-factor model with the return on an AI-technology sector ETF as a fifth factor. As we show in Appendix A.10, the estimated coefficients on C remain similar and continue to be economically and statistically significant, indicating that our findings are not driven by an unexpected boom in AI stocks.

6.3. Trading strategy

We next construct trading strategies that exploit the return predictability associated with constrained ownership. At the end of each month t, we sort stocks into the same two groups based on $C_{s,t}$: a *High-C* group with $C > 0$ and a *Low-C* group with $C = 0$. We form value-weighted portfolios for each group and hold them for one year. Even though stocks with $C > 0$ are not numerous, the *High-C* portfolio contains 382 stocks, on average. We assess portfolio performance using the four-factor model of Carhart (1997), with daily factor returns downloaded from Ken French's website.

Table 9 reports annualized alphas for each portfolio. The alphas of the *High-C* portfolio are positive, 1.7% in 2019-2024 and 2.3% in 2023-2024, with marginal statistical significance (the corresponding t-statistics are 1.9 and 2.3). The alphas of the *Low-C* portfolio are negative in both periods and not significantly different from zero. The *High-C* alphas do not simply reflect the AI boom because their magnitudes are very similar when we augment the four-factor model with the return on an AI-technology sector ETF.

Given that high-volatility stocks with $C > 0$ exhibit the strongest return predictability in Section 6.2, we further sort by volatility. At the end of each month, we independently sort stocks into two groups by volatility (above and below the median) and into the two C groups defined above, producing 2×2 value-weighted portfolios, each held for one year.

Table 9 also presents annualized alphas for these double-sorted portfolios. The pattern is consistent with the predictability results in Section 6.2: portfolios composed of stocks with positive C and above-median volatility deliver large positive alphas. Specifically, the *High-C-High-Volatility* portfolio earns the alphas of 7.9% in 2019–2024 and 11.8% in 2023–2024. These alphas are economically large but only marginally statistically significant (the t-statistics are 1.8 and 2.0, respectively), which is not surprising, given the short sample period. All other portfolios in this double sort have negative alpha estimates that are not statistically different from zero.

How large is the mispricing induced by the 50/5/10 rule? We perform a back-of-the-envelope calculation. In Table 9, the *High-C* portfolio earns an annualized alpha of 2.32% in 2023–2024. Interpreting this alpha as the annual correction of constraint-induced underpricing and applying it to the total market capitalization of *High-C* stocks ($27 trillion in 2023Q1 and $35 trillion in 2024Q1; see Figure 12), we estimate that the 50/5/10 rule reduced prices by roughly $\$27\,\text{trillion} \times 2.32\% \approx \$626$ billion in 2023 and $\$35\,\text{trillion} \times 2.32\% \approx \$812$ billion in 2024, for a cumulative effect exceeding $1.4 trillion. Although subject to large uncertainty, this estimate illustrates that even modest percentage mispricing of mega-cap stocks can translate into economically large dollar magnitudes, making it difficult for unconstrained investors to eliminate the mispricing.

The above investment strategies shed light on the economic magnitude of the return predictability associated with constrained ownership. Those strategies' returns may not be achievable in practice, though, because the C values are computed off funds' portfolio holdings that are typically available only with a lag. The regulatory reporting lag for NPORT-P filings is two months. To construct feasible trading strategies, we repeat the analysis using lagged constrained-ownership measures, sorting stocks on their previous quarter's C values rather than current ones. The resulting strategies continue to earn positive alphas whose magnitudes are similar to those based on contemporaneous C. For example, the *High-C* portfolio's alphas are 1.7% in 2019-2024 and 2.2% in 2023-2024, and the *High-C-High-Volatility* portfolio's alphas are 9.7% in 2019-2024 and 10.9% in 2023-2024, with marginal significance (all four alphas are significant at the 90% level but only two are significant at the 95% level; see Appendix A.11). These strategies are unlikely subject to large trading costs because *High-C* stocks are among the most liquid securities in the market. Overall, the return predictability associated with constrained ownership seems economically exploitable.

6.4. Model

To help interpret the evidence, we build a simple asset pricing model with heterogeneous beliefs and a portfolio constraint capping long positions. The model features two types of investors, optimists and pessimists, who have different expectations of asset payoffs. We solve the model analytically and derive two propositions. First, when the constraint binds, assets favored by optimists are underpriced in equilibrium as pessimists become marginal price setters. The second proposition contains four comparative statics: the underpricing is larger when the constraint is tighter, when the constrained asset is in greater supply, when the asset's payoff is more volatile, and when disagreement between optimists and pessimists is larger. We present the intuition and all the other details in the Appendix A.1.

The first proposition helps us understand why stocks held disproportionately by constrained funds earn higher average returns. The second proposition explains why return predictability is stronger both in the 2023–2024 period, in which the 50/5/10 constraint was tighter, and for more volatile stocks. It also helps us understand the evidence in the next section that predictability is stronger when the constrained funds are active rather than passive (as disagreement matters less for passive funds).

The purpose of the model is to clarify the economic mechanism behind our predictability evidence: long-side portfolio constraints can depress asset prices by limiting the influence of optimistic investors' views. The mechanism is a mirror image of that of Miller (1977), who explains how overpricing arises when short-sale constraints prevent pessimists from participating fully in the market. In Miller's argument, prices are set by optimistic investors because pessimists are excluded from holding negative positions. Here, by contrast, prices are set by pessimists when optimists face binding constraints on long positions.

While our model is similar to Miller's verbal framework, there are some important differences. Unlike Miller, who studies frictional constraints on short selling that exclude pessimists from the market, we study regulatory constraints on long positions that handicap optimists' views. These long-side constraints are hard and pervasive among institutional investors, whereas short-sale constraints tend to be softer and affecting a different set of investors. Moreover, while short-sale constraints are more likely to bind for small and illiquid stocks, our long-side constraints tend to bind for large, widely held stocks.

7. Active versus passive funds

In this section, we explore whether funds respond differently to the 50/5/10 constraint depending on whether they are actively or passively managed. Since passive funds track an index, their response depends on whether the index itself is constrained; if so, they may be more affected than active funds, which can tolerate larger tracking errors. If the index is unconstrained, however, active funds may be more affected, especially those optimistic about their largest positions, as the constraint could limit the size of those positions. Whether active or passive funds are more constrained is therefore an empirical question.

We proceed in three steps. Section 7.1 studies whether constrained active and passive funds exhibit differences in portfolio rebalancing. Section 7.2 analyzes the performance of constrained active and passive funds. Section 7.3 explores return predictability by measures of constrained ownership computed from either active or passive fund holdings.

7.1. How do funds respond?

We first examine whether active and passive funds differ in how they adjust their portfolios when their buffers are low. To do so, we estimate panel regressions analogous to those in Section 4 separately for active and passive funds. We classify funds using the CRSP mutual fund database, defining a fund as passive if the CRSP index-fund flag is ever nonblank during our sample period, and active otherwise.

We find that both active and passive funds significantly trim large positions, and that higher stock volatility intensifies this trimming. Passive funds rebalance more preemptively: for constrained funds, the marginal effects are larger and more significant among passive funds. Constrained active funds also rebalance preemptively, but primarily for highly volatile marginal large positions, where trimming is most effective. Negative-buffer active funds engage in particularly significant trimming of both volatile marginal large positions and total equity exposure in 2023-2024. Overall, the adjustment patterns are broadly similar across active and passive funds. See Appendices A.12 and A.13 for details.

7.2. Fund performance

Next, we evaluate whether approaching the 50/5/10 limit affects fund performance differently for active versus passive funds. Using the same performance evaluation framework as in Section 5, we estimate risk-adjusted return differences separately for the two groups and conduct a counterfactual portfolio return decomposition. As before, we focus primarily on large-cap growth funds when analyzing realized performance.

We find that both active and passive funds experience similar and economically meaningful underperformance when constrained. However, the sources of this underperformance differ. For active funds, both reduced equity exposure and rebalancing away from large positions contribute to the performance loss, especially in 2023-2024. For passive funds, most of the underperformance stems from trimming large positions rather than adjusting equity exposure. See Appendices A.12 and A.13 for details.

7.3. Stock return predictability

Finally, we analyze return predictability separately for active and passive funds, following Section 6. We construct constrained-ownership measures based on the holdings of active or passive funds with near-zero buffers. Specifically, we define C as in equation (18), replacing $D^{B<5}_{f,t}$ with either $D^{B<5}_{f,t} \times D^{Act}_{f,t}$ or $D^{B<5}_{f,t} \times D^{Pas}_{f,t}$, where $D^{Act}_{f,t}$ and $D^{Pas}_{f,t}$ are 0/1 indicators of whether fund f is active or passive, respectively. We then estimate predictive regressions (19) and (20) using this redefined C.

We find substantially stronger predictability for active funds. C constructed from active-fund holdings generally predicts returns a bit more strongly than C based on all funds' holdings, whereas the opposite holds for C constructed from passive-fund holdings. For active-fund C, the β estimates from regression (19) are close to those in Table 8, while the η_3 estimates from regression (20) are larger and more statistically significant, especially in 2023-2024. In contrast, for passive-fund C, the estimates of β and η_3 are typically smaller and weaker statistically. See Appendices A.12 and A.13.

In sum, the 50/5/10 rule affects both active and passive funds. Both trim large positions, though passive funds do so more preemptively, and both underperform when constrained. Constrained-ownership measures based on active-fund holdings have greater power to predict stock returns, consistent with temporary underpricing driven by optimistic active funds that are unable to scale their largest positions. These findings reinforce our main results.

8. Diversification under the 1940 Act

In this section, we examine how constraints implied by a different regulatory rule—75/5/10, which applies to funds classified as diversified—manifest in the data. Our analysis parallels that of the 50/5/10 rule. After describing the 75/5/10 rule and assessing how often it binds (Section 8.1), we study whether diversified funds adjust their portfolios as they approach the limit (Section 8.2), then analyze fund performance (Section 8.3) and stock return predictability (Section 8.4). Our findings resemble those for the 50/5/10 rule, though they are somewhat weaker. Although the 75/5/10 rule is softer than the 50/5/10 rule, it affects fund behavior and performance in similar ways, generating some return predictability.

8.1. The 75/5/10 rule

The Investment Company Act of 1940 classifies funds as "diversified" or "non-diversified" based on a 75/5/10 test. A fund may market itself as diversified if at least 75% of its total assets are invested in securities for which no single issuer exceeds 5% of assets and the fund holds no more than 10% of the issuer's voting securities. This requirement closely resembles the 50/5/10 rule, except that the concentration limits apply to 75% rather than 50% of portfolio assets. Funds classified as non-diversified may exceed these limits.

Although conceptually similar to the 50/5/10 rule, the 75/5/10 rule is less binding, for three reasons. First, broadly diversified index funds and ETFs are effectively unconstrained because in 2019, the SEC issued a no-action letter allowing them to exceed the 75/5/10 limits when necessary to replicate an index, provided they make appropriate disclosures. This relief does not extend to funds tracking narrow-based indices, such as sector or thematic indices, which are inherently concentrated. Second, funds may elect to operate as non-diversified companies with shareholder approval, thereby opting out of the 40-Act diversification requirement entirely. Third, while a fund cannot avoid breaching the 50/5/10 rule by creating synthetic exposure using derivatives such as total return swaps, such instruments may, under certain circumstances, help prevent breaches of the 75/5/10 rule.[13] For these reasons,

[13] Neither rule explicitly addresses derivatives, but industry practice generally interprets the 50/5/10 test

industry practice treats the 75/5/10 rule as substantially less restrictive than the 50/5/10 rule. Nonetheless, even the former rule could in principle induce portfolio adjustments for funds seeking to maintain diversified status.

We classify funds as diversified or not using the "Diversification Status" variable in the SEC's N-CEN filings. Because these filings are annual, we do not observe intra-year status changes, so some classifications may be stale. Despite this limitation, the N-CEN flag consistently distinguishes funds subject to the 75/5/10 rule from those opting out.

To assess how binding the 75/5/10 rule is in practice, we compute fund buffers as before, following equation (2). However, we measure a fund's distance from the 25% buffer threshold rather than from 0%, since a 25% buffer is the effective limit under the 75/5/10 rule.

Recall that Figure 3 displays the cross-sectional distribution of fund buffers across all funds. Figures 16 and 17 are its counterparts, showing the same distributions for the subsets of diversified and non-diversified funds, respectively.

Figure 16 closely resembles Figure 3, except for a sharper discontinuity at the 25% buffer level—the two plots look similar for buffers above 25% but differ below that threshold. This pattern is expected, as diversified funds must generally maintain buffers above 25%, as explained earlier. Diversified funds also display substantial mass in the $[25, 30)\%$ region of the buffer distribution, indicating that many are close to exhausting the allowable concentration. This is especially true at the end of our sample, when the $[25, 30)\%$ region contains more than $3 trillion in assets under management, including most S&P 500 index funds (recall from Figure 15 that the S&P 500's buffer fell just below 30% in 2024). Many diversified funds are therefore likely to feel constrained by the 75/5/10 rule.

In contrast, non-diversified funds are exempt from this rule, and Figure 17 looks very different from Figure 16. Non-diversified funds show no bunching around 25%; most maintain buffers below that level. Instead, they display considerable mass in the $[0, 5)\%$ buffer region, in line with the binding 50/5/10 rule.

8.2. How do funds respond?

We next examine whether diversified funds reduce large positions when their buffers are close to 25%. We augment equation (4) with triple interactions involving indicators for a

as based on economic exposure, while the 75/5/10 test may be satisfied based on legal ownership or control.

diversified fund ($D^{Div}_{f,t}$), large position ($D^{W>5}_{f,s,t}$), and buffer ranges of $[20, 25)\%$ and $[25, 30)\%$:

$$\begin{aligned}\Delta\text{Weight}_{f,s,t+1} \;=\;& \beta_0 + \beta_1 D^{W>5}_{f,s,t} + \beta_2 D^{Div}_{f,t} + \beta_3 D^{20\leq B<25}_{f,t} + \beta_4 D^{25\leq B<30}_{f,t} + \beta_5 \left(D^{W>5}_{f,s,t} \times D^{Div}_{f,t}\right) \\ & +\beta_6 \left(D^{Div}_{f,t} \times D^{20\leq B<25}_{f,t}\right) + \beta_7 \left(D^{Div}_{f,t} \times D^{25\leq B<30}_{f,t}\right) \\ & +\beta_8 \left(D^{W>5}_{f,s,t} \times D^{20\leq B<25}_{f,t}\right) + \beta_9 \left(D^{W>5}_{f,s,t} \times D^{Div}_{f,t} \times D^{20\leq B<25}_{f,t}\right) \\ & +\beta_{10} \left(D^{W>5}_{f,s,t} \times D^{25\leq B<30}_{f,t}\right) + \beta_{11} \left(D^{W>5}_{f,s,t} \times D^{Div}_{f,t} \times D^{25\leq B<30}_{f,t}\right) + \varepsilon_{f,s,t+1}. \quad (21)\end{aligned}$$

The buffer ranges are inspired by our prior definitions of negative-buffer and constrained funds, except that in the sub-25% range, we exclude buffers below 20% to avoid confounding effects from near-zero buffers, where the 50/5/10 rule is more relevant. The triple-interaction coefficients β_9 and β_{11} indicate whether diversified funds are more likely than non-diversified funds to rebalance away from large positions as their buffers approach 25%. As before, we exclude stocks with prices below \$5 and stocks with below-median market caps.

Table 10 reports the results. Across all ten specifications (five sets of fixed effects and two time periods), the estimates of both β_9 and β_{11} are always negative, though not always statistically significant. These estimates indicate that diversified funds with buffers near 25% trim large positions more aggressively than non-diversified funds. In fact, non-diversified funds trim large positions less when their buffers are in the $[20, 25)\%$ range, as indicated by the significantly positive estimates of β_8. Notably, the point estimates are such that $\beta_9 \approx -\beta_8$, as if among funds with buffers in $[20, 25)\%$, diversified funds were selling their large positions to non-diversified funds. Finally, although rising market concentration pushed more funds toward the 75/5/10 limit in 2023-2024 (Figure 16), the effects are not markedly stronger in that period, likely because the 75/5/10 rule is a softer constraint. For example, recall that in 2024, most of the assets in the $[25, 30)\%$ buffer range were managed by S&P 500 index funds, which can readily obtain exemptions from the 75/5/10 rule, as noted earlier.

8.3. Fund performance

Do funds underperform as they approach the 75/5/10 limit? To answer this question, we estimate regressions of FF4-adjusted returns on buffer dummies, following Section 5. Specifically, we estimate regression (10), replacing the original buffer ranges with the more relevant $[20, 25)\%$ and $[25, 30)\%$. We exclude from the sample funds with buffers below 20%, again to avoid confounding effects from near-zero buffers. We run the regressions separately for diversified and non-diversified funds, since only the former are subject to the 75/5/10 rule.

We find significant underperformance among diversified funds after their buffers fall in the $[25, 30)\%$ range, but only in 2023-2024 and only at horizons of 5 to 12 months. The corresponding performance drag is economically meaningful, ranging from 46 bps at 5 months to 1.85% at 12 months, but overall, the results are weaker than those for the 50/5/10 rule. For non-diversified funds, we find no performance differences around the 75/5/10 limit, as expected, since the limit does not apply to them. See Appendix A.14 for details.

8.4. Stock return predictability

Finally, we test whether underweighting by diversified funds near the 75/5/10 limit generates stock-level return predictability. We construct a constrained ownership measure based on the holdings of diversified funds with buffers in the $[20, 30)\%$ range and estimate predictive regressions analogous to those in Section 6. Specifically, we define C as in equation (18), replacing $D_{f,t}^{B<5}$ by $D_{f,t}^{20\leq B<30} \times D_{f,t}^{Div}$, and estimate regressions (19) and (20).

We find return predictability patterns that are similar in direction and magnitude to those based on the 50/5/10 rule, but weaker statistically. The β estimates from regression (19) are close to those from Table 8 over the full sample, but are smaller and only marginally significant in 2023-2024. The η_3 estimates from regression (20) are also similar in the full period but mostly insignificant in 2023-2024. The trading strategy that buys high-C stocks earns positive alphas that are larger in magnitude but less significant than those in Table 9, while the strategy targeting high-C, high-volatility stocks performs slightly better, with annualized alphas of 10.2% ($t = 2.04$) in the full period and 14.6% ($t = 2.07$) in 2023-2024. See Appendix A.14 for details. These results must be interpreted cautiously given the short sample and the use of annual N-CEN filings, but they provide suggestive evidence that even 40-Act diversification limits can transmit to stock prices.

9. Conclusion

When the stock market is highly concentrated, portfolio-concentration limits affect both fund behavior and stock prices. Our analysis centers on the long-standing 50/5/10 regulatory constraint, which limits concentration in U.S. fund portfolios. Once largely a formality, this constraint has become binding for a growing share of fund assets, especially in the large-cap growth category. To remain compliant, funds rebalance away from their largest positions, particularly those with highly volatile returns, and reduce their equity exposure.

If enough funds restrict their largest holdings to avoid breaching the constraint, these stocks may become underpriced and later outperform as the mispricing corrects. Consistent with this mechanism, which we formalize in a simple model, stocks held disproportionately in large positions by constrained funds earn abnormally high future returns. This effect is stronger (i) in 2023–2024, when the 50/5/10 limit was especially tight; (ii) for high-volatility stocks, which pose greater compliance risk; and (iii) when the constrained funds are active rather than passive—all consistent with the model. Our finding that funds underperform after becoming constrained also supports this mechanism.

As the regulatory constraint became meaningfully binding only recently, our sample period is short and our findings should be interpreted with caution. They are nonetheless notable for revealing return predictability among mega-cap stocks, where market anomalies are rarely observed. Our findings are consistent with these stocks being temporarily underpriced in 2023–2024 as the 50/5/10 constraint tightened. We find similar, though a bit weaker, patterns for diversified funds subject to a separate 75/5/10 rule. Our suggestive evidence of regulation distorting market valuations merits further study.

Our findings have broader implications for the interplay among market concentration, portfolio regulation, and benchmark design. As a few mega-cap firms increasingly dominate the market, the 50/5/10 rule effectively caps institutional ownership of these firms, creating persistent underweights relative to some funds' desired positions. This tension is not confined to active funds that choose concentrated portfolios; even some passive index-tracking funds have become constrained. A reassessment of the 50/5/10 rule seems appropriate as this regulatory constraint collides with benchmark construction in a concentrated market.

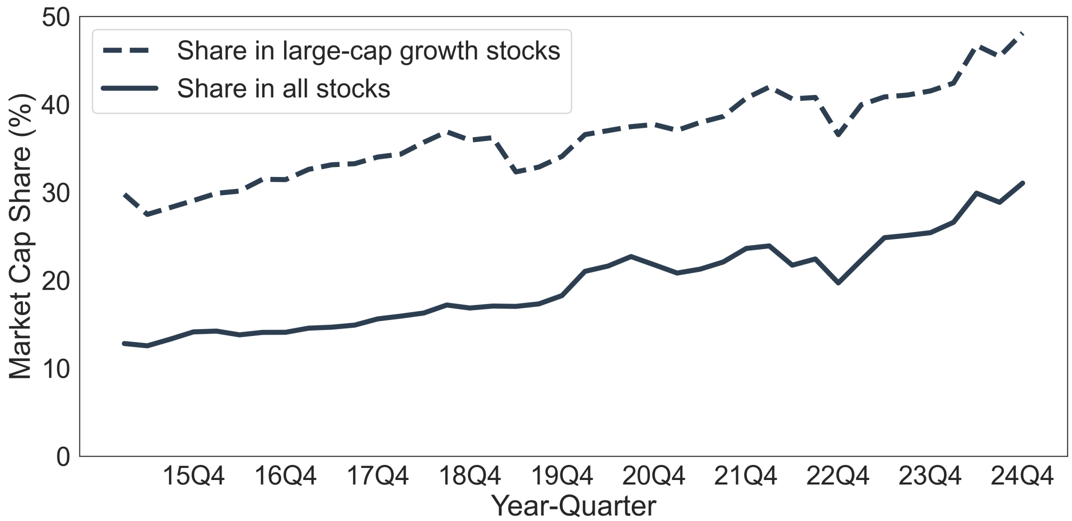


Figure 1. Stock market concentration: Share of top 10 stocks. This figure plots quarterly market concentration from 2015Q1 to 2024Q4. The solid line depicts the market–capitalization share of the ten largest stocks in the entire market, where “all stocks” comprise all common shares in the CRSP universe. The dashed line depicts the market–capitalization share of the ten largest stocks within the large–cap growth segment. A stock is classified as large–cap growth if, in a given year, its market equity exceeds the 70th NYSE percentile, and its book–to–market ratio is below or equal to the 30th NYSE percentile. The construction of book–to–market ratio follows the methodology in Fama and French (1992).

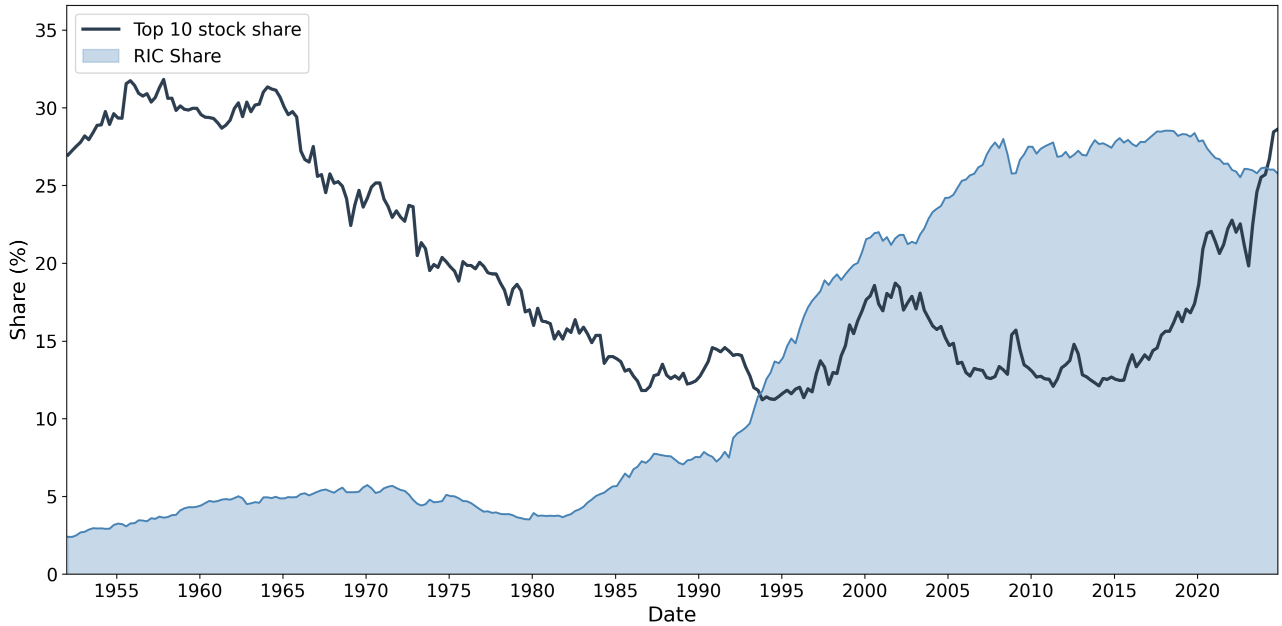


Figure 2. Stock market concentration and RIC equity ownership. This figure plots the quarterly market capitalization share of the ten largest stocks in the CRSP universe (solid line) and the share of U.S. corporate equities held by Regulated Investment Companies (RICs—shaded area) from 1952 to 2024. The concentration measure is based on all common shares in CRSP. RICs include mutual funds, ETFs, and closed-end funds. Data are sourced from CRSP and the Federal Reserve's Financial Accounts of the United States (Z.1). The sample period begins in 1952, the year the Federal Reserve initiated quarterly reporting for equity ownership.

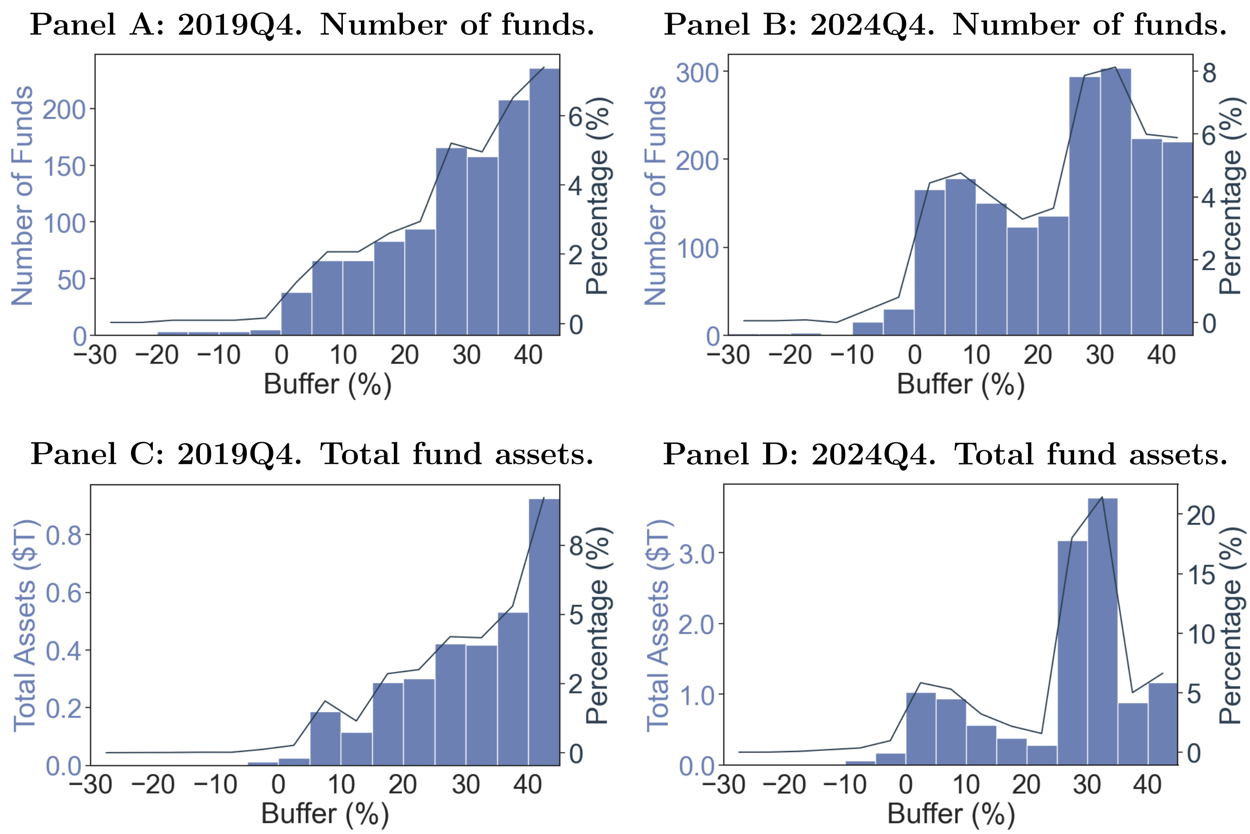
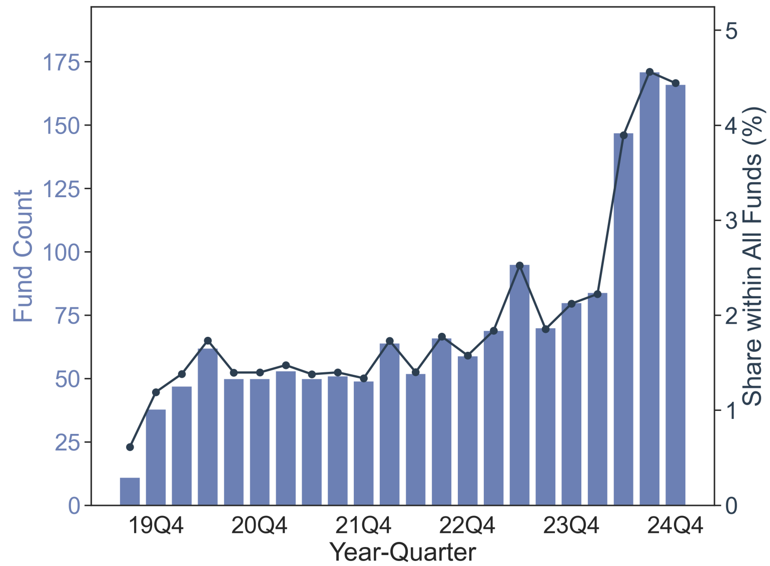


Figure 3. Distribution of buffers across funds. This figure shows the distribution of buffers across funds. Bars (left axis) depict the number of funds or total assets (in trillions of USD) within each 5% buffer interval from −30% to 45%, and lines (right axis) show their corresponding shares among all funds. Panels A and B plot fund counts and their shares for 2019Q4 and 2024Q4. Panels C and D plot total assets and their shares. In 2019Q4, among 3,191 funds, 64.5% had buffers of at least 45%, and 64.0% had buffers exactly equal to 50%. These funds accounted for 67.8% and 56.6% of total assets ($10 trillion), respectively. In 2024Q4, among 3,737 funds, 50.5% had buffers of at least 45%, and 50.3% had buffers exactly equal to 50%. These funds represented 29.4% and 27.5% of total assets ($18 trillion), respectively.

Panel A: Number of constrained funds



Panel B: Total assets of constrained funds

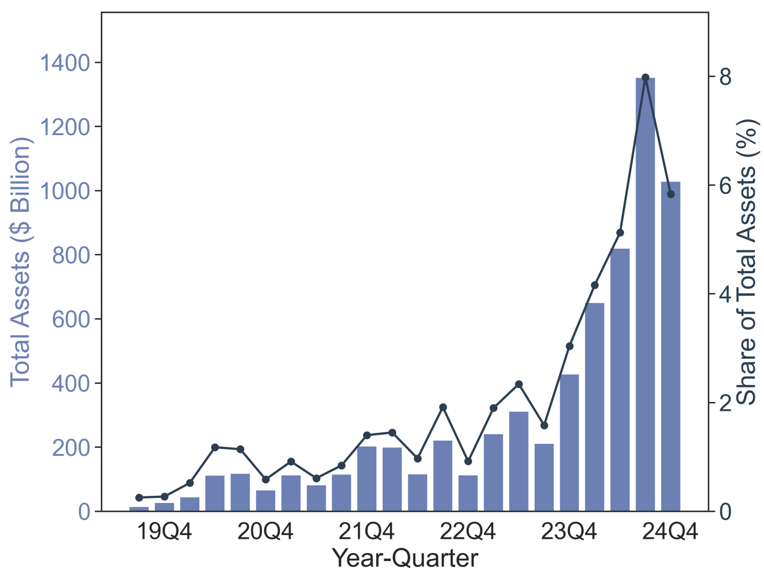
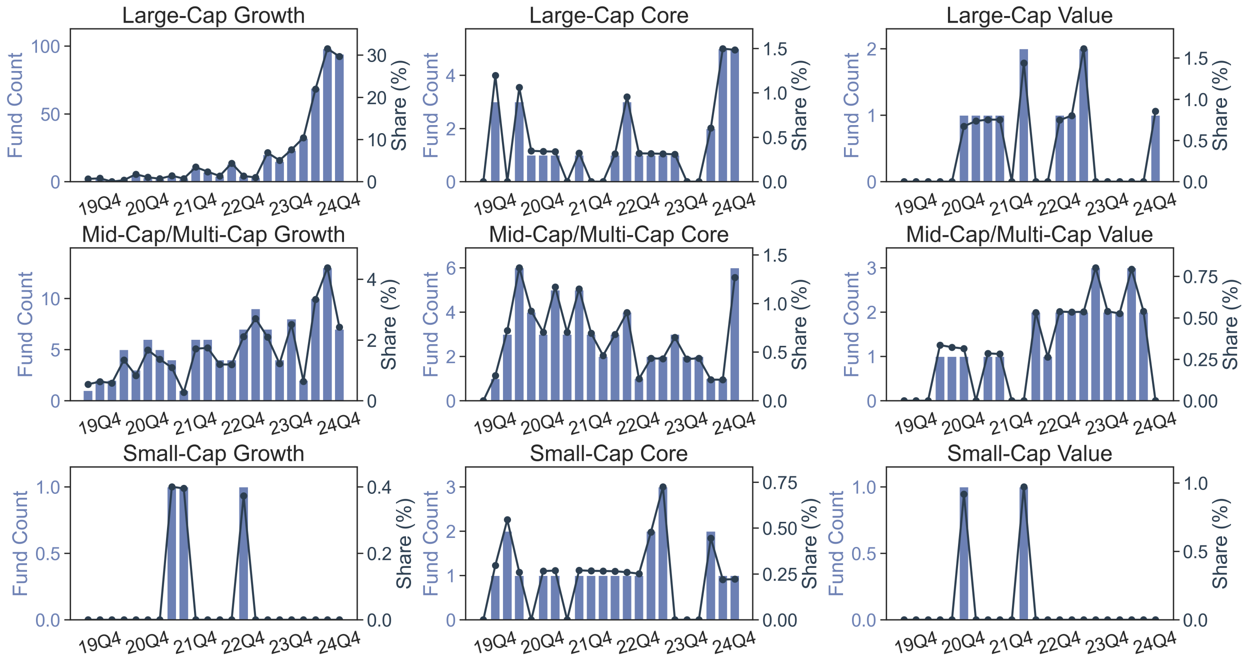


Figure 4. Constrained funds. This figure reports the time-series variation in the number and total assets of funds whose buffers fall within the interval $[0, 5\%)$. Panel A plots, for each quarter t, the number of such funds (bars, left axis) and their fraction of all funds (line, right axis). Panel B plots, for each quarter t, the total assets of these funds (bars, left axis) and their fraction of total fund assets (line, right axis).

Panel A: Number of constrained funds



Panel B: Total assets of constrained funds

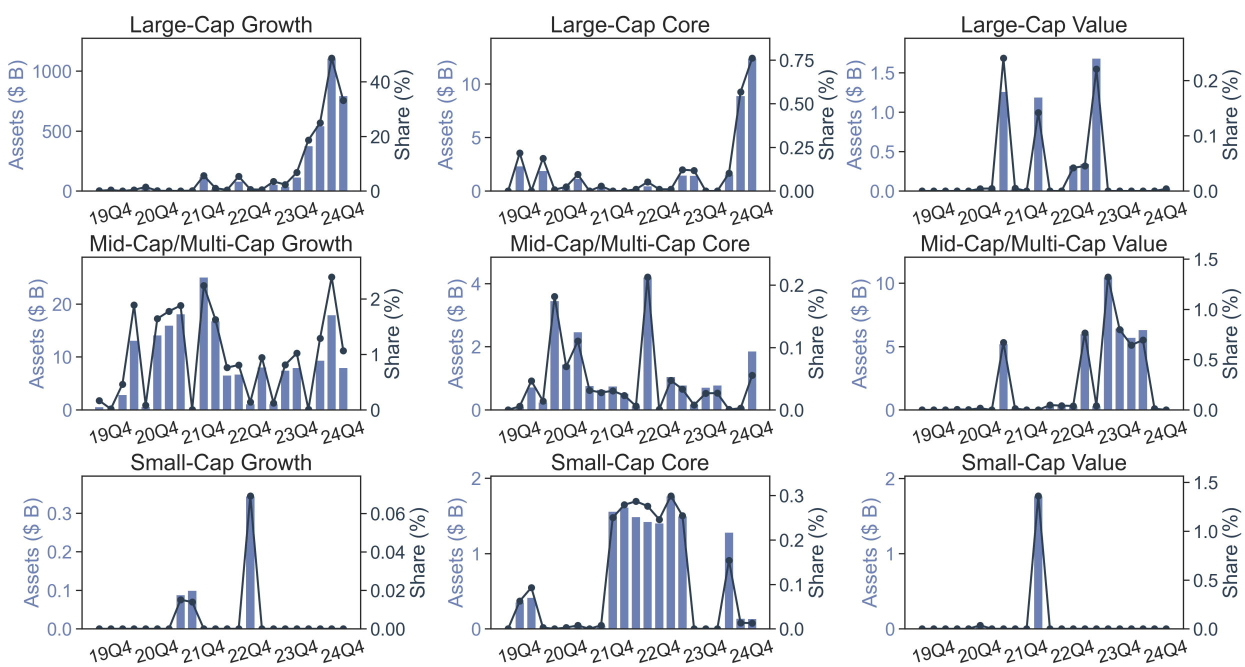
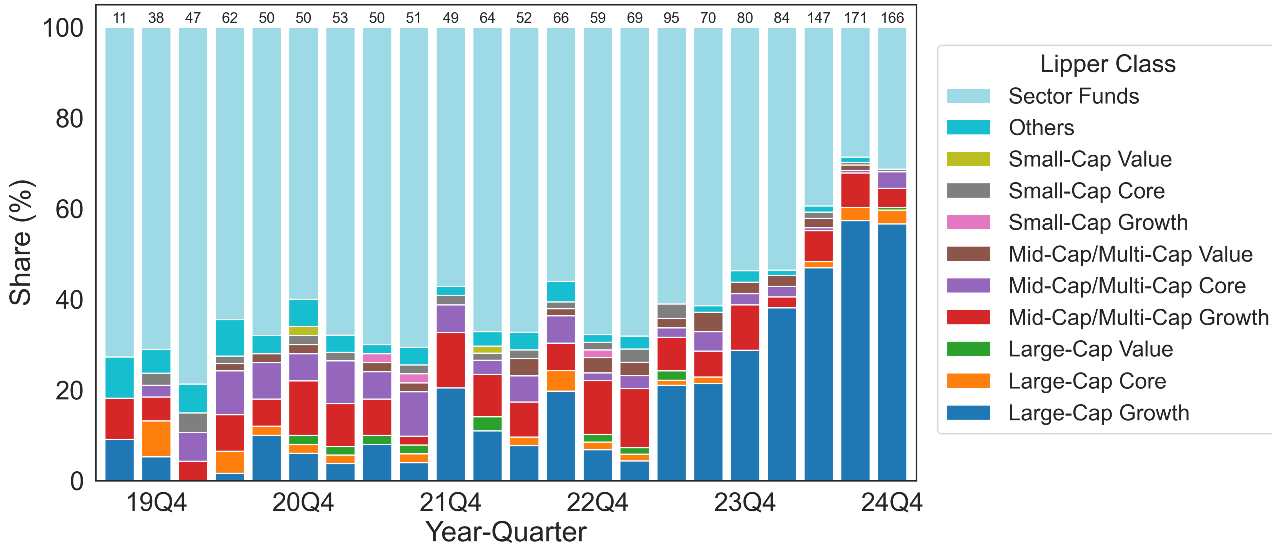


Figure 5. Constrained funds by investment style. This figure reports, for each quarter t and each Lipper classification, the number and total assets of funds whose buffers fall within the interval $[0, 5\%)$. Panel A plots the number of such funds (bars, left axis) and their fraction within the corresponding classification (line, right axis). Panel B plots the total assets of these funds (bars, left axis) and their fraction of total assets within the corresponding classification (line, right axis).

Panel A: By number of funds



Panel B: By total assets ($ billion)

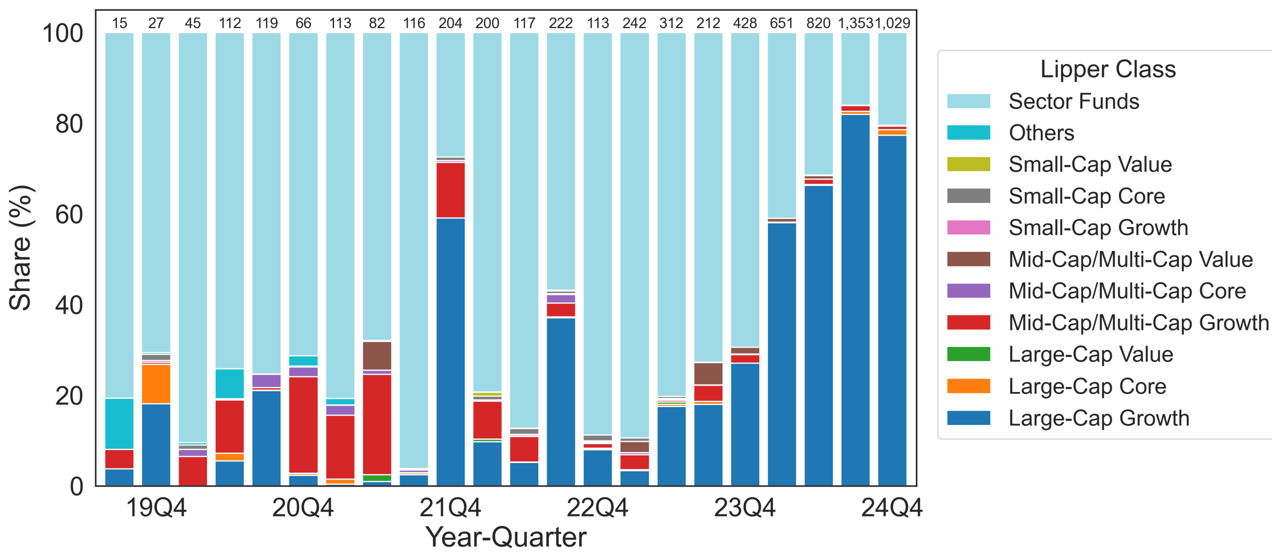


Figure 6. Shares of constrained funds by investment style. This figure reports constrained funds, which we define as funds with $0 \leq \text{Buffer} < 5\%$, across Lipper classifications. Panel A displays the quarterly fraction of constrained funds by number of funds, and places the total number of constrained funds above each bar. Panel B displays the quarterly fraction of constrained funds by total assets, and places the total assets of constrained funds in billions of dollars above each bar.

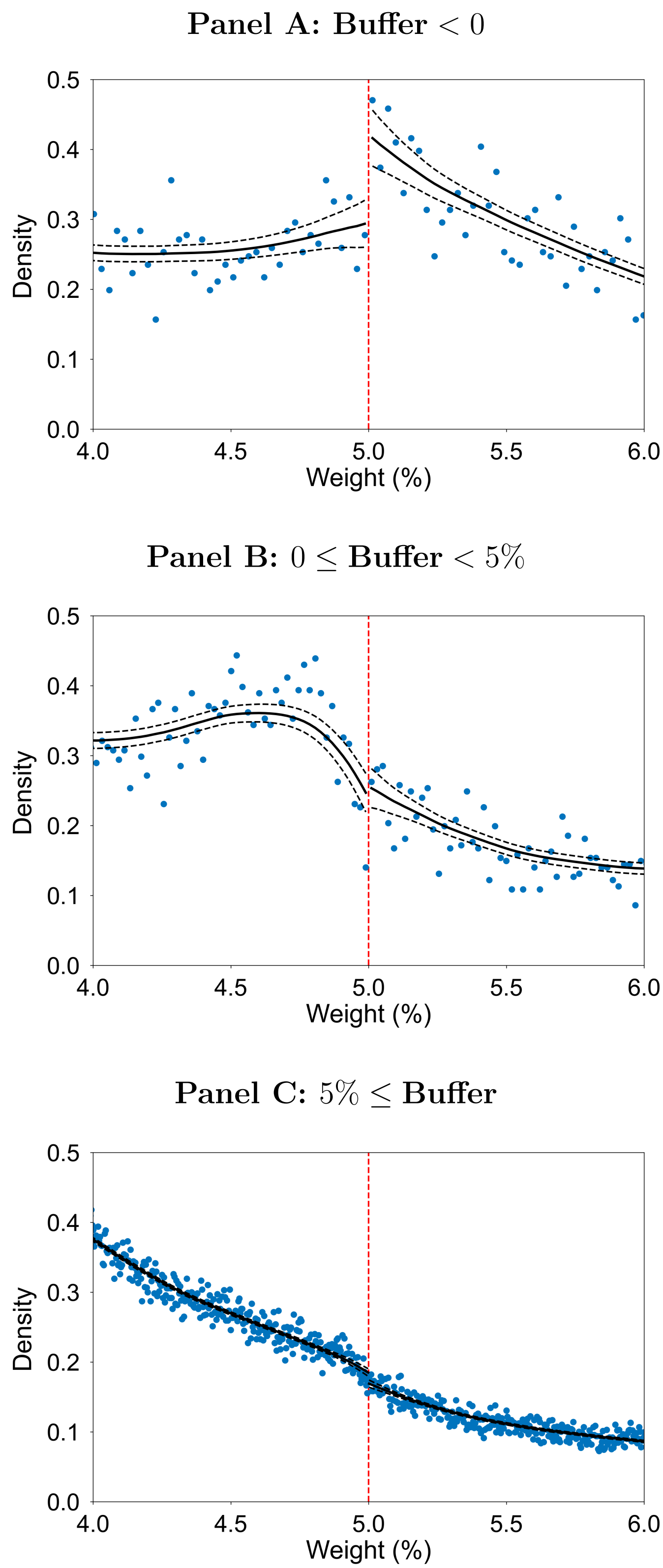


Figure 7. Bunching in funds' portfolio weights. This figure plots McCrary (2008) density estimates for 2019–2024 fund-stock-quarter observations. Circles denote histogram bins, solid lines show smooth densities, and dashed lines represent 95% confidence intervals. Panels A, B, and C correspond to funds with Buffer < 0, $0 \leq$ Buffer $< 5\%$, and $5\% \leq$ Buffer, respectively.

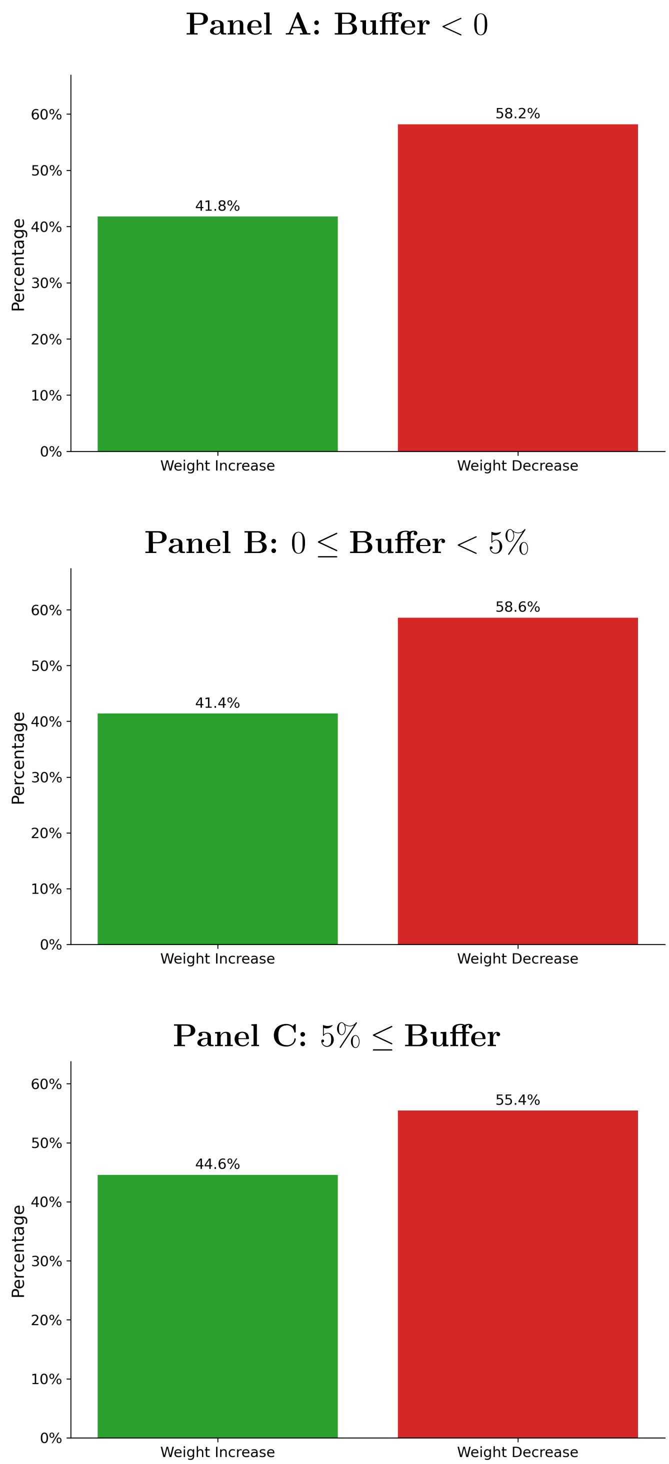


Figure 8. Changes in funds' large positions. The figure plots, for funds' large positions ($\text{Weight}_{f,s,t} > 5\%$), the proportion of cases in which portfolio weights increase or decrease in fiscal quarter $t+1$. We separately analyze funds with buffers below zero, those with buffers in the interval [0, 5%), and those with buffers at or above 5%.

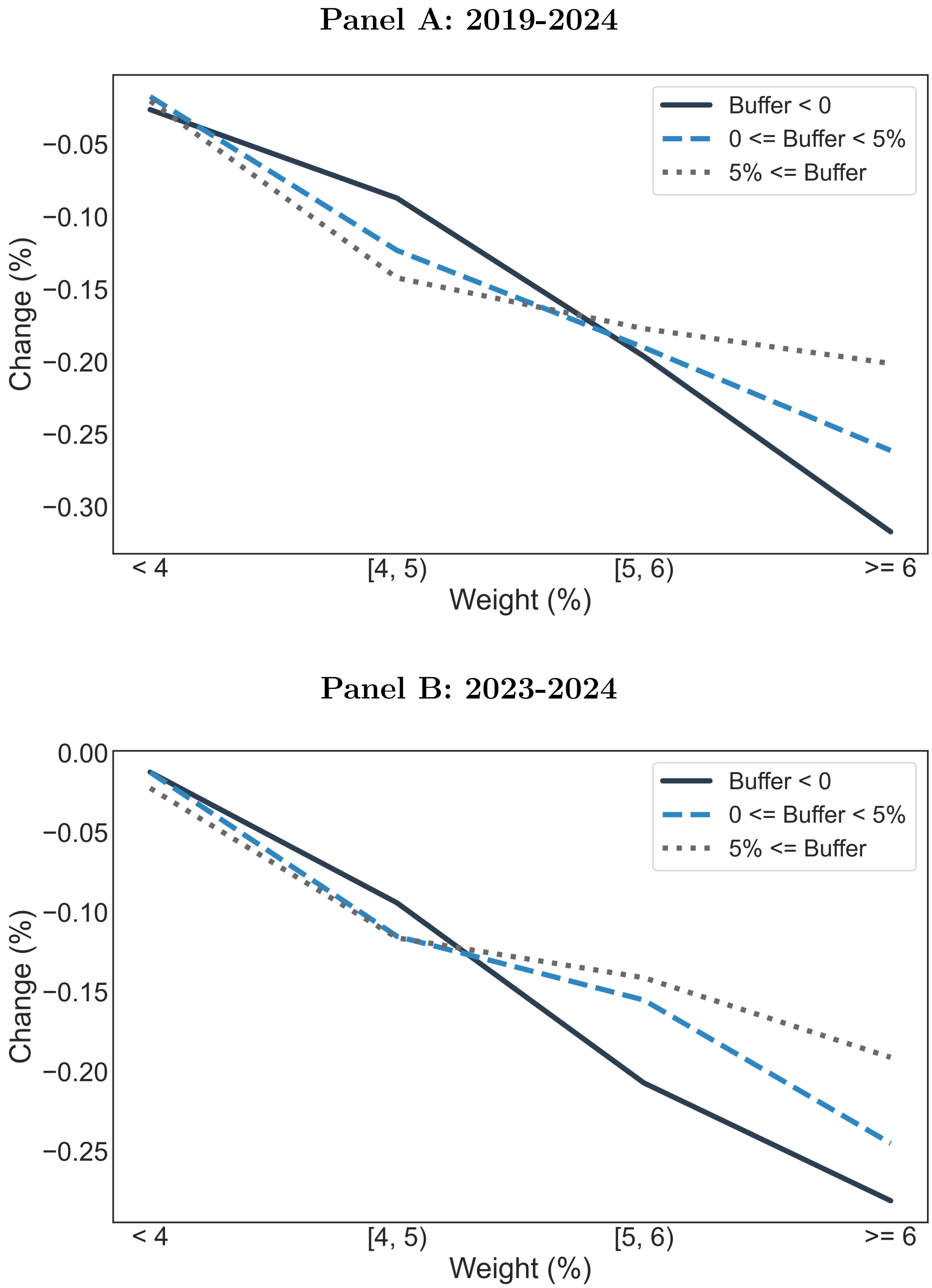


Figure 9. Predicted rebalancing by position size and regulatory buffer. This figure shows predicted changes in portfolio weights as a function of current position size, separately by regulatory buffer category. Predictions are obtained from the regression specification in Table 2 with stock-by-quarter and fund fixed effects. Panel A uses data from 2019–2024, and Panel B focuses on 2023–2024. The sample is restricted to stocks in the top half of the market capitalization distribution.

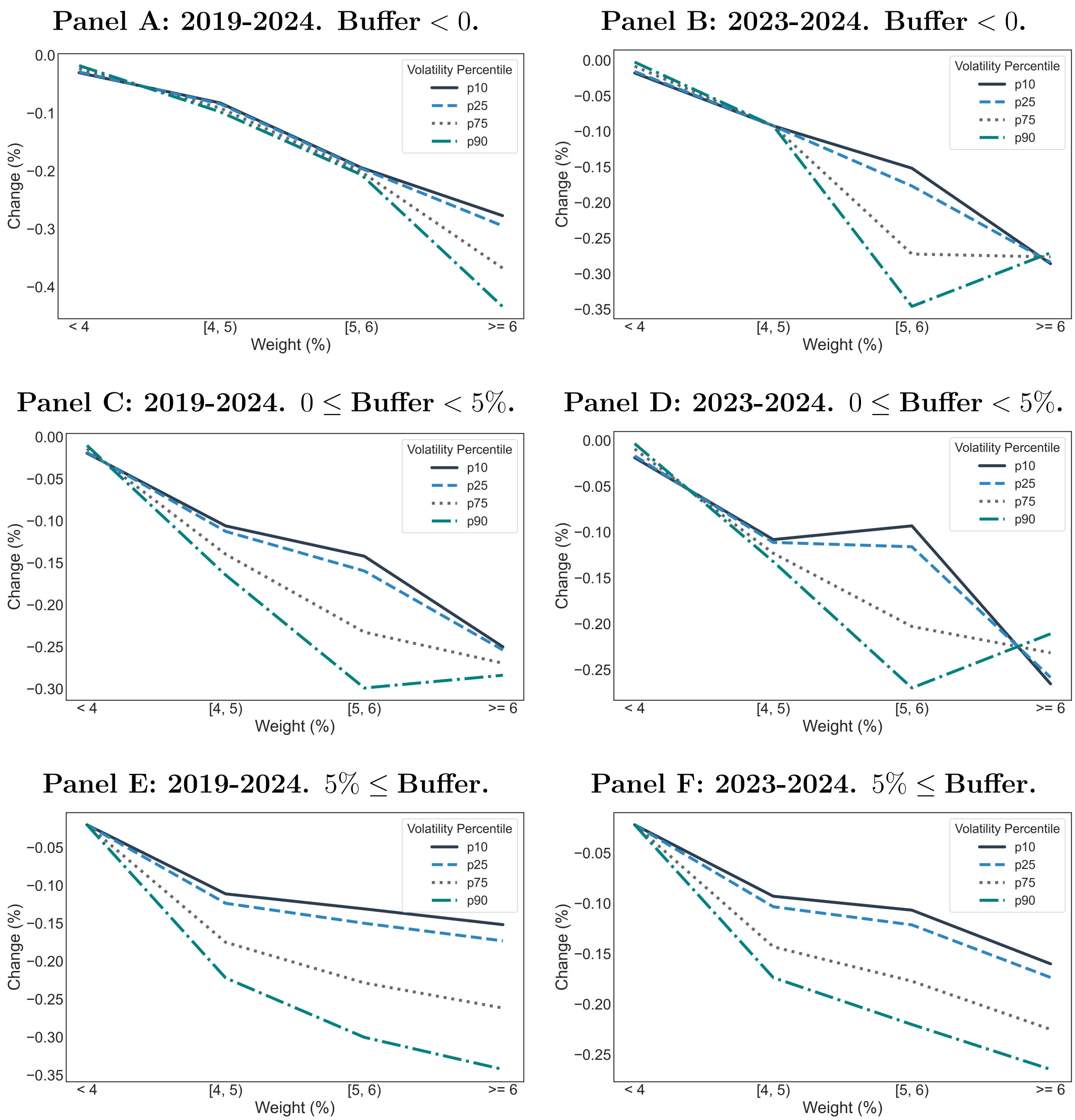


Figure 10. Predicted rebalancing by position size, stock volatility, and fund buffer. This figure illustrates the predicted rebalancing behavior across initial position sizes and volatility percentiles for funds with different regulatory buffers. The predicted values are constructed from specification (6) augmented with the same buffer interactions as in specification (4) and estimated in the full sample of funds with stock-by-quarter and fund fixed effects. Panels A–B use estimates for funds with negative buffers, Panels C–D for buffers between 0 and 5%, and Panels E–F for buffers above 5%. Volatility is measured as the standard deviation of daily stock returns within the fiscal quarter. The sample is restricted to stocks in the top half of the market capitalization distribution.

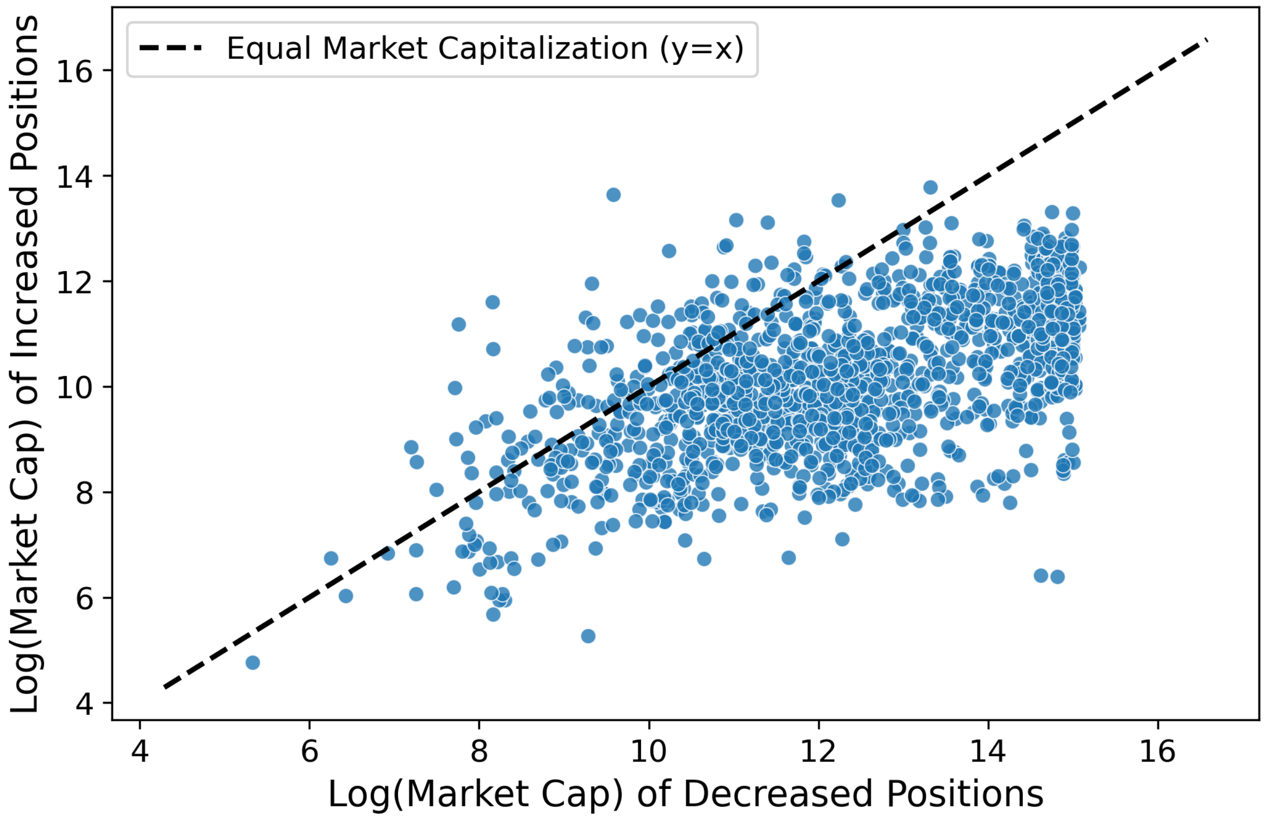
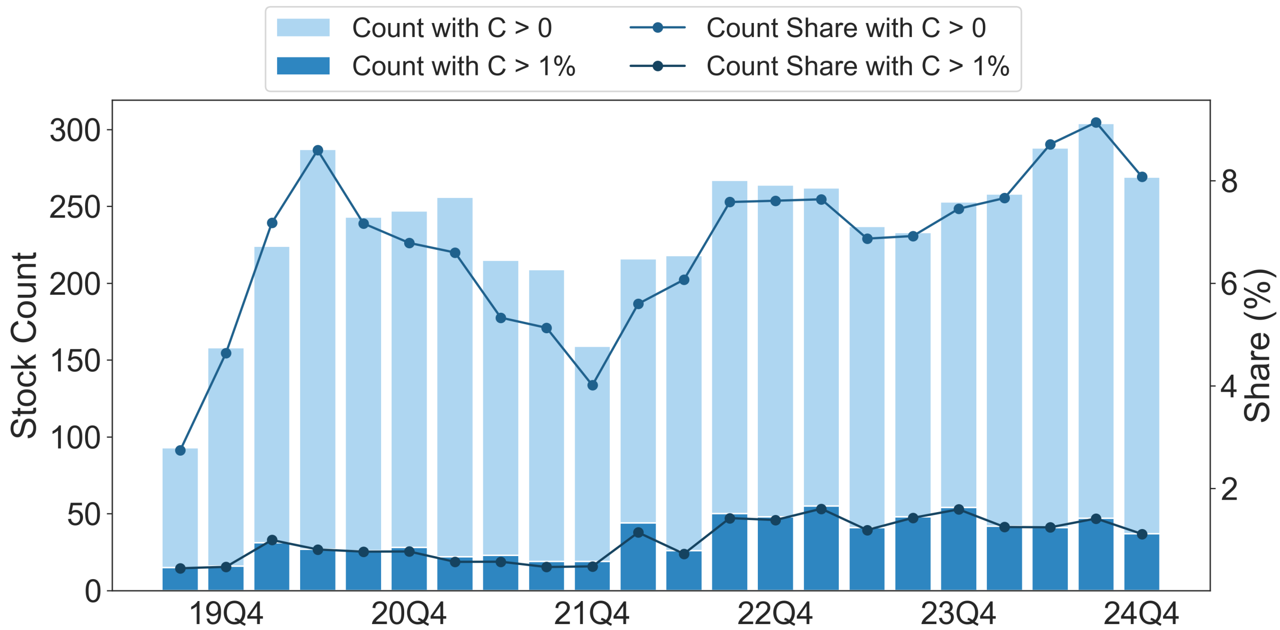


Figure 11. Constrained funds' rebalancing to smaller-cap stocks. This figure plots, for each constrained fund f and quarter t, the average market capitalization (log of millions USD) of large positions whose weights decrease (x-axis) versus the average market capitalization of positions whose weights increase (y-axis). Each point represents a fund-quarter observation. We define constrained funds as those with $\text{Buffer}_{f,t}$ in the interval $[0, 5\%)$ and large positions as holdings with $\text{Weight}_{f,s,t} > 5\%$.

Panel A: Number of stocks with C > 0 and C > 1%



Panel B: Total market cap of stocks with C > 0 and C > 1%

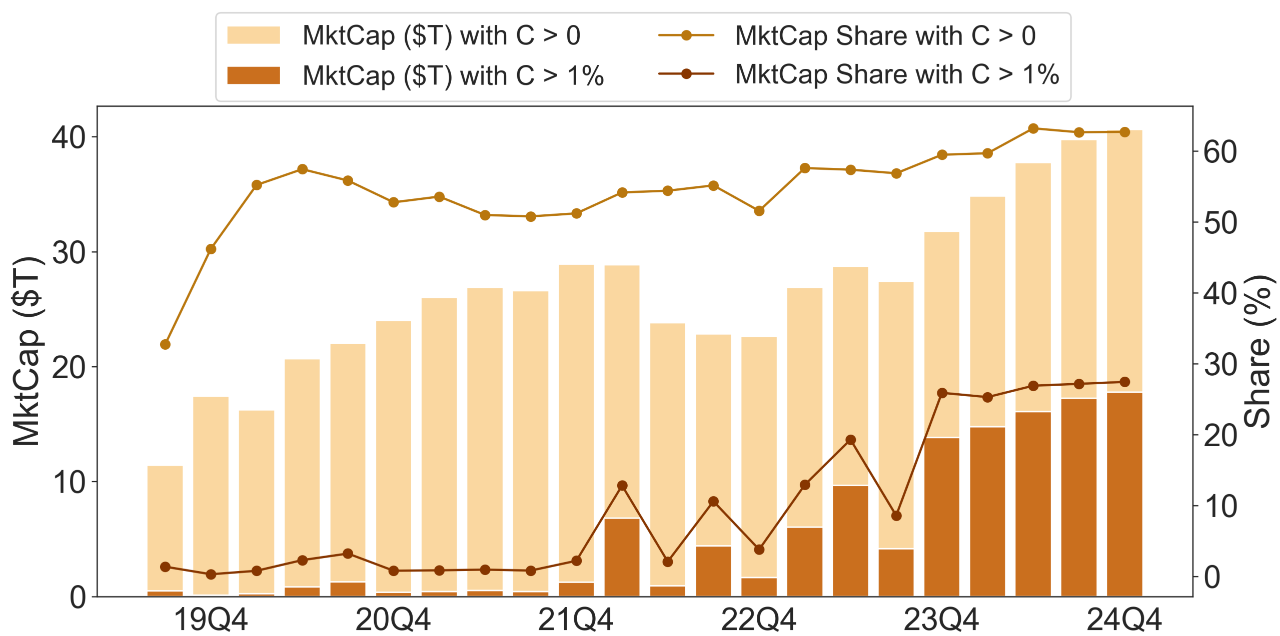
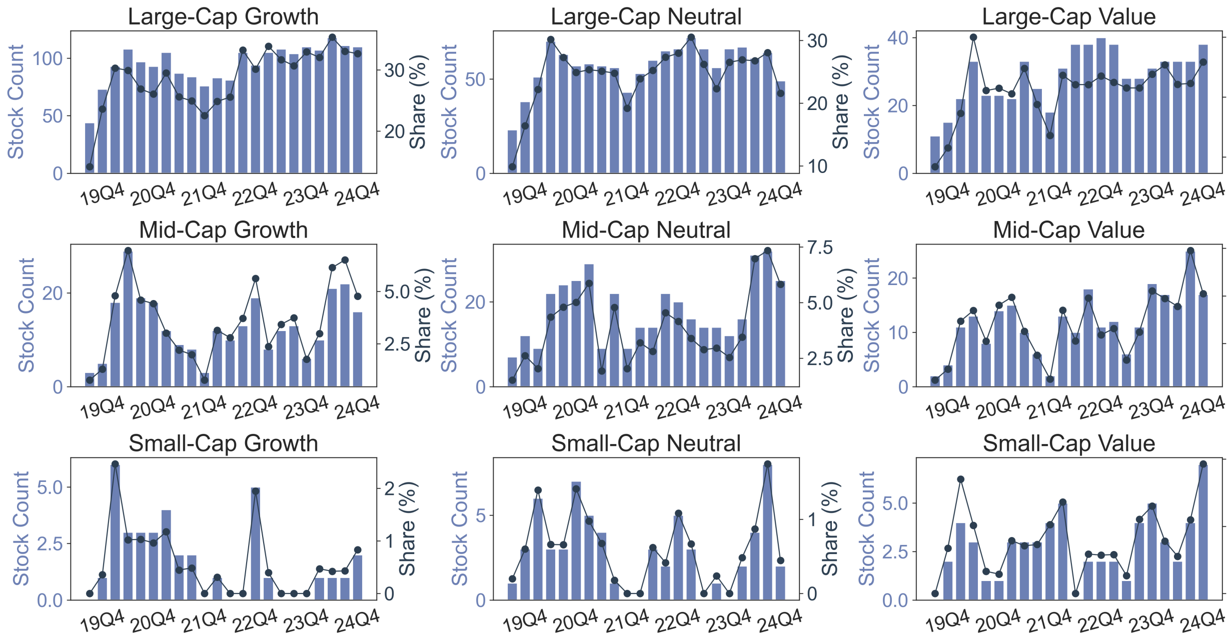


Figure 12. Stocks with positive constrained ownership shares. This figure plots, for the last month of each quarter, the number and market capitalization (in trillions of USD) of stocks with positive constrained ownership. Panel A shows the number of stocks with $C_{s,t} > 0$ and $C_{s,t} > 1\%$ among all stocks in that month (bars, left axis) and their fraction (lines, right axis), where $C_{s,t}$ denotes the constrained ownership share. Panel B shows the market capitalization of stocks with $C_{s,t} > 0$ and $C_{s,t} > 1\%$ (bars, left axis) and their fraction of total market capitalization (lines, right axis).

Panel A: Number of stocks with C > 0



Panel B: Total market cap of stocks with C > 0

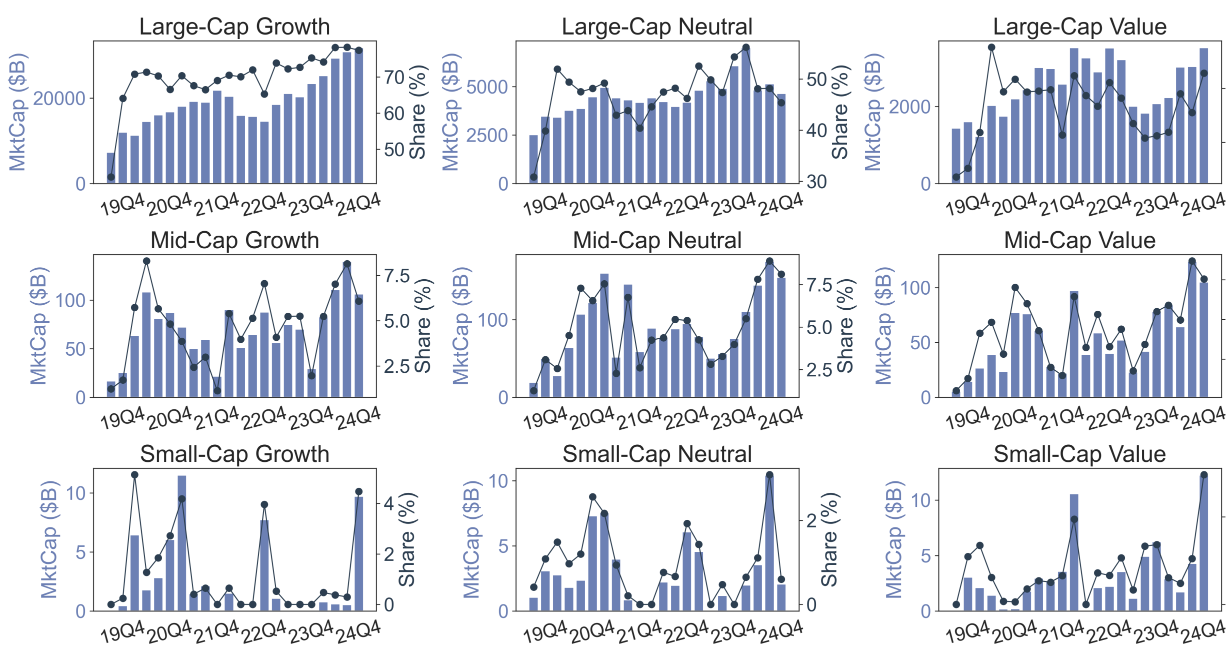


Figure 13. Stocks with positive constrained ownership shares, by investment style. This figure plots, for the last month of each quarter and for each stock classification, the number and market capitalization (in billions of USD) of stocks with positive constrained ownership. Panel A shows the number of stocks with $C_{s,t} > 0$ (bars, left axis) and their fraction within each classification (lines, right axis), where $C_{s,t}$ denotes the constrained ownership share. Panel B shows the market capitalization of stocks with $C_{s,t} > 0$ (bars, left axis) and their fraction within each classification (lines, right axis).

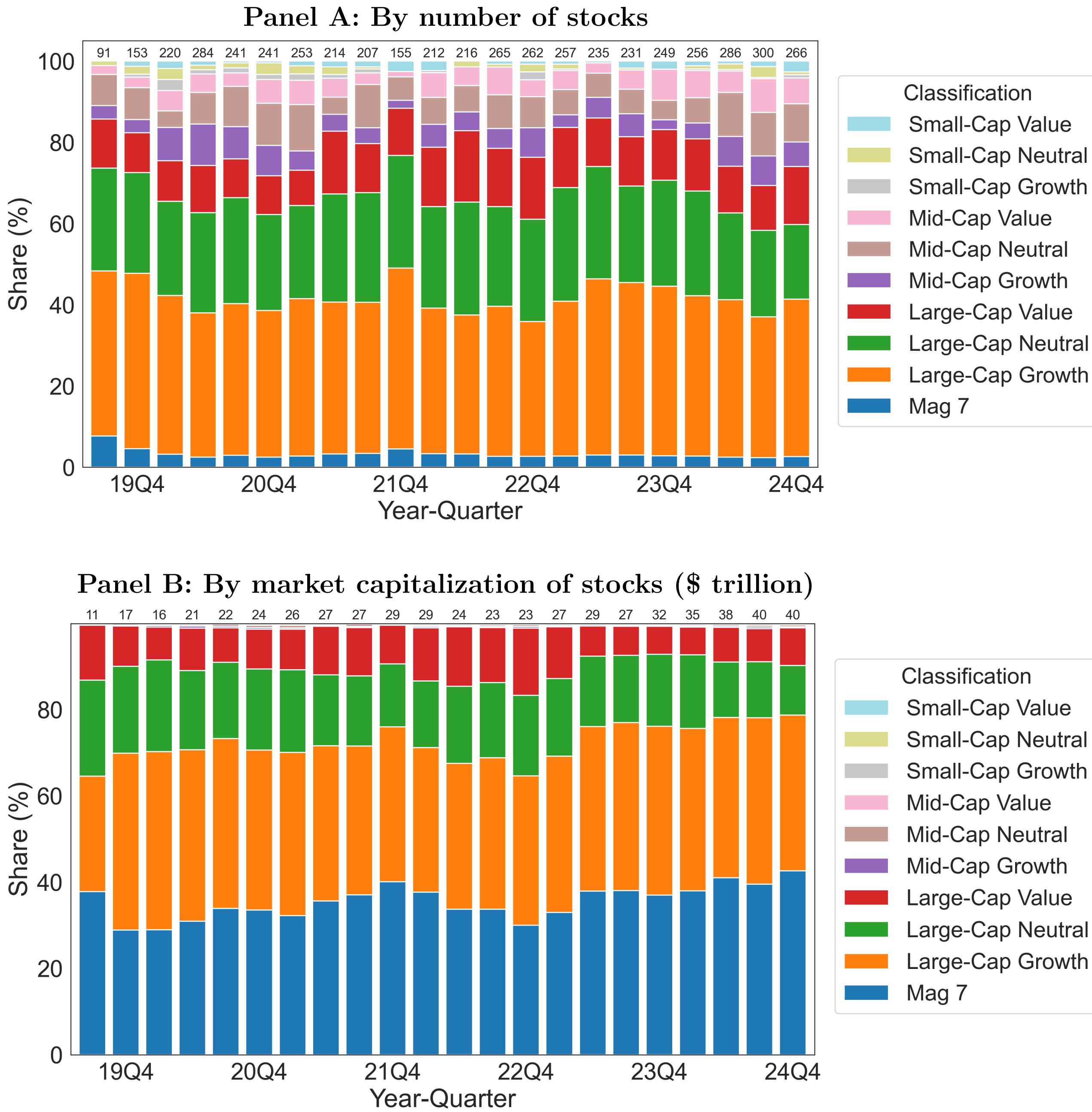


Figure 14. Shares of stocks with positive constrained ownership shares, by investment style. This figure shows the distribution of stocks with positive constrained ownership ($C_{s,t} > 0$) across classifications. In Panel A, we calculate the fraction based on the number of stocks and display the total number of stocks with $C_{s,t} > 0$ on top of each bar. In Panel B, we calculate the fraction based on market capitalization (in trillions USD) and display the total market capitalization of stocks with $C_{s,t} > 0$ on top of each bar. We separate the Magnificent 7 stocks from the large-cap growth category (i.e., 'Large-Cap Growth' excludes the Mag 7).

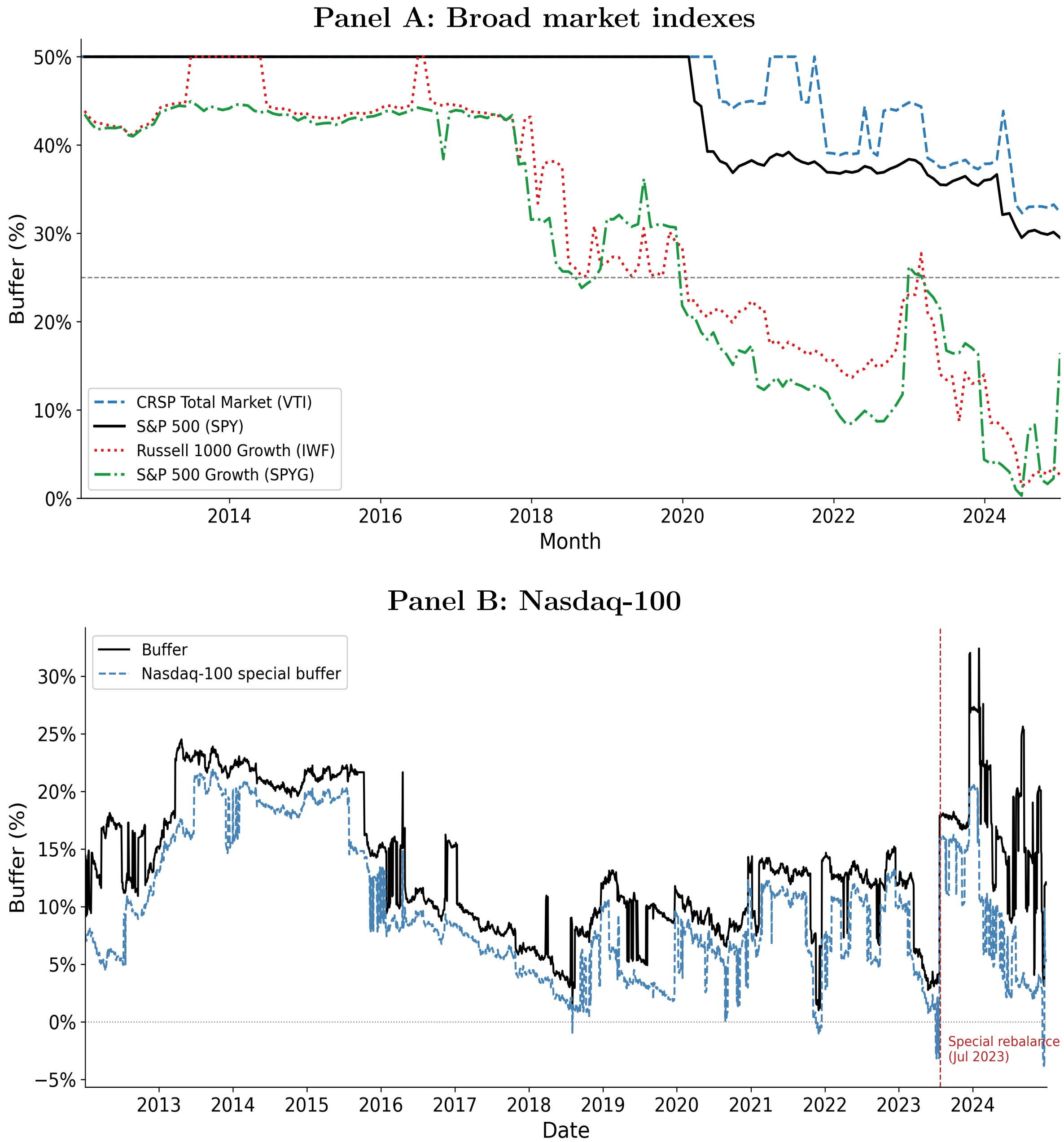


Figure 15. Buffers for major U.S. equity indexes. This figure reports buffers of U.S. equity indexes from 2012 to 2024, based on corresponding ETF constituent holdings obtained from ETF Global. The buffer is defined as 50% minus the sum of portfolio weights in large positions (with weight above 5%). Panel A reports month-end values for four broad market indexes: CRSP total market (corresponding ETF: VTI), S&P 500 (SPY), Russell 1000 growth (IWF), and S&P 500 growth (SPYG). Horizontal lines at 0% and 25% mark the 50/5/10 and 75/5/10 rules thresholds, respectively. Panel B reports the daily buffer of the Nasdaq-100 index, approximated using constituent holdings of the Invesco QQQ ETF that tracks the index. The dashed blue line additionally plots the Nasdaq-100 special buffer, defined as 48% minus the sum of portfolio weights above 4.5%. The Nasdaq-100 index undergoes a special rebalance when this buffer is non-positive, and the vertical dashed line marks the rebalance on July 24, 2023.

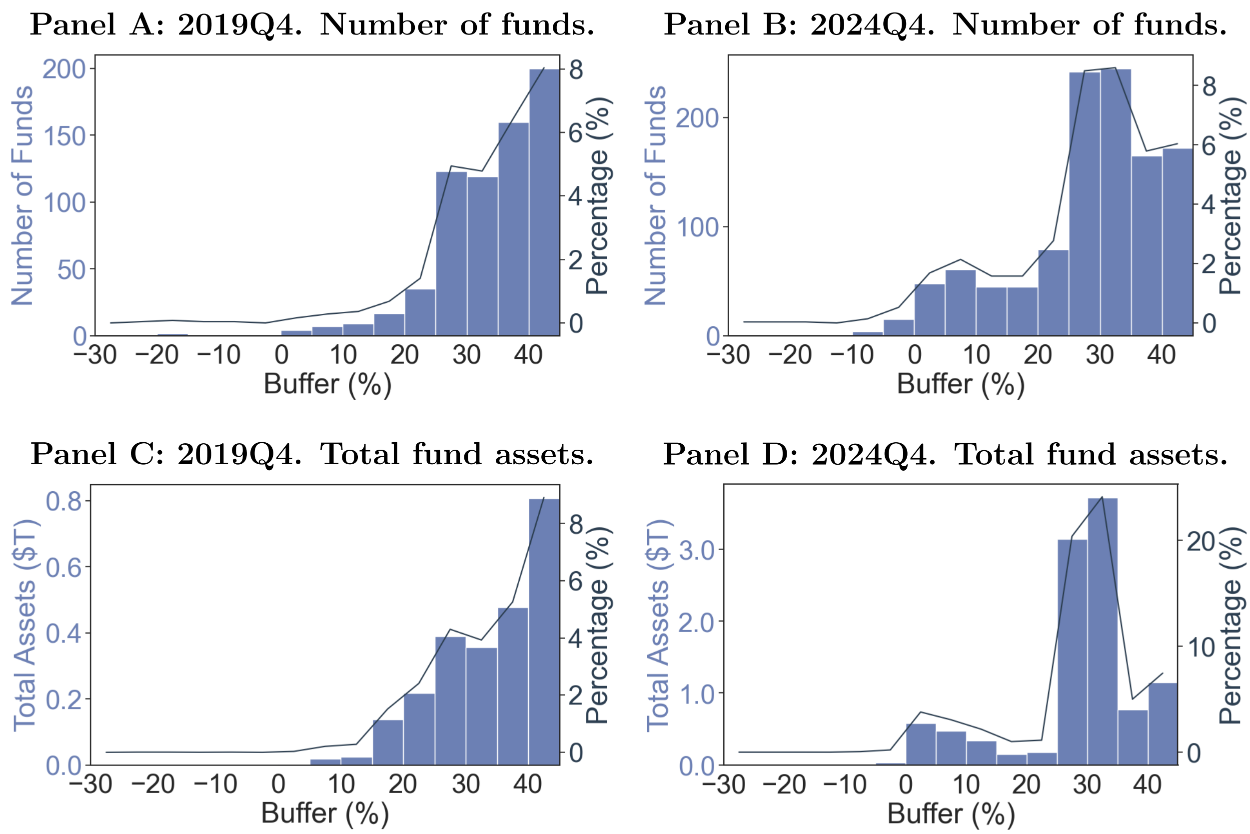


Figure 16. Distribution of buffers across diversified funds. This figure shows the distribution of buffers across diversified funds. Bars (left axis) depict the number of funds or total assets (in trillions of USD) within each 5% buffer interval from −30% to 45%, and lines (right axis) show their corresponding shares among all diversified funds. Panels A and B plot fund counts and their shares, while Panels C and D plot total assets and their shares for 2019Q4 and 2024Q4.

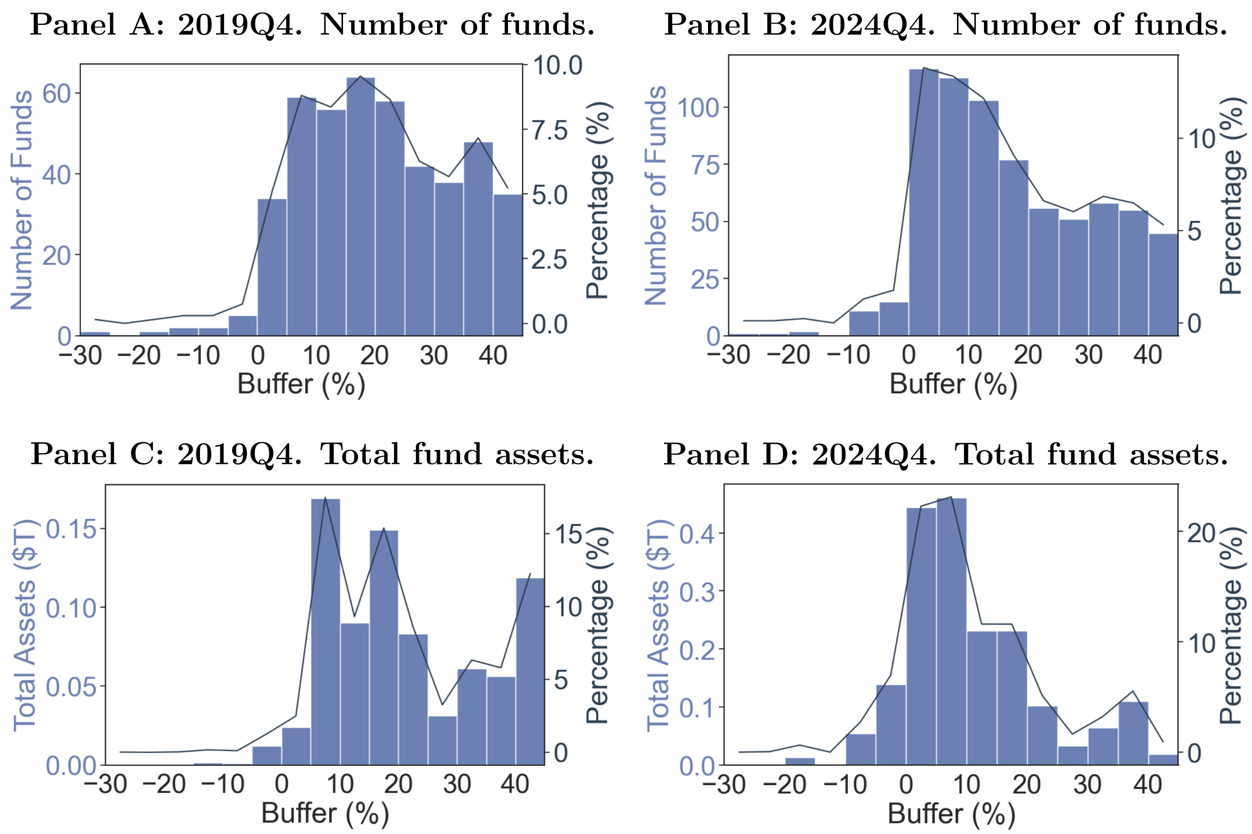


Figure 17. Distribution of buffers across non-diversified funds. This figure shows the distribution of buffers across non-diversified funds. Bars (left axis) depict the number of funds or total assets (in trillions of USD) within each 5% buffer interval from −30% to 45%, and lines (right axis) show their corresponding shares among all non-diversified funds. Panels A and B plot fund counts and their shares, while Panels C and D plot total assets and their shares for 2019Q4 and 2024Q4.

Table 1
Fund buffers and index buffers

This table presents coefficients from OLS regressions of fund buffers on their benchmark index buffers, estimated separately for passive and active funds, of the form

$$\text{Buffer}_{f,t} = \alpha + \beta \cdot \text{IndexBuffer}_{b(f),t} + \gamma' X_{f,t} + \mu_f + \tau_t + \varepsilon_{f,t},$$

where t denotes fiscal quarters, $b(f)$ is fund f's benchmark index, and $X_{f,t}$ is a vector of fund-level controls, including fund size, age, expense ratio, turnover ratio, flows, returns, return volatility, Carhart four-factor loadings, number of equity holdings, a diversified-fund dummy, Morningstar rating, fund family size, and the volatility of the benchmark index. We identify each fund's benchmark $b(f)$ using the prospectus benchmark reported in the Morningstar database. For each benchmark, we use the buffer of the passive fund (ETF or index fund) with the lowest 2019–2024 tracking error as $\text{IndexBuffer}_{b(f),t}$. Both $\text{Buffer}_{f,t}$ and $\text{IndexBuffer}_{b(f),t}$ are in %. Standard errors are double-clustered by fiscal quarter and fund, and t-statistics are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. Q denotes fiscal quarter.

	Passive				Active			
	Panel A: 2019–2024							
Index buffer	0.988***	0.971***	0.952***	0.952***	0.737***	0.406***	0.368***	0.327***
	(162.59)	(91.41)	(104.63)	(105.93)	(27.10)	(14.76)	(11.11)	(11.90)
Controls	No	Yes	No	Yes	No	Yes	No	Yes
Q+Fund Fixed Effects	No	No	Yes	Yes	No	No	Yes	Yes
Adjusted R-squared	0.9749	0.9760	0.9936	0.9936	0.3657	0.6116	0.9059	0.9122
Observations	14,302	14,302	14,302	14,302	25,747	25,747	25,747	25,747
	Panel B: 2023–2024							
Index buffer	0.989***	0.958***	0.932***	0.932***	0.754***	0.363***	0.394***	0.364***
	(177.02)	(81.83)	(57.21)	(57.63)	(28.37)	(11.93)	(9.10)	(8.60)
Controls	No	Yes	No	Yes	No	Yes	No	Yes
Q+Fund Fixed Effects	No	No	Yes	Yes	No	No	Yes	Yes
Adjusted R-squared	0.9705	0.9724	0.9935	0.9935	0.4101	0.6501	0.9448	0.9471
Observations	5,846	5,846	5,846	5,846	10,284	10,284	10,284	10,284

Table 2
Changes in funds' large positions

This table presents coefficients from OLS regressions of

$$\Delta\text{Weight}_{f,s,t+1} = \beta_0 + \beta_1 D^{W>5}_{f,s,t} + \beta_2 D^{B<0}_{f,t} + \beta_3 D^{0\leq B<5}_{f,t} + \beta_4 (D^{W>5}_{f,s,t} \times D^{B<0}_{f,t}) + \beta_5 (D^{W>5}_{f,s,t} \times D^{0\leq B<5}_{f,t}) + \epsilon_{f,s,t+1}.$$

The weight indicator, D^W, is based on $\text{Weight}_{f,s,t}$ (%). Buffer indicators, D^B, are based on $\text{Buffer}_{f,t}$ (%). The regression sample includes stocks with prices above \$5 and, within each fiscal quarter, the largest 50% of stocks by market capitalization, resulting in 2,806 stocks. Standard errors are clustered at the stock level, and t-statistics are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. Q denotes fiscal quarter.

	Panel A: 2019-2024				
5<W × Buffer<0	-0.080**	-0.081**	-0.052*	-0.082***	-0.076***
	(-2.14)	(-2.16)	(-1.96)	(-3.35)	(-2.77)
5<W × 0≤Buffer<5	-0.080**	-0.081**	-0.052**	-0.055***	-0.051**
	(-2.10)	(-2.12)	(-2.28)	(-2.71)	(-2.28)
5<W	-0.124***	-0.124***	-0.165***	-0.148***	-0.142***
	(-4.41)	(-4.40)	(-8.69)	(-9.44)	(-8.98)
Fixed Effects	No	Q	Q×Stock	Q×Stock + Fund	Q×Stock + Q×Fund
Adjusted R-squared	0.0029	0.0033	0.1275	0.1610	0.2054
Observations	11,513,919	11,513,919	11,513,919	11,513,919	11,513,919
	Panel B: 2023-2024				
5<W × Buffer<0	-0.076**	-0.077**	-0.052**	-0.093***	-0.083***
	(-2.10)	(-2.12)	(-1.97)	(-3.71)	(-3.03)
5<W × 0≤Buffer<5	-0.073*	-0.074*	-0.059**	-0.061**	-0.058**
	(-1.76)	(-1.77)	(-2.16)	(-2.38)	(-2.12)
5<W	-0.108***	-0.108***	-0.151***	-0.131***	-0.126***
	(-5.42)	(-5.39)	(-10.08)	(-9.67)	(-9.25)
Fixed Effects	No	Q	Q×Stock	Q×Stock + Fund	Q×Stock + Q×Fund
Adjusted R-squared	0.0027	0.0030	0.1329	0.1739	0.2113
Observations	4,354,870	4,354,870	4,354,870	4,354,870	4,354,870

Table 3
Changes in funds' positions and volatility

This table presents coefficients from OLS regressions of

$$\Delta\text{Weight}_{f,s,t+1} = \gamma_0 + \gamma_1\text{Weight}_{f,s,t} + \gamma_2\text{Volatility}_{s,t} + \gamma_3(\text{Weight}_{f,s,t} \times \text{Volatility}_{s,t}) + \varphi_{f,s,t+1}.$$

We define Volatility$_{s,t}$ (%) as the standard deviation of daily returns within the corresponding fiscal quarter. The regression sample includes stocks with prices above \$5 and, within each fiscal quarter, the largest 50% of stocks by market capitalization, resulting in 2,806 stocks. Standard errors are clustered at the stock level, and t-statistics are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. Q denotes fiscal quarter.

			Panel A: 2019-2024		
Weight	-0.016***	-0.016***	-0.026***	-0.032***	-0.025***
	(-2.96)	(-2.90)	(-8.59)	(-7.06)	(-5.69)
Weight × Volatility	-0.009***	-0.009***	-0.009***	-0.008***	-0.010***
	(-4.19)	(-4.14)	(-8.71)	(-7.47)	(-7.26)
Fixed Effects	No	Q	Q×Stock	Q×Stock + Fund	Q×Stock + Q×Fund
Adjusted R-squared	0.0236	0.0241	0.1534	0.1752	0.2181
Observations	11,513,919	11,513,919	11,513,919	11,513,919	11,513,919
			Panel B: 2023-2024		
Weight	-0.024***	-0.024***	-0.021***	-0.025***	-0.023***
	(-2.72)	(-2.72)	(-4.71)	(-5.87)	(-5.54)
Weight × Volatility	-0.004	-0.003	-0.012***	-0.010***	-0.010***
	(-0.59)	(-0.58)	(-4.41)	(-3.56)	(-3.59)
Fixed Effects	No	Q	Q×Stock	Q×Stock + Fund	Q×Stock + Q×Fund
Adjusted R-squared	0.0191	0.0194	0.1580	0.1858	0.2219
Observations	4,354,870	4,354,870	4,354,870	4,354,870	4,354,870

Table 4
Changes in constrained and negative-buffer funds' positions and volatility

This table reports coefficients from OLS regressions run separately for funds with $\text{Buffer}_{f,t} < 0$ and $0 \leq \text{Buffer}_{f,t} < 5\%$:

$$\Delta\text{Weight}_{f,s,t+1} = \delta_0 + \delta_1(D^{W>6}_{f,s,t} \times \text{Volatility}_{s,t}) + \delta_2(D^{5<W\leq 6}_{f,s,t} \times \text{Volatility}_{s,t}) + \delta_3(D^{4<W\leq 5}_{f,s,t} \times \text{Volatility}_{s,t}) + \delta_4 D^{W>6}_{f,s,t} + \delta_5 D^{5<W\leq 6}_{f,s,t} + \delta_6 D^{4<W\leq 5}_{f,s,t} + \delta_7 \text{Volatility}_{s,t} + \eta_{f,s,t+1}.$$

Weight indicators, D^W, are based on $\text{Weight}_{f,s,t}$ (%). $\text{Volatility}_{s,t}$ (%) is the standard deviation of daily returns within fiscal quarter t. The sample includes stocks with prices above \$5 and, within each fiscal quarter, the largest 50% of stocks by market capitalization, resulting in 2,806 stocks. Standard errors are clustered at the stock level, with t-statistics reported in parentheses. ***, **, and * denote significance at 1%, 5%, and 10% levels. Q denotes fiscal quarter.

	Buffer < 0					0 ≤ Buffer < 5%				
					Panel A: 2019-2024					
6<W × Volatility	-0.057***	-0.057**	-0.091***	-0.075**	-0.063*	0.009	0.010	-0.040*	-0.027	-0.039*
	(-2.62)	(-2.51)	(-2.91)	(-2.36)	(-1.87)	(0.35)	(0.37)	(-1.76)	(-1.24)	(-1.81)
5<W≤6 × Volatility	-0.025	-0.026	-0.043	-0.030	-0.015	-0.073***	-0.074***	-0.095***	-0.089***	-0.083***
	(-1.12)	(-1.15)	(-1.35)	(-0.84)	(-0.42)	(-4.17)	(-4.18)	(-3.62)	(-3.23)	(-2.71)
4<W≤5 × Volatility	-0.021	-0.022	-0.028	-0.005	0.002	-0.035***	-0.034***	-0.048***	-0.039***	-0.039**
	(-1.08)	(-1.12)	(-1.09)	(-0.19)	(0.06)	(-2.85)	(-2.73)	(-3.14)	(-2.58)	(-2.46)
Fixed Effects	No	Q	Q×Stock	Q×Stock + Fund	Q×Stock + Q×Fund	No	Q	Q×Stock	Q×Stock + Fund	Q×Stock + Q×Fund
Adjusted R-squared	0.0319	0.0363	0.4572	0.4805	0.5234	0.0263	0.0278	0.3537	0.3783	0.4055
Observations	21,679	21,679	21,679	21,679	21,679	80,317	80,317	80,317	80,317	80,317
					Panel B: 2023-2024					
6<W × Volatility	0.025	0.026	-0.076	-0.058	-0.067	0.091***	0.091***	-0.052	-0.035	-0.037
	(0.73)	(0.75)	(-1.64)	(-1.25)	(-1.49)	(2.85)	(2.87)	(-1.39)	(-1.00)	(-1.04)
5<W≤6 × Volatility	-0.114**	-0.114**	-0.121***	-0.105**	-0.114**	-0.112***	-0.112***	-0.129***	-0.119**	-0.116**
	(-2.13)	(-2.15)	(-2.60)	(-2.28)	(-2.51)	(-3.17)	(-3.18)	(-2.60)	(-2.29)	(-2.16)
4<W≤5 × Volatility	-0.023	-0.022	-0.050	-0.059*	-0.067**	-0.031	-0.031	-0.044*	-0.040*	-0.048**
	(-0.64)	(-0.61)	(-1.38)	(-1.72)	(-1.99)	(-1.15)	(-1.16)	(-1.96)	(-1.72)	(-2.13)
Fixed Effects	No	Q	Q×Stock	Q×Stock + Fund	Q×Stock + Q×Fund	No	Q	Q×Stock	Q×Stock + Fund	Q×Stock + Q×Fund
Adjusted R-squared	0.0278	0.0304	0.4656	0.4982	0.5169	0.0247	0.0254	0.3324	0.3619	0.3806
Observations	12,272	12,272	12,272	12,272	12,272	54,542	54,542	54,542	54,542	54,542

Table 5
Changes in funds' equity exposure

This table reports estimates from regressions relating a fund's buffer, $\text{Buffer}_{f,t}$, to changes in equity exposure. $\Delta\text{EE}_{f,t\to t+1}$ denotes the change in fund f's equity exposure between fiscal quarters t and $t+1$. Active-$\Delta\text{EE}_{f,t\to t+1}$ isolates the component of this change attributable to active portfolio rebalancing, after netting out passive changes driven by stock returns. The indicator $D^{B<0}_{f,t}$ equals one if $\text{Buffer}_{f,t} < 0$ and zero otherwise; $D^{0\leq B<5}_{f,t}$ is defined analogously. Control variables, measured at quarter t for each fund, include the log of the total net assets, the log of return standard deviation, net flow, and gross return. Standard errors are clustered by fiscal quarter and fund, and t-statistics are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels. Q denotes fiscal quarter.

	ΔEE (%)				Active-ΔEE (%)			
				Panel A: 2019-2024				
Buffer<0	-0.763***	-0.780***	-1.692***	-1.665***	-0.676***	-0.687***	-1.582***	-1.565***
	(-4.27)	(-4.47)	(-5.37)	(-5.21)	(-4.45)	(-4.63)	(-6.07)	(-5.96)
0≤Buffer<5	-0.296***	-0.297***	-0.667***	-0.652***	-0.225***	-0.234***	-0.613***	-0.602***
	(-3.95)	(-4.59)	(-6.67)	(-6.34)	(-3.27)	(-3.53)	(-6.09)	(-5.87)
Fixed Effects	No	Q	Q+Fund	Q+Fund	No	Q	Q+Fund	Q+Fund
Controls	No	No	No	Yes	No	No	No	Yes
Adjusted R-squared	0.0006	0.0159	-0.0195	-0.0185	0.0004	0.0151	-0.0042	-0.0037
Observations	75,754	75,754	75,754	75,754	75,754	75,754	75,754	75,754
				Panel B: 2023-2024				
Buffer<0	-0.483**	-0.488**	-1.556***	-1.497***	-0.346*	-0.348*	-1.218***	-1.240***
	(-2.54)	(-2.60)	(-3.68)	(-3.49)	(-1.97)	(-2.01)	(-3.95)	(-3.94)
0≤Buffer<5	-0.240**	-0.215**	-0.603***	-0.578***	-0.194**	-0.173**	-0.493***	-0.496***
	(-2.49)	(-2.57)	(-5.56)	(-5.02)	(-2.53)	(-2.29)	(-4.14)	(-4.00)
Fixed Effects	No	Q	Q+Fund	Q+Fund	No	Q	Q+Fund	Q+Fund
Controls	No	No	No	Yes	No	No	No	Yes
Adjusted R-squared	0.0004	0.0045	-0.0845	-0.0815	0.0003	0.0056	-0.0586	-0.0568
Observations	28,921	28,921	28,921	28,921	28,921	28,921	28,921	28,921

Table 6
Large-cap growth funds' performance drag

This table reports estimates from OLS regressions relating fund performance to buffer indicators:

$$\text{Ret(FF4)}_{f,t+h} = \delta_0 + \delta_1 D_{f,t}^{B<0} + \delta_2 D_{f,t}^{0\leq B<5} + \gamma_f + \varphi_{f,t+h}.$$

$\text{Ret(FF4)}_{f,t+h}$ is the cumulative Carhart four-factor risk-adjusted returns (%) for fund f over horizons $h = 1, 2, 3, 4, 5, 6, 9$, and 12 months following quarter t. $D_{f,t}^{B<0}$ equals one if $\text{Buffer}_{f,t} < 0$ and zero otherwise; $D_{f,t}^{0\leq B<5}$ is defined analogously. The regression sample consists of large-cap growth funds. Fund fixed effects γ_f absorb time-invariant differences across funds within this segment. We cluster standard errors at the fund level and report t-statistics in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Return horizon							
	1M	2M	3M	4M	5M	6M	9M	12M
				Panel A: 2019-2024				
Buffer<0	-0.408**	-0.457*	-0.558**	-0.908**	-1.169***	-0.683	-1.133*	-0.665
	(-2.22)	(-1.88)	(-2.06)	(-2.26)	(-2.70)	(-1.32)	(-1.67)	(-0.62)
0≤Buffer<5	-0.296***	-0.663***	-0.572***	-0.897***	-1.051***	-0.621***	-0.604*	-0.548
	(-3.46)	(-5.50)	(-4.23)	(-5.41)	(-5.80)	(-2.84)	(-1.88)	(-1.15)
Adjusted R-squared	0.0007	-0.0030	-0.0123	0.0125	0.0190	0.0272	0.0648	0.0927
Observations	5,866	5,861	5,862	5,858	5,845	5,828	5,786	5,469
				Panel B: 2023-2024				
Buffer<0	-0.990***	-1.559***	-2.111***	-2.953***	-3.383***	-3.234***	-5.078***	-6.957***
	(-5.69)	(-5.80)	(-9.15)	(-9.18)	(-8.57)	(-7.58)	(-11.82)	(-10.15)
0≤Buffer<5	-0.542***	-1.160***	-1.309***	-1.953***	-2.117***	-2.029***	-3.061***	-3.978***
	(-4.65)	(-6.83)	(-7.21)	(-8.77)	(-8.52)	(-7.27)	(-9.00)	(-8.13)
Adjusted R-squared	-0.0127	-0.0016	-0.0284	0.0150	0.0338	0.0570	0.1298	0.2266
Observations	2,229	2,226	2,228	2,227	2,221	2,216	2,198	1,901

Table 7
Components of funds' performance drag

This table presents the sources of underperformance for constrained and negative-buffer funds. The exposure-adjustment effect captures the performance effect of adjusting total equity exposure while keeping the within-equity portfolio weights unchanged. The large-position rebalancing effect isolates the effect of rebalancing large positions ($\text{Weight}_{f,s,t} > 5\%$) while keeping both the total equity exposure and non-large positions fixed. The mean is the annualized equal-weighted average of performance drags across funds. The impact, measured in billions of USD, represents the dollar value of the performance drag, scaled by funds' total assets. For 2019–2024, the number of fund–quarter observations with $0 \leq \text{Buffer}_{f,t} < 5\%$ is 1,572, whereas the number of observations with $\text{Buffer}_{f,t} < 0$ is 733. For 2023–2024, the number of fund–quarter observations with $0 \leq \text{Buffer}_{f,t} < 5\%$ is 875, and the number of observations with $\text{Buffer}_{f,t} < 0$ is 363. We report t-statistics in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels.

	$0 \leq$ Buffer $< 5\%$		Buffer < 0	
	Mean (%)	Impact ($B)	Mean (%)	Impact ($B)
	Panel A: 2019-2024			
Exposure adjustment	-0.013	-0.286	-0.174*	-0.205
	(-0.24)		(-1.74)	
Large-position rebalancing	-0.247***	-1.349	-0.265***	-0.182
	(-3.53)		(-3.22)	
	Panel B: 2023-2024			
Exposure adjustment	-0.082**	-0.411	-0.145	-0.282
	(-2.13)		(-1.17)	
Large-position rebalancing	-0.259***	-1.511	-0.123**	0.062
	(-3.31)		(-1.99)	

Table 8
Stock return predictability

This table presents the ability of constrained ownership share $C_{s,t}$ to predict stock returns adjusted for the Carhart four risk factors. The dependent variable is the risk-adjusted cumulative return over 1, 3, 6, 9, and 12 months following month t. Each month t, we sort stocks into 2 groups: *High C* stocks with $C_{s,t} > 0$, and *Low C* stocks with $C_{s,t} = 0$. $C_{s,t}$ represents the proportion of stock shares held by funds with a buffer less than 5% and a position weight greater than 5%. We define $High\ Vol_{s,t}$ as an indicator equal to 1 if $Volatility_{s,t}$ exceeds the cross-sectional median across all stocks, and 0 otherwise. The regression sample includes stocks with prices above $5 and, within each month, the largest 50% of stocks by market capitalization, resulting in 2,806 stocks. We include year–month fixed effects, cluster standard errors at the stock level, and report t-statistics in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Return horizon					Return horizon				
	1M	3M	6M	9M	12M	1M	3M	6M	9M	12M
					Panel A: 2019-2024					
High C	0.112	0.337	0.805*	1.546**	2.252**	0.091	0.359*	0.549	1.044*	1.319*
	(1.43)	(1.53)	(1.85)	(2.25)	(2.37)	(1.28)	(1.82)	(1.49)	(1.90)	(1.79)
High C × High Vol						0.030	-0.182	0.578	1.258	2.630
						(0.15)	(-0.34)	(0.54)	(0.75)	(1.14)
High Vol						-0.056	-0.181	-0.359	-0.511	-0.544
						(-0.93)	(-1.09)	(-1.11)	(-1.04)	(-0.82)
Adjusted R-squared	0.0097	0.0092	0.0078	0.0072	0.0064	0.0097	0.0092	0.0078	0.0072	0.0065
Observations	109,335	108,672	107,767	102,129	96,552	109,335	108,672	107,767	102,129	96,552
					Panel B: 2023-2024					
High C	0.309**	1.100***	2.301***	3.343***	4.391***	0.067	0.557*	0.835	1.591*	1.931
	(2.57)	(3.34)	(3.47)	(3.17)	(2.89)	(0.61)	(1.84)	(1.41)	(1.66)	(1.43)
High C × High Vol						0.661**	1.473**	3.847***	4.416**	6.280*
						(2.34)	(2.00)	(2.65)	(2.01)	(1.95)
High Vol						-0.103	-0.247	-0.898	-1.467	-2.125
						(-0.99)	(-0.84)	(-1.57)	(-1.58)	(-1.61)
Adjusted R-squared	0.0077	0.0070	0.0039	0.0041	0.0025	0.0078	0.0072	0.0046	0.0048	0.0033
Observations	39,846	39,627	39,350	34,301	29,294	39,846	39,627	39,350	34,301	29,294

Table 9
Investment strategy

This table reports annualized daily alphas (%) based on the Carhart four-factor model. The *Single-sort* column presents results from sorting stocks each month into two groups based on $C_{s,t}$: a High C group with $C > 0$, and a Low C group with $C = 0$. $C_{s,t}$ represents the proportion of stock shares held by funds with a buffer less than 5% and a position weight greater than 5%. We form two value-weighted portfolios and hold them for one year. *Double-sort with volatility* columns present results from independently sorting stocks each month into two volatility groups and the same two C groups, forming 2×2 value-weighted portfolios held for one year. The sample includes stocks priced above \$5 and, within each month, the largest 50% of stocks by market capitalization, resulting in 2,806 stocks. We report Newey–West t-statistics using a five-day lag in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Single-sort	Double-sort with volatility	
		High Vol	Low Vol
		Panel A: 2019-2024	
High C	1.68*	7.91*	-0.70
	(1.88)	(1.82)	(-0.46)
Low C	-2.00	-0.75	-2.47
	(-1.11)	(-0.25)	(-1.09)
		Panel B: 2023-2024	
High C	2.32**	11.85**	-1.32
	(2.34)	(2.00)	(-0.53)
Low C	-2.12	-2.11	-2.13
	(-0.94)	(-0.65)	(-0.70)

Table 10
Changes in funds' large positions (75/5/10 rule)

This table presents coefficients from OLS regressions of

$$\begin{aligned}\Delta\text{Weight}_{f,s,t+1} = {} & \beta_0 + \beta_1 D^{W>5}_{f,s,t} + \beta_2 D^{Div}_{f,t} + \beta_3 D^{20\le B<25}_{f,t} + \beta_4 D^{25\le B<30}_{f,t} + \beta_5 \left(D^{W>5}_{f,s,t} \times D^{Div}_{f,t}\right) \\ & + \beta_6 \left(D^{Div}_{f,t} \times D^{20\le B<25}_{f,t}\right) + \beta_7 \left(D^{Div}_{f,t} \times D^{25\le B<30}_{f,t}\right) \\ & + \beta_8 \left(D^{W>5}_{f,s,t} \times D^{20\le B<25}_{f,t}\right) + \beta_9 \left(D^{W>5}_{f,s,t} \times D^{Div}_{f,t} \times D^{20\le B<25}_{f,t}\right) \\ & + \beta_{10} \left(D^{W>5}_{f,s,t} \times D^{25\le B<30}_{f,t}\right) + \beta_{11} \left(D^{W>5}_{f,s,t} \times D^{Div}_{f,t} \times D^{25\le B<30}_{f,t}\right) + \varepsilon_{f,s,t+1}.\end{aligned}$$

The weight indicator, D^W, is based on $\text{Weight}_{f,s,t}$ (%). Buffer indicators, D^B, are based on $\text{Buffer}_{f,t}$ (%). $D^{Div}_{f,t}$ is the diversified fund indicator. The sample includes stocks with prices above $5 and, within each fiscal quarter, the largest 50% of stocks by market capitalization, resulting in 2,806 stocks. Standard errors are clustered at the stock level, and t-statistics are reported in parentheses. ***, **, and * denote 1%, 5%, and 10% significance. Q denotes fiscal quarter.

			Panel A: 2019-2024		
$5<W \times 20\le B<25 \times D^{Div}$	-0.044*	-0.043*	-0.037**	-0.042***	-0.026
	(-1.84)	(-1.84)	(-2.19)	(-2.68)	(-1.56)
$5<W \times 25\le B<30 \times D^{Div}$	-0.009	-0.010	-0.010	-0.023	-0.014
	(-0.36)	(-0.38)	(-0.63)	(-1.59)	(-0.88)
$5<W \times 20\le B<25$	0.046***	0.045***	0.038***	0.045***	0.034***
	(3.13)	(3.09)	(3.25)	(3.89)	(2.99)
$5<W \times 25\le B<30$	-0.004	-0.004	-0.001	0.015	0.005
	(-0.23)	(-0.28)	(-0.04)	(1.12)	(0.37)
$5<W$	-0.181***	-0.180***	-0.201***	-0.191***	-0.182***
	(-13.62)	(-13.49)	(-20.69)	(-21.02)	(-20.56)
Fixed Effects	No	Q	Q×Stock	Q×Stock + Fund	Q×Stock + Q×Fund
Adjusted R-squared	0.0033	0.0037	0.1278	0.1609	0.2053
Observations	11,505,963	11,505,963	11,505,963	11,505,963	11,505,963
			Panel B: 2023-2024		
$5<W \times 20\le B<25 \times D^{Div}$	-0.042	-0.042	-0.050*	-0.057**	-0.045
	(-1.02)	(-1.01)	(-1.69)	(-2.01)	(-1.47)
$5<W \times 25\le B<30 \times D^{Div}$	-0.062	-0.063	-0.042*	-0.054**	-0.039*
	(-1.62)	(-1.62)	(-1.82)	(-2.52)	(-1.73)
$5<W \times 20\le B<25$	0.043*	0.043	0.036*	0.045**	0.035*
	(1.65)	(1.63)	(1.90)	(2.37)	(1.82)
$5<W \times 25\le B<30$	0.003	0.002	0.001	0.019	0.006
	(0.13)	(0.08)	(0.05)	(0.92)	(0.30)
$5<W$	-0.155***	-0.154***	-0.188***	-0.178***	-0.170***
	(-6.78)	(-6.73)	(-12.60)	(-10.97)	(-10.32)
Fixed Effects	No	Q	Q×Stock	Q×Stock + Fund	Q×Stock + Q×Fund
Adjusted R-squared	0.0032	0.0035	0.1334	0.1736	0.2111
Observations	4,350,424	4,350,424	4,350,424	4,350,424	4,350,424

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Appendix

Contents

A.1. Theoretical model

This appendix provides a stylized model intended to clarify the economic mechanism behind our empirical finding of return predictability. In our simple asset pricing model, investors have heterogeneous beliefs and are subject to a portfolio concentration constraint inspired by the regulatory 50/5/10 rule. The model shows that this constraint, which effectively constrains investors' largest long positions, can depress asset prices by limiting the influence of optimistic investors' views. The basic idea is that when optimists face binding constraints on long positions, prices are set by pessimistic investors.

We proceed as follows. In Section A.1.1, we lay out a simple one-period model with heterogeneous beliefs and a portfolio concentration constraint. In Section A.1.2, we solve the model both with and without the constraint. In Section A.1.3, we present our main theoretical results. First, we show that a binding concentration constraint induces underpricing of an asset about which there is disagreement and whose holdings are constrained. Second, we show that the underpricing is larger when the constraint is tighter, when the constrained asset is in greater supply, when that asset has more volatile payoffs, and when disagreement between optimists and pessimists is larger.

A.1.1. Assumptions

There are two dates. At date $t = 0$, investors trade assets; at date $t = 1$, payoffs are realized.

There are N risky assets indexed by $j = 1, \ldots, N$. Asset j has price p_j at date 0 and random payoff X_j at date 1. We assume that the payoffs have known variances $\sigma_j^2 \equiv \text{Var}(X_j)$ and are mutually uncorrelated, $\text{Cov}(X_j, X_k) = 0$ for $j \neq k$. There is also a risk-free asset 0 with elastic supply whose price is normalized to 1 and payoff equal to 1.

There are two types of investors indexed by $t \in \{O, P\}$. Type O ("optimists") has wealth share $\alpha \in (0, 1)$; type P ("pessimists") has wealth share $1 - \alpha$. Optimists and pessimists differ in their beliefs about some of the risky assets' expected payoffs, $\mu_j^t \equiv E_t[X_j]$. We assume there is a single risky asset $j^\star$ over which the optimists are more optimistic:

$$\mu_{j^\star}^O > \mu_{j^\star}^P \,, \tag{A.1}$$

whereas $\mu_j^O = \mu_j^P$ for all other assets $j \neq j^\star$. Thus, the disagreement among investors is concentrated in a single asset $j^\star$. We assume this asset is sufficiently attractive to optimists that they would hold a large position in it if unconstrained and also that optimists' holdings of this asset are constrained (we provide specifics later).

Each investor of type t chooses portfolio weights $w^t = \{w_0^t, w_1^t, \ldots, w_N^t\}$ that add up to one: $w_0^t + \sum_{j=1}^N w_j^t = 1$. We require all weights to be nonnegative, consistent with common practice in the mutual fund industry. To preserve closed-form expressions, we focus on parameter values such that the nonnegativity constraints do not bind in the unconstrained solution (so the interior first-order conditions characterize the optimum).

Investors are subject to a portfolio concentration limit inspired by the 50/5/10 rule. Let $\mathcal{Q}(w^t)$ denote the set of all risky assets in which an investor of type t holds a "large" position, defined as a position whose portfolio weight exceeds 5%:[14]

$$\mathcal{Q}(w^t) \;\equiv\; \left\{ j \in \{1, \ldots, N\} \;:\; w_j^t > 0.05 \right\}. \tag{A.2}$$

The 50/5/10 rule imposes the constraint that at least 50% of assets be invested in non-large positions or the risk-free asset. Under our assumptions, this is equivalent to assuming that the sum of large positions must not exceed 50% of the investor's total assets:

$$\sum_{j \in \mathcal{Q}(w^t)} w_j^t \leq 0.50\,. \tag{A.3}$$

For tractability, we implement a simplified version of this constraint, which caps the optimists' holdings of asset $j^\star$, as we explain in detail later.

Investors have mean-variance preferences over risky assets. Risk aversion $\gamma > 0$ is equal across investors. Type-t investors maximize the objective function

$$\max_{w^t} \; \sum_{j=1}^{N} w_j^t(\mu_j^t - p_j) - \frac{\gamma}{2} \sum_{j=1}^{N} \sigma_j^2 (w_j^t)^2\,, \tag{A.4}$$

subject to the portfolio concentration constraint. The objective function (A.4) does not depend on w_0^t because the risk-free asset's price and payoff are normalized to one.

A.1.2. Solving the model

Unconstrained solution

First, we solve for the optimal risky-asset weights in the absence of constraint (A.3), taking prices $p = (p_1, \ldots, p_N)$ as given. Since the objective function in equation (A.4) is strictly concave in w^t, a unique maximizer exists. The first-order condition for asset j is

$$0 = \frac{\partial}{\partial w_j^t} \left[\sum_{k=1}^{N} w_k^t(\mu_k^t - p_k) - \frac{\gamma}{2} \sum_{k=1}^{N} \sigma_k^2 (w_k^t)^2 \right] = \mu_j^t - p_j - \gamma \sigma_j^2 w_j^t\,.$$

Solving yields the optimal unconstrained weight in risky asset j for an investor of type t:

$$w_j^{t,U}(p) = \frac{\mu_j^t - p_j}{\gamma \sigma_j^2}\,, \qquad j = 1, \ldots, N\,. \tag{A.5}$$

[14] According to the regulatory rule, large positions include also those in which an investor holds more than 10% of the issuer's voting securities. In practice, it is rare for an investor to hold such a large fraction of a single issuer. To simplify the algebra, we do not impose the 10% voting-stock test in our model.

The value of w_0^t is pinned down residually, ensuring that the portfolio weights sum to one.

Next, we solve for the unconstrained equilibrium price vector $p^U = \{p_1^U, \ldots, p_N^U\}$. Let $m_j \geq 0$ denote the market portfolio weight of risky asset j. Market clearing requires

$$\alpha\, w_j^{O,U}(p) + (1-\alpha)\, w_j^{P,U}(p) = m_j\,. \tag{A.6}$$

Substituting from (A.5) into (A.6) yields

$$\alpha\, \frac{\mu_j^O - p_j}{\gamma\sigma_j^2} \;+\; (1-\alpha)\, \frac{\mu_j^P - p_j}{\gamma\sigma_j^2} \;=\; m_j. \tag{A.7}$$

Solving for p_j, the unique unconstrained equilibrium price of any risky asset j is

$$p_j^U = \alpha\mu_j^O + (1-\alpha)\mu_j^P - \gamma\sigma_j^2 m_j\,. \tag{A.8}$$

Constrained solution

We now solve for constrained optimal risky-asset weights. In general, a solution subject to the portfolio concentration constraint (A.3) is available only numerically. To provide more clarity in the form of an analytical solution, we impose a simplified version of the constraint—a cap on the optimists' exposure to the disputed asset $j^\star$:

$$w_{j^\star}^O \leq \bar{w}\,, \tag{A.9}$$

where $\bar{w}$ is exogenously given. No other asset $j \neq j^\star$ is directly capped. This reduced-form cap captures the effective implication of the original portfolio concentration constraint for the marginal asset where optimism is concentrated. The original constraint induces a Lagrange multiplier on the set of large positions; equation (9) captures the implied marginal cap on the asset with the highest unconstrained demand.

While the original constraint (A.3) imposes a cap (of 50%) on the sum of all large positions, our simplified version (A.9) puts a cap on a single large position. The two constraints trivially coincide when there is a single large position, but they differ in general, because investors can adjust any of their large positions, not only $j^\star$, to meet constraint (A.3). This difference notwithstanding, the economic mechanism behind the effect of the constraint on asset prices is the same in both cases. By imposing a cap on a single large position on which optimists and pessimists disagree, we are able to convey the underlying mechanism analytically.

We assume that the cap in equation (A.9) is sufficiently low so that at the unconstrained equilibrium price, the optimists' unconstrained desired holding would exceed the cap:

$$w_{j^\star}^{O,U}(p_{j^\star}^U) = \frac{\mu_{j^\star}^O - p_{j^\star}^U}{\gamma\sigma_{j^\star}^2} > \bar{w}\,. \tag{A.10}$$

This ensures the cap is binding in the constrained equilibrium (otherwise the constrained and unconstrained equilibria coincide).

We now solve for constrained equilibrium prices $p^C = \{p_1^C, \ldots, p_N^C\}$ under constraint (A.9).

For any risky asset $j \neq j^\star$, both types' demands coincide with unconstrained demands:

$$w_j^{t,C}(p) = \frac{\mu_j^t - p_j}{\gamma \sigma_j^2}\,, \qquad t \in \{O, P\}, \quad j \neq j^\star. \tag{A.11}$$

Imposing market clearing, we arrive at the same unique solution for the constrained equilibrium price as in the unconstrained case. Therefore, $p_j^C = p_j^U$ for any $j \neq j^\star$.

For risky asset $j^\star$, pessimists remain unconstrained,

$$w_{j^\star}^{P,C}(p) = \frac{\mu_{j^\star}^P - p_{j^\star}}{\gamma \sigma_{j^\star}^2}, \tag{A.12}$$

but optimists' demand is truncated by the cap in equation (A.9), which we assume is binding (otherwise the constrained and unconstrained solutions coincide). At constrained prices p,

$$w_{j^\star}^{O,C}(p) = \bar{w}\,. \tag{A.13}$$

Imposing market clearing and substituting from equations (A.12) and (A.13), we obtain

$$\begin{aligned} \alpha\, w_{j^\star}^{O,C}(p) + (1-\alpha)\, w_{j^\star}^{P,C}(p) &= m_{j^\star} \\ \alpha\, \bar{w} + (1-\alpha)\, \frac{\mu_{j^\star}^P - p_{j^\star}}{\gamma \sigma_{j^\star}^2} &= m_{j^\star}\,. \end{aligned} \tag{A.14}$$

Solving for $p_{j^\star}$ yields the constrained equilibrium price:

$$p_{j^\star}^C = \mu_{j^\star}^P - \frac{\gamma \sigma_{j^\star}^2}{1-\alpha} \big(m_{j^\star} - \alpha \bar{w}\big). \tag{A.15}$$

This equation shows that, once the cap binds, the price of asset $j^\star$ is pinned down by pessimists' marginal willingness to absorb the asset's residual supply $m_{j^\star} - \alpha\bar{w}$. We now compare $p^C_{j^\star}$ in equation (A.15) with $p^U_{j^\star}$ in equation (A.8):

$$\begin{aligned}
p^U_{j^\star} - p^C_{j^\star} &= \left[\alpha\mu^O_{j^\star} + (1-\alpha)\mu^P_{j^\star} - \gamma\sigma^2_{j^\star} m_{j^\star}\right] - \left[\mu^P_{j^\star} - \frac{\gamma\sigma^2_{j^\star}}{1-\alpha}\left(m_{j^\star} - \alpha\bar{w}\right)\right] \\
&= \alpha\mu^O_{j^\star} + (1-\alpha)\mu^P_{j^\star} - \mu^P_{j^\star} - \gamma\sigma^2_{j^\star} m_{j^\star} + \frac{\gamma\sigma^2_{j^\star}}{1-\alpha}\left(m_{j^\star} - \alpha\bar{w}\right) \\
&= \alpha\left(\mu^O_{j^\star} - \mu^P_{j^\star}\right) + \gamma\sigma^2_{j^\star}\left[\frac{m_{j^\star} - \alpha\bar{w}}{1-\alpha} - m_{j^\star}\right] \\
&= \alpha\left(\mu^O_{j^\star} - \mu^P_{j^\star}\right) + \gamma\sigma^2_{j^\star}\left[\frac{m_{j^\star} - \alpha\bar{w} - (1-\alpha)m_{j^\star}}{1-\alpha}\right] \\
&= \alpha\left(\mu^O_{j^\star} - \mu^P_{j^\star}\right) + \frac{\alpha\gamma\sigma^2_{j^\star}}{1-\alpha}\left(m_{j^\star} - \bar{w}\right) \\
&= \alpha\left[\left(\mu^O_{j^\star} - \mu^P_{j^\star}\right) + \frac{\gamma\sigma^2_{j^\star}}{1-\alpha}\left(m_{j^\star} - \bar{w}\right)\right]. \qquad \text{(A.16)}
\end{aligned}$$

To sign the expression in equation (A.16), recall from equation (A.10) that at the unconstrained equilibrium price, the optimists' unconstrained desired holding exceeds the cap:

$$w^{O,U}_{j^\star}(p^U_{j^\star}) = \frac{\mu^O_{j^\star} - p^U_{j^\star}}{\gamma\sigma^2_{j^\star}} > \bar{w}. \qquad \text{(A.17)}$$

Substituting for $p^U_{j^\star}$ from equation (A.8) into equation (A.17), we have

$$\begin{aligned}
w^{O,U}_{j^\star}(p^U_{j^\star}) &= \frac{\mu^O_{j^\star} - \left(\alpha\mu^O_{j^\star} + (1-\alpha)\mu^P_{j^\star} - \gamma\sigma^2_{j^\star} m_{j^\star}\right)}{\gamma\sigma^2_{j^\star}} \\
&= \frac{(1-\alpha)(\mu^O_{j^\star} - \mu^P_{j^\star}) + \gamma\sigma^2_{j^\star} m_{j^\star}}{\gamma\sigma^2_{j^\star}} \\
&= m_{j^\star} + \frac{1-\alpha}{\gamma\sigma^2_{j^\star}}\left(\mu^O_{j^\star} - \mu^P_{j^\star}\right). \qquad \text{(A.18)}
\end{aligned}$$

Combining equations (A.17) and (A.18), we see that

$$\mu^O_{j^\star} - \mu^P_{j^\star} > \frac{\gamma\sigma^2_{j^\star}}{1-\alpha}\left(\bar{w} - m_{j^\star}\right). \qquad \text{(A.19)}$$

Using equation (A.19), we see immediately that the expression in equation (A.16) is positive:

$$p^U_{j^\star} - p^C_{j^\star} > 0\,. \qquad \text{(A.20)}$$

A.1.3. Main results

In equation (A.20), we proved the following proposition.

Proposition 1. *Assume that the long-position constraint $w^O_{j^\star} \leq \bar{w}$ binds. Then:*

1. *Asset $j^\star$ is priced lower in the constrained equilibrium:*
$$p^C_{j^\star} < p^U_{j^\star}.$$
2. *The prices of all other assets are unaffected by the constraint:*
$$p^C_j = p^U_j \qquad \text{for all } j \neq j^\star.$$

The intuition behind Proposition 1 is as follows. In the unconstrained economy, the price of asset $j^\star$ reflects the combined demand of optimists and pessimists. Because optimists expect a higher payoff, they hold a disproportionately large share of the asset in equilibrium. When the concentration cap binds, optimists are prevented from holding as much of $j^\star$ as they would like at the unconstrained price. At that price, aggregate demand therefore falls short of supply. The only way to restore market clearing is for the price of $j^\star$ to decline until pessimists are willing to absorb the residual supply. Assets about which beliefs coincide are unaffected, because the constraint does not distort demand for those assets.

Next, we analyze the constrained-induced underpricing wedge, which we denote as

$$\Delta p \equiv p^U_{j^\star} - p^C_{j^\star}\,. \tag{A.21}$$

While Proposition 1 shows that $\Delta p > 0$, Proposition 2 examines the determinants of Δp, under the same assumptions. While computing the comparative statics, we restrict attention to the regime in which the concentration constraint binds and market clearing requires pessimists to absorb a strictly positive share of the constrained asset, i.e., $m_{j^\star} - \alpha\bar{w} > 0$. This ensures that the identity of the marginal investor and the form of the pricing equation remain unchanged under the comparative statics considered.

Proposition 2. *Assume that the long-position constraint $w^O_{j^\star} \leq \bar{w}$ binds in equilibrium. Then the price wedge Δp satisfies the following comparative statics:*

1. $\dfrac{\partial \Delta p}{\partial \bar{w}} < 0$ *(i.e., Δp is larger when the portfolio constraint is tighter)*
2. $\dfrac{\partial \Delta p}{\partial m_{j^\star}} > 0$ *(i.e., Δp is larger when the asset is in larger supply)*
3. $\dfrac{\partial \Delta p}{\partial (\mu^O_{j^\star} - \mu^P_{j^\star})} > 0$ *(i.e., Δp is larger when there is more disagreement)*

If, additionally, $\bar{w} < m_{j^\star}$, then Δp satisfies also the following comparative static:

4. $\dfrac{\partial \Delta p}{\partial \sigma^2_{j^\star}} > 0$ *(i.e., Δp is larger when the asset has more volatile payoffs)*

The proof of Proposition 2 is straightforward. Recall from equation (A.16) that

$$\Delta p \;=\; \alpha \left[\left(\mu^O_{j^\star} - \mu^P_{j^\star} \right) + \frac{\gamma \sigma^2_{j^\star}}{1-\alpha} \left(m_{j^\star} - \bar{w} \right) \right] . \tag{A.22}$$

To derive the four comparative statics, we simply differentiate equation (A.22):

$$\frac{\partial \Delta p}{\partial \bar{w}} \;=\; -\frac{\alpha \gamma \sigma^2_{j^\star}}{1-\alpha} < 0 \tag{A.23}$$

$$\frac{\partial \Delta p}{\partial m_{j^\star}} \;=\; \frac{\alpha \gamma \sigma^2_{j^\star}}{1-\alpha} > 0 \tag{A.24}$$

$$\frac{\partial \Delta p}{\partial (\mu^O_{j^\star} - \mu^P_{j^\star})} \;=\; \alpha > 0 \tag{A.25}$$

$$\frac{\partial \Delta p}{\partial \sigma^2_{j^\star}} \;=\; \frac{\alpha \gamma}{1-\alpha} \left(m_{j^\star} - \bar{w} \right) \;>\; 0 \, . \tag{A.26}$$

The intuition behind Proposition 2 is as follows. The wedge Δp measures how much the binding long-position cap prevents optimists from bidding up the price of the disputed asset $j^\star$. (1) A tighter cap (lower $\bar{w}$) reduces optimists' ability to absorb supply at high prices, so the price must fall until pessimists are willing to hold the residual supply. (2) A larger supply $m_{j^\star}$ amplifies this effect: more shares must be placed with pessimists when optimists are capped, requiring a larger price concession. (3) Greater disagreement $\mu^O_{j^\star} - \mu^P_{j^\star}$ raises the value optimists place on the asset relative to pessimists, so restricting optimists has a larger effect on the equilibrium price. (4) Higher payoff risk $\sigma^2_{j^\star}$ reduces the willingness of the unconstrained pessimists to absorb the additional supply released by the constrained optimists, requiring a larger price discount. This fourth result holds only if the cap lies below the asset's market weight, $\bar{w} < m_{j^\star}$, so that the binding constraint forces pessimists to absorb a strictly positive additional position in the asset relative to the unconstrained benchmark. In this case, higher payoff risk increases the compensation pessimists require to hold this residual supply, which magnifies the price concession needed to clear the market. By contrast, if the cap exceeds the asset's market weight, the constraint does not shift risk-bearing at the margin, and greater payoff variance does not amplify underpricing.

A.2. Additional figures

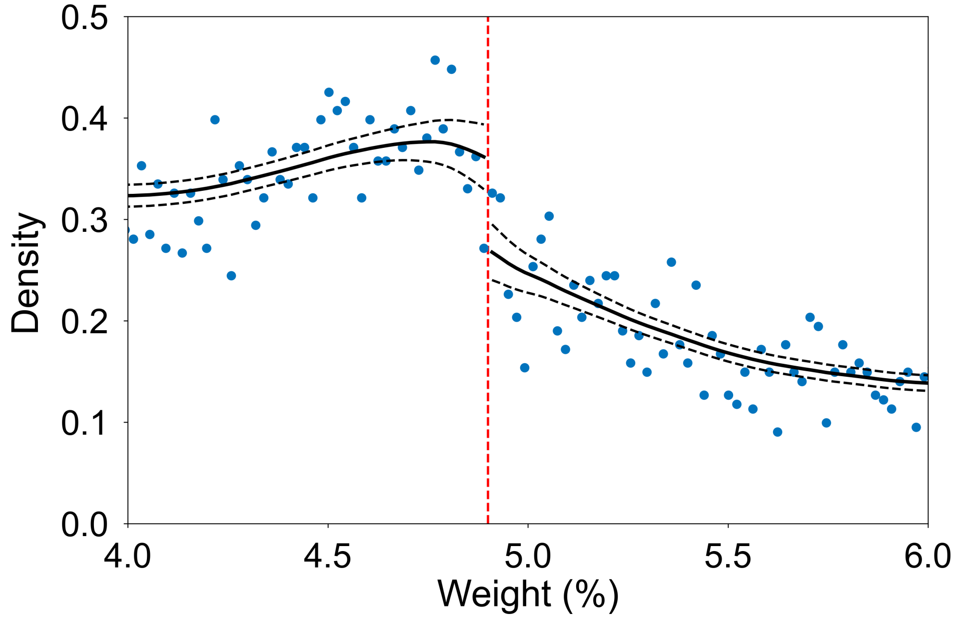
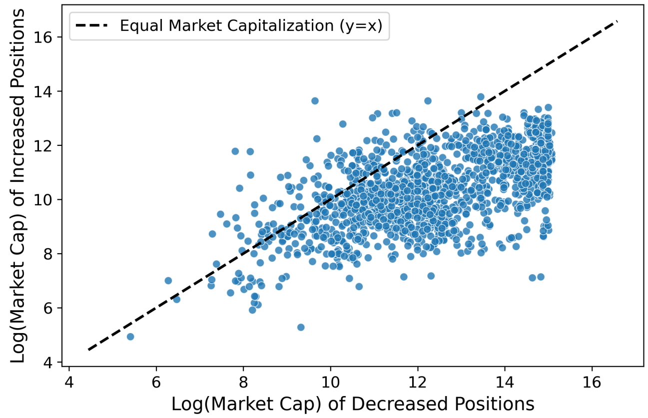
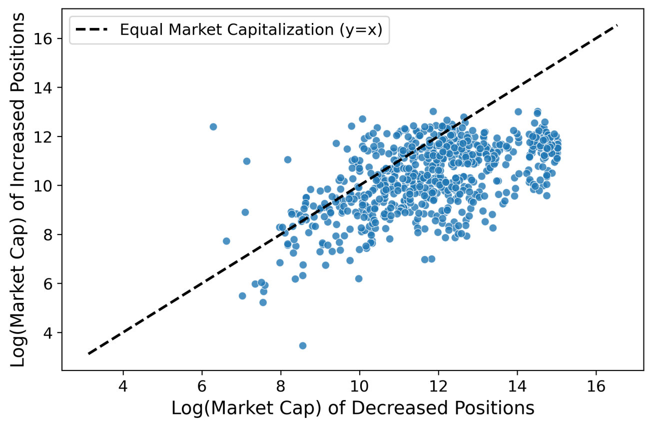


Figure A.1. Bunching in constrained funds' portfolio weights. This figure plots McCrary (2008) density estimates for 2019–2024 fund-stock-quarter observations. Circles denote histogram bins, solid lines show smooth densities, and dashed lines represent 95% confidence intervals. The sample corresponds to constrained funds with a buffer between 0 and 5%. The vertical red line indicates the 4.9% threshold.

Panel A: Constrained funds, weight changes, cap-weighted



Panel B: Negative-buffer funds, weight changes



Panel C: Constrained funds, share changes

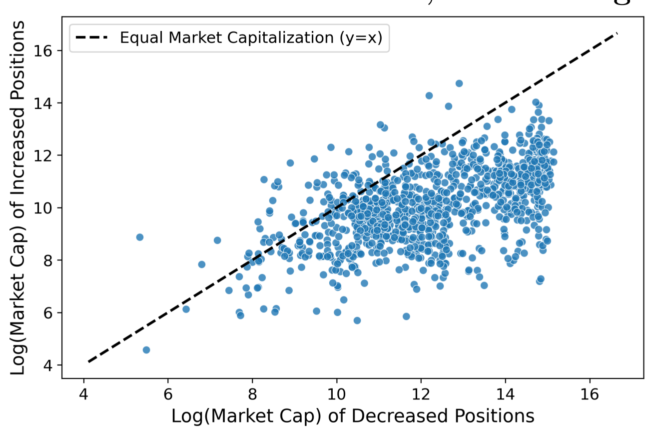


Figure A.2. Funds' rebalancing to smaller-cap stocks. This figure plots the average market capitalization (log) of large positions ($\text{Weight}_{f,s,t} > 5\%$) whose weights or shares decrease (x-axis) versus those that increase (y-axis). Each point represents a fund-quarter observation. Panel A plots the market-cap-weighted average for constrained funds with $\text{Buffer}_{f,t} \in [0, 5\%)$ based on weight changes. Panels B and C report simple averages. Panel B replicates the analysis for funds with negative buffers, while Panel C uses changes in the number of shares held for constrained funds.

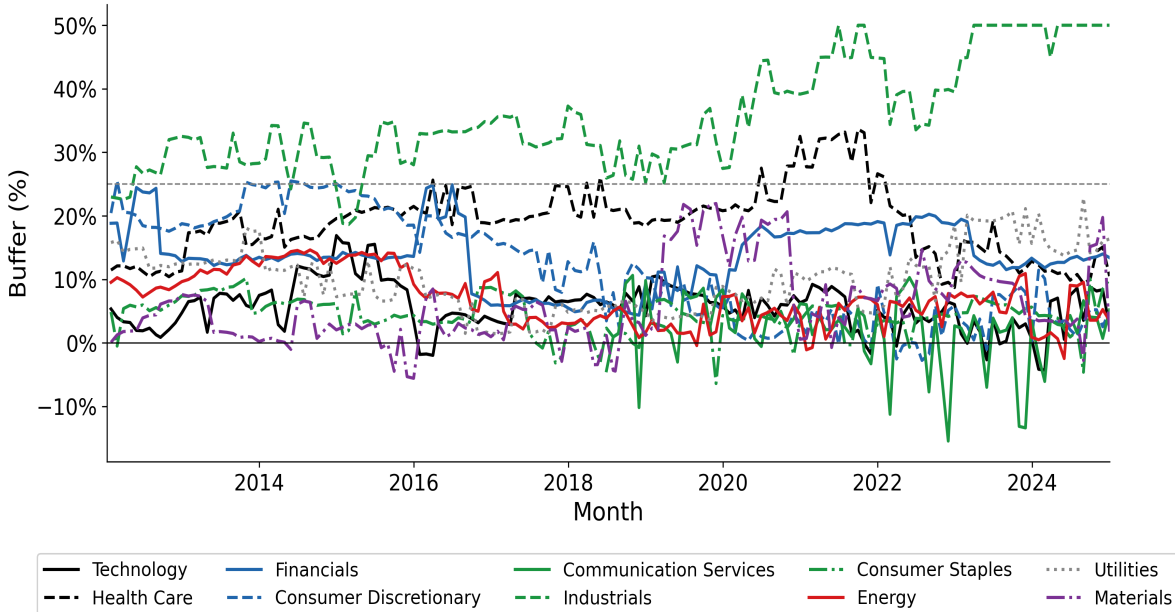


Figure A.3. Buffers for sector indexes. This figure reports monthly buffers of U.S. equity sector indexes, which are computed based on corresponding ETF constituent holding weights from ETF Global. The figure shows sector indexes using the holdings of the Select Sector SPDR ETFs: technology (XLK), health care (XLV), financials (XLF), consumer discretionary (XLY), communication services (XLC), industrials (XLI), consumer staples (XLP), energy (XLE), utilities (XLU), and materials (XLB). The buffer is defined as 50% minus the sum of portfolio weights in large positions (with weight above 5%). Horizontal lines at 0% and 25% mark the 50/5/10 and 75/5/10 rules thresholds, respectively.

A.3. Instrumental variable estimates

In this appendix, we implement an instrumental-variables alternative to the baseline design in Section 4. Because funds may window-dress around quarter-ends, reported buffers may reflect not only underlying constraint tightness but also endogenous trading intended to improve reported positions. To address this concern, we construct a no-trade buffer, $\text{Buffer}^{\text{NT}}_{f,t}$, which measures where a fund's distance to the regulatory limit would have been at the end of quarter t absent within-quarter rebalancing.

We first calculate the no-trade weight of stock s in fund f at time t as

$$\text{Weight}^{\text{NT}}_{f,s,t} = \text{Weight}_{f,s,t-1} \times \frac{1 + hpr_s^{t-1\to t}}{1 + R^{\text{fund}}_{f,t-1\to t}}\,, \tag{A.27}$$

where $R^{\text{fund}}_{f,t-1\to t}$ is the gross fund return from $t-1$ to t and $hpr_s^{t-1\to t}$ is the cumulative return of stock s over the same period, computed from monthly returns.

Using these no-trade weights, we define the no-trade buffer as

$$\text{Buffer}^{\text{NT}}_{f,t} = 50\% \;-\; \sum_{s\in \text{LargePos}^{\text{NT}}_{f,t}} \text{Weight}^{\text{NT}}_{f,s,t}\,, \tag{A.28}$$

where $\text{LargePos}^{\text{NT}}_{f,t}$ denotes the set of the fund's no-trade large positions. A position is included in this set if its no-trade weight exceeds 5% or if its held shares at $t-1$ represent more than 10% of the issuer's voting securities (assuming both shares held and total voting shares remain constant between $t-1$ and t).

We estimate equation (4) by two-stage least squares (2SLS), treating the observed large-position indicator, the buffer indicators, and their interactions as endogenous. As excluded instruments, we use the corresponding no-trade indicators and their interactions:

$$D^{NT,W\geq 5}_{f,s,t},\; D^{NT,B<0}_{f,t},\; D^{NT,0\leq B<5}_{f,t},\; D^{NT,W\geq 5}_{f,s,t}\times D^{NT,B<0}_{f,t},\; D^{NT,W\geq 5}_{f,s,t}\times D^{NT,0\leq B<5}_{f,t}.$$

The first stage projects the endogenous indicators and interaction terms onto this instrument set together with the fixed effects. The second stage estimates equation (4) using the fitted values from the first stage. Table A.1 reports the resulting 2SLS estimates. Because the specification includes multiple instruments, we assess instrument strength using the Kleibergen–Paap rk Wald F-statistic for the equation as a whole. This statistic is above 60 in all specifications, indicating that the no-trade instruments are not weak.

Analogously, we estimate the 2SLS version of equation (9), treating $D^{B<0}_{f,t}$ and $D^{0\leq B<5}_{f,t}$ as endogenous and instrumenting them with their no-trade counterparts, $D^{NT,B<0}_{f,t}$ and $D^{NT,0\leq B<5}_{f,t}$. As in the baseline, control variables include log total net assets, log return volatility, net flow, and gross return. Table A.2 reports the resulting 2SLS estimates.

Table A.1
Changes in funds' large positions (IV Version)

This table reports two-stage least squares (2SLS) estimates of the equation (4). The buffer indicators, large-position indicators, and their interactions are instrumented by their corresponding no-trade counterparts. The regression sample includes stocks with prices above $5 and, within each fiscal quarter, the largest 50% of stocks by market capitalization, resulting in 2,806 stocks. Standard errors are clustered at the stock level, and t-statistics are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. Q denotes fiscal quarter.

	Panel A: 2019-2024				
$5< \widehat{\text{W}} \times \widehat{\text{Buffer}} <0$	-0.055	-0.056	-0.018	-0.080*	-0.079
	(-1.07)	(-1.09)	(-0.39)	(-1.74)	(-1.63)
$5< \widehat{\text{W}} \times 0 \leq \widehat{\text{Buffer}} <5$	-0.129*	-0.130*	-0.079*	-0.082**	-0.074**
	(-1.87)	(-1.88)	(-1.93)	(-2.35)	(-2.04)
$5< \widehat{\text{W}}$	-0.135***	-0.135***	-0.184***	-0.152***	-0.148***
	(-3.99)	(-3.98)	(-7.68)	(-8.11)	(-7.81)
Fixed Effects	No	Q	Q×Stock	Q×Stock + Fund	Q×Stock + Q×Fund
Kleibergen–Paap rk Wald F-statistics	67.23	67.29	68.51	117.71	176.97
Observations	10,107,248	10,107,248	10,107,248	10,107,248	10,107,248
	Panel B: 2023-2024				
$5< \widehat{\text{W}} \times \widehat{\text{Buffer}} <0$	-0.059	-0.061	-0.012	-0.074	-0.075
	(-1.29)	(-1.31)	(-0.27)	(-1.56)	(-1.50)
$5< \widehat{\text{W}} \times 0 \leq \widehat{\text{Buffer}} < 5$	-0.142**	-0.143**	-0.127***	-0.135***	-0.126***
	(-2.09)	(-2.09)	(-3.05)	(-3.55)	(-3.38)
$5< \widehat{\text{W}}$	-0.107***	-0.107***	-0.157***	-0.122***	-0.119***
	(-4.57)	(-4.54)	(-8.46)	(-7.66)	(-7.48)
Fixed Effects	No	Q	Q×Stock	Q×Stock + Fund	Q×Stock + Q×Fund
Kleibergen–Paap rk Wald F-statistics	60.01	60.04	60.83	111.58	79.43
Observations	4,029,587	4,029,587	4,029,587	4,029,587	4,029,587

Table A.2
Changes in funds' equity exposure (IV Version)

This table reports two-stage least squares (2SLS) estimates relating a fund's buffer to changes in equity exposure. $\Delta \text{EE}_{f,t\to t+1}$ denotes the change in fund f's equity exposure between fiscal quarters t and $t+1$. Active-$\Delta \text{EE}_{f,t\to t+1}$ isolates the component of this change attributable to active portfolio rebalancing, after netting out passive changes driven by stock returns. The buffer indicators are instrumented by their corresponding no-trade counterparts. Control variables, measured at quarter t for each fund, include the log of total net assets, the log of return standard deviation, net flow, and gross return. Standard errors are clustered by fiscal quarter and fund, and t-statistics are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels. Q denotes fiscal quarter.

	ΔEE (%)				Active-ΔEE (%)			
				Panel A: 2019-2024				
$\widehat{\text{Buffer}}$ <0	-0.642**	-0.664**	-2.202**	-2.296***	-0.356	-0.407	-1.640**	-1.706**
	(-2.02)	(-2.09)	(-2.64)	(-2.69)	(-1.34)	(-1.51)	(-2.37)	(-2.39)
0≤ $\widehat{\text{Buffer}}$ <5	-0.008	-0.007	-0.261	-0.304	-0.176	-0.174	-0.659**	-0.687**
	(-0.04)	(-0.03)	(-0.69)	(-0.80)	(-1.05)	(-0.97)	(-2.07)	(-2.08)
Fixed Effects	No	Q	Q+Fund	Q+Fund	No	Q	Q+Fund	Q+Fund
Controls	No	No	No	Yes	No	No	No	Yes
Kleibergen–Paap rk Wald F-statistics	65.96	66.49	36.40	36.46	65.96	66.49	36.40	36.46
Observations	71,609	71,609	71,609	71,609	71,609	71,609	71,609	71,609
				Panel B: 2023-2024				
$\widehat{\text{Buffer}}$ <0	-0.046	0.008	-1.045	-1.302	0.168	0.203	-0.251	-0.124
	(-0.12)	(0.02)	(-1.29)	(-1.49)	(0.49)	(0.61)	(-0.36)	(-0.18)
0≤ $\widehat{\text{Buffer}}$ <5	-0.257	-0.229	-0.884	-0.915	-0.335	-0.308	-0.771	-0.733
	(-0.90)	(-0.76)	(-1.40)	(-1.46)	(-1.56)	(-1.35)	(-1.61)	(-1.54)
Fixed Effects	No	Q	Q+Fund	Q+Fund	No	Q	Q+Fund	Q+Fund
Controls	No	No	No	Yes	No	No	No	Yes
Kleibergen–Paap rk Wald F-statistics	50.81	51.16	28.18	28.35	50.81	51.16	28.18	28.35
Observations	28,742	28,742	28,742	28,742	28,742	28,742	28,742	28,742

A.4. Additional results on fund rebalancing

A.4.1. Additional results for $\Delta Weight$

Table A.3
Changes in funds' positions

This table presents coefficients from OLS regressions of

$$\begin{aligned}\Delta \text{Weight}_{f,s,t+1} = & \beta_0 + \beta_1 D^{4<W\leq 5}_{f,s,t} + \beta_2 D^{5<W\leq 6}_{f,s,t} + \beta_3 D^{W>6}_{f,s,t} \\ & + \beta_4 D^{B<0}_{f,t} + \beta_5 D^{0\leq B<5}_{f,t} \\ & + \sum \beta_{i,j} (D^{W_i}_{f,s,t} \times D^{B_j}_{f,t}) + \epsilon_{f,s,t+1}.\end{aligned}$$

Weight indicators, D^W, are based on $\text{Weight}_{f,s,t}$. Buffer indicators, D^B, are based on $\text{Buffer}_{f,t}$. The base categories absorbed by the constant are $\text{Weight}_{f,s,t} \leq 4\%$ and $\text{Buffer}_{f,t} \geq 5\%$. The regression sample includes stocks with prices above \$5 and, within each fiscal quarter, the largest 50% of stocks by market capitalization, resulting in 2,806 stocks. Standard errors are clustered at the stock level, and t-statistics are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. Q denotes fiscal quarter.

	Panel A: 2019-2024				
6<W × B<0	-0.110***	-0.111***	-0.079***	-0.110***	-0.097***
	(-2.72)	(-2.73)	(-2.93)	(-4.11)	(-3.23)
6<W × 0≤B<5	-0.088**	-0.089**	-0.059***	-0.063***	-0.057**
	(-2.15)	(-2.17)	(-2.68)	(-2.93)	(-2.44)
5<W≤6 × B<0	-0.026	-0.027	0.019	-0.013	0.004
	(-0.64)	(-0.67)	(0.74)	(-0.55)	(0.15)
5<W≤6 × 0≤B<5	-0.055	-0.057	-0.016	-0.016	-0.002
	(-1.49)	(-1.52)	(-0.64)	(-0.74)	(-0.10)
4<W≤5 × B<0	0.085***	0.084***	0.106***	0.061***	0.077***
	(3.08)	(3.02)	(5.40)	(3.30)	(3.67)
4<W≤5 × 0≤B<5	0.022	0.021	0.039**	0.016	0.024
	(0.83)	(0.76)	(2.54)	(1.10)	(1.49)
6<W	-0.133***	-0.133***	-0.188***	-0.181***	-0.174***
	(-5.23)	(-5.21)	(-12.12)	(-11.38)	(-10.62)
5<W≤6	-0.111***	-0.111***	-0.174***	-0.157***	-0.150***
	(-2.98)	(-2.98)	(-8.51)	(-8.57)	(-8.12)
4<W≤5	-0.124***	-0.124***	-0.151***	-0.122***	-0.113***
	(-5.95)	(-5.93)	(-14.54)	(-12.58)	(-11.76)
FE	No	Q	Q×Stock	Q×Stock + Fund	Q×Stock + Q×Fund
Adjusted R-squared	0.0049	0.0053	0.1302	0.1627	0.2067
Observations	11,513,919	11,513,919	11,513,919	11,513,919	11,513,919

Table continues on next page

	Panel B: 2023-2024				
6<W × B<0	-0.083*	-0.084*	-0.063**	-0.100***	-0.091***
	(-1.80)	(-1.82)	(-1.97)	(-3.17)	(-2.73)
6<W × 0≤B<5	-0.075	-0.076	-0.063**	-0.064**	-0.063**
	(-1.52)	(-1.54)	(-2.12)	(-2.24)	(-2.11)
5<W≤6 × B<0	-0.061	-0.062	-0.015	-0.076***	-0.048*
	(-1.45)	(-1.47)	(-0.56)	(-2.94)	(-1.72)
5<W≤6 × 0≤B<5	-0.035	-0.036	-0.023	-0.024	-0.006
	(-0.89)	(-0.92)	(-0.77)	(-0.78)	(-0.19)
4<W≤5 × B<0	0.053	0.051	0.076***	0.012	0.028
	(1.61)	(1.55)	(3.00)	(0.49)	(1.01)
4<W≤5 × 0≤B<5	-0.003	-0.005	0.014	-0.009	-0.007
	(-0.09)	(-0.13)	(0.72)	(-0.42)	(-0.31)
6<W	-0.130***	-0.130***	-0.181***	-0.169***	-0.163***
	(-6.57)	(-6.55)	(-10.73)	(-9.74)	(-9.17)
5<W≤6	-0.067*	-0.066*	-0.140***	-0.119***	-0.114***
	(-1.88)	(-1.87)	(-7.57)	(-6.94)	(-6.69)
4<W≤5	-0.090***	-0.090***	-0.127***	-0.094***	-0.087***
	(-3.79)	(-3.77)	(-12.13)	(-9.40)	(-8.77)
FE	No	Q	Q×Stock	Q×Stock + Fund	Q×Stock + Q×Fund
Adjusted R-squared	0.0040	0.0043	0.1350	0.1750	0.2122
Observations	4,354,870	4,354,870	4,354,870	4,354,870	4,354,870

A.4.2. Additional results for trade direction and size

Table A.4
Funds' trade direction

This table presents coefficients from OLS regressions of

$$\text{TradeDirection}_{f,s,t+1} = \beta_0 + \beta_1 D^{W>5}_{f,s,t} + \beta_2 D^{B<0}_{f,t} + \beta_3 D^{0\leq B<5}_{f,t} + \beta_4 (D^{W>5}_{f,s,t} \times D^{B<0}_{f,t}) + \beta_5 (D^{W>5}_{f,s,t} \times D^{0\leq B<5}_{f,t}) + \epsilon_{f,s,t+1}.$$

The weight indicator, D^W, is based on $\text{Weight}_{f,s,t}$ (%). Buffer indicators, D^B, are based on $\text{Buffer}_{f,t}$ (%). The regression sample includes stocks with prices above \$5 and, within each fiscal quarter, the largest 50% of stocks by market capitalization, resulting in 2,806 stocks. Standard errors are clustered at the stock level, and t-statistics are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. Q denotes fiscal quarter.

	Panel A: 2019-2024				
5<W × Buffer<0	-0.087***	-0.096***	-0.103***	-0.102***	-0.088***
	(-3.47)	(-3.66)	(-3.55)	(-4.17)	(-3.56)
5<W × 0≤Buffer<5	-0.079***	-0.085***	-0.102***	-0.087***	-0.029*
	(-4.86)	(-4.85)	(-5.72)	(-5.86)	(-1.85)
5<W	-0.213***	-0.207***	-0.171***	-0.159***	-0.159***
	(-17.10)	(-16.35)	(-11.48)	(-12.00)	(-11.47)
Fixed Effects	No	Q	Q×Stock	Q×Stock + Fund	Q×Stock + Q×Fund
Adjusted R-squared	0.0006	0.0112	0.0352	0.1797	0.4530
Observations	11,513,919	11,513,919	11,513,919	11,513,919	11,513,919
	Panel B: 2023-2024				
5<W × Buffer<0	-0.072**	-0.077**	-0.083**	-0.134***	-0.108***
	(-2.05)	(-2.21)	(-2.27)	(-4.56)	(-3.53)
5<W × 0≤Buffer<5	-0.097***	-0.094***	-0.106***	-0.040**	-0.026
	(-5.35)	(-5.04)	(-5.35)	(-2.34)	(-1.47)
5<W	-0.211***	-0.206***	-0.197***	-0.170***	-0.170***
	(-10.25)	(-10.19)	(-8.65)	(-8.38)	(-8.06)
Fixed Effects	No	Q	Q×Stock	Q×Stock + Fund	Q×Stock + Q×Fund
Adjusted R-squared	0.0008	0.0111	0.0332	0.2300	0.4539
Observations	4,354,870	4,354,870	4,354,870	4,354,870	4,354,870

Table A.5
Changes in funds' shares held

This table presents coefficients from OLS regressions of

$$\Delta\text{Shares}_{f,s,t+1} = \beta_0+\beta_1 D^{W>5}_{f,s,t}+\beta_2 D^{B<0}_{f,t}+\beta_3 D^{0\leq B<5}_{f,t}+\beta_4(D^{W>5}_{f,s,t}\times D^{B<0}_{f,t})+\beta_5(D^{W>5}_{f,s,t}\times D^{0\leq B<5}_{f,t})+\epsilon_{f,s,t+1}.$$

The weight indicator, D^W, is based on $\text{Weight}_{f,s,t}$ (%). Buffer indicators, D^B, are based on $\text{Buffer}_{f,t}$ (%). The regression sample includes stocks with prices above \$5 and, within each fiscal quarter, the largest 50% of stocks by market capitalization, resulting in 2,806 stocks. Standard errors are clustered at the stock level, and t-statistics are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. Q denotes fiscal quarter.

	Panel A: 2019-2024				
5<W × Buffer<0	-1.579	-2.085*	-0.847	-3.003***	-1.712*
	(-1.48)	(-1.96)	(-0.89)	(-3.49)	(-1.79)
5<W × 0≤Buffer<5	1.366*	0.784	0.865	-1.091*	-0.518
	(1.73)	(0.99)	(1.33)	(-1.66)	(-0.88)
5<W	2.973***	3.138***	-1.447***	-1.105**	-1.163**
	(3.18)	(3.39)	(-2.63)	(-2.01)	(-1.99)
Fixed Effects	No	Q	Q×Stock	Q×Stock + Fund	Q×Stock + Q×Fund
Adjusted R-squared	0.0000	0.0017	0.0999	0.1563	0.2514
Observations	11,513,919	11,513,919	11,513,919	11,513,919	11,513,919
	Panel B: 2023-2024				
5<W × Buffer<0	0.437	0.045	1.231	-3.420***	-2.106*
	(0.32)	(0.03)	(1.02)	(-3.08)	(-1.86)
5<W × 0≤Buffer<5	2.729***	2.477**	2.219***	-0.340	0.079
	(2.72)	(2.51)	(2.75)	(-0.44)	(0.10)
5<W	4.317***	4.444***	-1.289*	-0.713	-0.908
	(3.93)	(4.15)	(-1.84)	(-0.97)	(-1.22)
Fixed Effects	No	Q	Q×Stock	Q×Stock + Fund	Q×Stock + Q×Fund
Adjusted R-squared	0.0001	0.0011	0.0851	0.1537	0.2325
Observations	4,354,870	4,354,870	4,354,870	4,354,870	4,354,870

Table A.6
Funds' trade direction and volatility

This table reports coefficients from OLS regressions run separately for funds with $\text{Buffer}_{f,t} < 0$ and $0 \leq \text{Buffer}_{f,t} < 5\%$:

$$\text{TradeDirection}_{f,s,t+1} = \delta_0 + \delta_1(D^{W>6}_{f,s,t} \times \text{Volatility}_{s,t}) + \delta_2(D^{5<W\leq 6}_{f,s,t} \times \text{Volatility}_{s,t}) + \delta_3(D^{4<W\leq 5}_{f,s,t} \times \text{Volatility}_{s,t}) + \delta_4 D^{W>6}_{f,s,t} + \delta_5 D^{5<W\leq 6}_{f,s,t} + \delta_6 D^{4<W\leq 5}_{f,s,t} + \delta_7 \text{Volatility}_{s,t} + \epsilon_{f,s,t+1}$$

Weight indicators, D^W, are based on $\text{Weight}_{f,s,t}$ (%). $\text{Volatility}_{s,t}$ (%) is the standard deviation of daily returns within fiscal quarter t. The sample includes stocks with prices above \$5 and, within each fiscal quarter, the largest 50% of stocks by market capitalization, resulting in 2,806 stocks. Standard errors are clustered at the stock level, with t-statistics reported in parentheses. ***, **, and * denote significance at 1%, 5%, and 10% levels. Q denotes fiscal quarter.

	Buffer < 0					0 ≤ Buffer < 5%				
	Panel A: 2019-2024									
6<W × Volatility	-0.045***	-0.045***	-0.104***	-0.063**	-0.023	-0.040***	-0.032***	-0.047**	-0.014	-0.013
	(-3.01)	(-2.95)	(-3.29)	(-2.13)	(-0.84)	(-3.23)	(-2.68)	(-2.31)	(-0.69)	(-0.64)
5<W≤6 × Volatility	-0.048***	-0.052***	-0.074*	-0.014	-0.010	-0.022	-0.014	-0.032	-0.053	-0.033
	(-2.64)	(-2.70)	(-1.81)	(-0.45)	(-0.32)	(-1.09)	(-0.72)	(-0.89)	(-1.40)	(-0.95)
4<W≤5 × Volatility	-0.044*	-0.041	-0.095**	-0.002	0.034	-0.014	-0.008	-0.022	-0.018	0.005
	(-1.92)	(-1.60)	(-2.06)	(-0.07)	(0.93)	(-0.80)	(-0.48)	(-0.73)	(-0.63)	(0.16)
Fixed Effects	No	Q	Q×Stock	Q×Stock + Fund	Q×Stock + Q×Fund	No	Q	Q×Stock	Q×Stock + Fund	Q×Stock + Q×Fund
Adjusted R-squared	0.0296	0.1014	0.1344	0.4321	0.5132	0.0111	0.0738	0.1247	0.3391	0.5001
Observations	21,679	21,679	21,679	21,679	21,679	80,317	80,317	80,317	80,317	80,317
	Panel B: 2023-2024									
6<W × Volatility	-0.041	-0.048	-0.153**	-0.114**	-0.080*	-0.082***	-0.066***	-0.061*	-0.018	-0.036
	(-1.42)	(-1.56)	(-2.56)	(-2.27)	(-1.74)	(-4.19)	(-3.39)	(-1.80)	(-0.46)	(-0.93)
5<W≤6 × Volatility	-0.057	-0.054	-0.143*	-0.083	-0.105	-0.028	-0.019	-0.062	-0.065	-0.078
	(-1.27)	(-1.16)	(-1.73)	(-1.34)	(-1.52)	(-0.86)	(-0.60)	(-1.17)	(-1.10)	(-1.38)
4<W≤5 × Volatility	-0.046	-0.045	-0.198**	-0.121**	-0.095*	0.018	0.027	0.014	-0.006	0.002
	(-0.95)	(-0.89)	(-2.50)	(-2.28)	(-1.86)	(0.57)	(0.93)	(0.29)	(-0.13)	(0.04)
Fixed Effects	No	Q	Q×Stock	Q×Stock + Fund	Q×Stock + Q×Fund	No	Q	Q×Stock	Q×Stock + Fund	Q×Stock + Q×Fund
Adjusted R-squared	0.0206	0.0460	0.1452	0.4535	0.5227	0.0107	0.0635	0.1257	0.3566	0.4964
Observations	12,272	12,272	12,272	12,272	12,272	54,542	54,542	54,542	54,542	54,542

Table A.7
Changes in funds' shares held and volatility

This table reports coefficients from OLS regressions run separately for funds with $\text{Buffer}_{f,t} < 0$ and $0 \leq \text{Buffer}_{f,t} < 5\%$:

$$\Delta\text{Shares}_{f,s,t+1}(\%) = \delta_0 + \delta_1(D^{W>6}_{f,s,t} \times \text{Volatility}_{s,t}) + \delta_2(D^{5<W\leq 6}_{f,s,t} \times \text{Volatility}_{s,t}) + \delta_3(D^{4<W\leq 5}_{f,s,t} \times \text{Volatility}_{s,t}) + \delta_4 D^{W>6}_{f,s,t} + \delta_5 D^{5<W\leq 6}_{f,s,t} + \delta_6 D^{4<W\leq 5}_{f,s,t} + \delta_7 \text{Volatility}_{s,t} + \epsilon_{f,s,t+1}.$$

Weight indicators, D^W, are based on $\text{Weight}_{f,s,t}$ (%). $\text{Volatility}_{s,t}$ (%) is the standard deviation of daily returns within fiscal quarter t. The sample includes stocks with prices above \$5 and, within each fiscal quarter, the largest 50% of stocks by market capitalization, resulting in 2,806 stocks. Standard errors are clustered at the stock level, with t-statistics reported in parentheses.***, **, and * denote significance at 1%, 5%, and 10% levels. Q denotes fiscal quarter.

	Buffer < 0					0 ≤ Buffer < 5%				
					Panel A: 2019-2024					
6<W × Volatility	-1.726**	-1.968**	-5.027**	-1.894	-0.281	-1.204*	-0.927	-3.703***	-0.603	-0.931
	(-2.13)	(-2.08)	(-2.47)	(-0.98)	(-0.14)	(-1.71)	(-0.91)	(-3.24)	(-0.42)	(-0.64)
5<W≤6 × Volatility	-1.566	-1.694*	-4.039**	-0.859	1.003	-2.666**	-2.600**	-3.001	-1.255	-1.655
	(-1.60)	(-1.72)	(-2.19)	(-0.40)	(0.48)	(-2.14)	(-2.12)	(-1.37)	(-0.62)	(-0.85)
4<W≤5 × Volatility	-1.888	-1.908	-6.752***	-2.201	-0.231	-1.469	-1.351	-2.246	-0.470	-0.478
	(-1.40)	(-1.42)	(-3.34)	(-1.22)	(-0.12)	(-1.60)	(-1.48)	(-1.56)	(-0.35)	(-0.35)
Fixed Effects	No	Q	Q×Stock	Q×Stock + Fund	Q×Stock + Q×Fund	No	Q	Q×Stock	Q×Stock + Fund	Q×Stock + Q×Fund
Adjusted R-squared	0.0007	0.0142	0.4313	0.4957	0.5087	0.0010	0.0209	0.2398	0.3066	0.3505
Observations	21,679	21,679	21,679	21,679	21,679	80,317	80,317	80,317	80,317	80,317
					Panel B: 2023-2024					
6<W × Volatility	2.348*	2.567*	-5.645**	-5.478*	-4.867	-0.569	0.266	-3.912**	0.796	0.511
	(1.66)	(1.71)	(-1.99)	(-1.67)	(-1.51)	(-0.54)	(0.19)	(-2.20)	(0.32)	(0.20)
5<W≤6 × Volatility	1.210	1.327	-7.820***	-6.219**	-6.244**	-3.184	-2.643	-3.982	-2.481	-1.985
	(0.65)	(0.72)	(-2.94)	(-2.20)	(-2.14)	(-1.53)	(-1.30)	(-1.14)	(-0.74)	(-0.59)
4<W≤5 × Volatility	0.840	1.120	-9.012***	-8.494***	-6.764**	1.961	2.216	-0.096	0.630	0.472
	(0.46)	(0.63)	(-2.82)	(-3.11)	(-2.48)	(1.30)	(1.47)	(-0.04)	(0.28)	(0.21)
Fixed Effects	No	Q	Q×Stock	Q×Stock + Fund	Q×Stock + Q×Fund	No	Q	Q×Stock	Q×Stock + Fund	Q×Stock + Q×Fund
Adjusted R-squared	0.0019	0.0083	0.4625	0.5186	0.5288	0.0019	0.0183	0.2494	0.3158	0.3537
Observations	12,272	12,272	12,272	12,272	12,272	54,542	54,542	54,542	54,542	54,542

A.5. How equity exposure is computed

We compute the equity exposure of fund f at fiscal quarter t as

$$\text{EquityExposure}_{f,t} = \frac{\sum_{s \in \mathcal{S}_{f,t}} \text{Value}_{f,s,t}}{\text{TotalAssets}_{f,t}},$$

where $\mathcal{S}_{f,t}$ denotes the set of stock holdings by fund f in fiscal quarter t, $\text{Value}_{f,s,t}$ denotes the market value of fund f's holding in stock s in fiscal quarter t, and $\text{TotalAssets}_{f,t}$ denotes the total assets of fund f in fiscal quarter t.

The observed change in equity exposure from t to $t+1$ is therefore

$$\Delta\text{EE}_{f,t \to t+1} = \text{EquityExposure}_{f,t+1} - \text{EquityExposure}_{f,t}.$$

To compute the implied active change in equity exposure, Active-$\Delta\text{EE}_{f,t \to t+1}$, we construct the following components.

The implied total assets of fund f at $t+1$ are

$$\text{ImpliedTA}_{f,t+1} = \text{TotalAssets}_{f,t} \times (1 + R^{\text{fund}}_{f,t \to t+1}),$$

where $R^{\text{fund}}_{f,t \to t+1}$ is the fund return from t to $t+1$.

Similarly, for each stock s held by fund f at t, the implied value of holdings at $t+1$ is

$$\text{ImpliedValue}_{f,s,t+1} = \text{Value}_{f,s,t} \times (1 + hpr_s^{t \to t+1}),$$

where $\text{Value}_{f,s,t}$ is the market value of fund f's holdings of stock s at t, and

$$hpr_s^{t \to t+1} = \prod_{m \in (t,t+1]} (1 + r_{s,m}) - 1$$

is the cumulative return of stock s from t to $t+1$, computed from monthly returns.

$\text{ImpliedValue}_{f,s,t+1}$ denotes the market value of stock s that fund f would hold at fiscal quarter $t+1$, assuming it keeps its holdings unchanged until the end of quarter $t+1$. Thus, $\text{ImpliedValue}_{f,s,t+1}$ reflects only the passive growth arising from stock returns.

Summing across all stocks yields the implied common equity at $t+1$:

$$\text{ImpliedCE}_{f,t+1} = \sum_{s \in \mathcal{U}_{f,t+1}} \text{ImpliedValue}_{f,s,t+1},$$

where $\mathcal{U}_{f,t+1}$ denotes the set of fund f's held stocks at time t+1, assuming the fund keeps its holdings unchanged.

We then define the implied passive equity exposure at $t+1$ as

$$\text{PassiveEquityExposure}_{f,t+1} = \frac{\text{ImpliedCE}_{f,t+1}}{\text{ImpliedTA}_{f,t+1}}.$$

The active change of equity exposure is then given by

$$\text{Active-}\Delta\text{EE}_{f,t\to t+1} = \text{EquityExposure}_{f,t+1} - \text{PassiveEquityExposure}_{f,t+1}.$$

A.6. Alternative measure of changes in equity exposure

A.6.1. Equity exposure including derivatives and ETFs

This section outlines the methodology for constructing a fund's total equity exposure ($EE^{total}_{f,t}$), which aggregates direct stock holdings, equity derivatives, and indirect exposure obtained through Exchange Traded Funds (ETFs). We define the total equity exposure for fund f in fiscal quarter t as follows:

$$EE^{total}_{f,t} = \text{EquityExposure}_{f,t} + \text{EquityExposure}^{\text{derivatives}}_{f,t} + \text{EquityExposure}^{\text{ETF}}_{f,t}.$$

The first component, $\text{EquityExposure}_{f,t}$, represents the aggregate market value of all direct stock holdings scaled by total assets, as detailed in Section A.5.

The second component, $\text{EquityExposure}^{\text{derivatives}}_{f,t}$, captures the exposure arising from equity derivatives. We rely on NPORT-P data to identify these positions, specifically filtering for holdings where the asset category (asset_cat) is classified as 'DE' (derivative-equity). This category includes forwards/futures, options, swaps, swaptions, warrants, and foreign exchange contracts. Form NPORT-P reports notional amounts for all derivative positions, except for options, which are extremely rare in our sample. (See Kaniel and Wang (2025) for a more systematic study of funds' derivatives positions using NPORT-P data.) $\text{EquityExposure}^{\text{derivatives}}_{f,t}$ is therefore calculated as the sum of these derivative positions divided by the fund's total assets.

To compute the third component, $\text{EquityExposure}^{\text{ETF}}_{f,t}$, we first identify domestic equity ETFs (et_flag = 'F' and crsp_obj_cd begins with 'ED') within the CRSP mutual fund database. Using CUSIP, we merge this list with NPORT-P holdings data. Within the matched sample, we retain observations where the NPORT-P asset category is recorded as either 'EC' (equity-common) or 'OTHER'. We calculate the ETF-implied equity exposure by weighting the held value of each ETF by the proportion of that ETF invested in common stocks, scaled by the fund's total assets:

$$\text{EquityExposure}^{\text{ETF}}_{f,t} = \frac{\sum_{i\in\Omega_{f,t}} \left(\text{Value}_{f,i,t} \times \text{per\_com}_{i,t}\right)}{\text{TotalAssets}_{f,t}},$$

where $\Omega_{f,t}$ represents the set of all domestic equity ETFs held by fund f in fiscal quarter t, $\text{Value}_{f,i,t}$ denotes the value of ETF i held by fund f, and $\text{per\_com}_{i,t}$ is the percentage of ETF i's portfolio invested in common stocks, as reported in CRSP.

The contributions of $\text{EquityExposure}_{f,t}^{\text{derivatives}}$ and $\text{EquityExposure}_{f,t}^{\text{ETF}}$ to $EE_{f,t}^{\text{total}}$ are small. In the 2019–2024 sample, they account for, on average, less than 0.2% of $EE_{f,t}^{\text{total}}$.

A.6.2. Alternative measure of active change in equity exposure

In this section, we explain an alternative approach to computing the implied active change in equity exposure, $\text{Active-}\Delta\text{EE}_{f,t\to t+1}$. In addition to variables defined in Appendix A.5, we construct the following components.

The implied total assets of fund f at t are given by

$$\text{ImpliedTA}_{f,t}^{alt} = \frac{\text{TotalAssets}_{f,t+1}}{1 + R_{f,t\to t+1}^{\text{fund}}},$$

where $\text{TotalAssets}_{f,t+1}$ is the total assets of fund f at $t+1$, and $R_{f,t\to t+1}^{\text{fund}}$ is the fund gross return from t to $t+1$.

Similarly, for each stock s held by fund f at $t+1$, the implied value of holdings at t is

$$\text{ImpliedValue}_{f,s,t}^{alt} = \frac{\text{Value}_{f,s,t+1}}{(1 + hpr_s^{t\to t+1})},$$

where $\text{Value}_{f,s,t+1}$ is the market value of fund f's holdings of stock s at $t+1$, and $hpr_s^{t\to t+1}$ of stock s is the cumulative return from fiscal quarter t to $t+1$, defined as before.

$\text{ImpliedValue}_{f,s,t}^{alt}$ denotes the market value of stock s that fund f would need to hold at fiscal quarter t, assuming it immediately adjusts its portfolio after the end of quarter t and keeps holdings unchanged until the end of quarter $t+1$, so that passive growth from returns yields the fund's actual holding value of stock s at $t+1$.

Summing the implied values across all stocks yields the implied common equity at t:

$$\text{ImpliedCE}_{f,t}^{alt} = \sum_{s\in\mathcal{V}_{f,t}} \text{ImpliedValue}_{f,s,t}^{alt},$$

where $\mathcal{V}_{f,t}$ denotes the set of fund f's held stocks at time t inferred backward from t+1, assuming the fund keeps its holdings unchanged after rebalancing at t until $t+1$.

We define the implied passive equity exposure at t as

$$\text{PassiveEquityExposure}_{f,t}^{alt} = \frac{\text{ImpliedCE}_{f,t}^{alt}}{\text{ImpliedTA}_{f,t}^{alt}}.$$

The active change of equity exposure is therefore

$$\text{Active-}\Delta\text{EE}^{alt}_{f,t\to t+1} = \text{PassiveEquityExposure}^{alt}_{f,t} - \text{EquityExposure}_{f,t}.$$

Table A.8
Changes in funds' equity exposure (alternative measure)

This table reports estimates from regressions relating changes in fund equity exposure to buffer indicators. The dependent variables are $\Delta EE^{total}_{f,t\to t+1}$ and Active-$\Delta EE^{alt}_{f,t\to t+1}$. $EE^{total}_{f,t}$ denotes the fund's total equity exposure in fiscal quarter t and includes direct equity holdings, equity derivatives, and equity ETFs, with ETF positions scaled by their underlying common-equity component. The indicator $D^{B<0}_{f,t}$ equals one if $\text{Buffer}_{f,t} < 0$ and zero otherwise; $D^{0\leq B<5}_{f,t}$ is defined analogously. Control variables, measured at quarter t for each fund, include the log of the total net assets, the log of return standard deviation, net flow, and gross return. Standard errors are clustered by fund and fiscal quarter, and t-statistics are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Q denotes fiscal quarter.

	ΔEE^{total} (%)				Active-ΔEE^{alt} (%)			
				Panel A: 2019-2024				
Buffer<0	-0.694***	-0.720***	-1.652***	-1.613***	-0.531***	-0.542***	-1.439***	-1.426***
	(-4.03)	(-4.26)	(-5.48)	(-5.31)	(-3.40)	(-3.59)	(-5.43)	(-5.33)
0≤Buffer<5	-0.279***	-0.280***	-0.636***	-0.595***	-0.152*	-0.152*	-0.549***	-0.537***
	(-3.30)	(-3.84)	(-6.25)	(-5.92)	(-1.76)	(-1.96)	(-5.39)	(-5.17)
Fixed Effects	No	Q	Q+Fund	Q+Fund	No	Q	Q+Fund	Q+Fund
Controls	No	No	No	Yes	No	No	No	Yes
Adjusted R-squared	0.0004	0.0147	-0.0226	-0.0214	0.0002	0.0141	0.0752	0.0758
Observations	75,754	75,754	75,754	75,754	75,754	75,754	75,754	75,754
				Panel B: 2023-2024				
Buffer<0	-0.370**	-0.383***	-1.271***	-1.295***	-0.266	-0.268	-1.105***	-1.121***
	(-2.81)	(-2.99)	(-3.90)	(-4.05)	(-1.52)	(-1.56)	(-3.68)	(-3.58)
0≤Buffer<5	-0.209*	-0.184*	-0.502***	-0.507***	-0.163	-0.132	-0.386***	-0.385***
	(-1.82)	(-1.86)	(-4.21)	(-4.32)	(-1.56)	(-1.36)	(-3.36)	(-3.32)
Fixed Effects	No	Q	Q+Fund	Q+Fund	No	Q	Q+Fund	Q+Fund
Controls	No	No	No	Yes	No	No	No	Yes
Adjusted R-squared	0.0002	0.0062	-0.0809	-0.0796	0.0001	0.0044	0.0659	0.0670
Observations	28,921	28,921	28,921	28,921	28,921	28,921	28,921	28,921

A.7. Computation of risk-adjusted fund and stock returns

At the end of each month t, we compute the forward-looking h-month risk-adjusted return for each asset $i \in \{f, s\}$, where f indexes a fund and s a stock. The procedure is identical for funds and stocks. For a stock we use its own return, and for a fund we use its own gross return. We risk-adjust returns following the Carhart four-factor model.

First, for the period from month $t+1$ to $t+h$, we compute the cumulative return of asset i ($R_{i,t+1\to t+h}$), the cumulative risk-free rate ($\mathrm{RF}_{t+1\to t+h}$), and the cumulative returns of the four factors. The cumulative return of any asset or factor j over this period is

$$R_{j,t+1\to t+h} = \prod_{m=t+1}^{t+h} (1 + R_{j,m}) - 1, \tag{A.29}$$

where $R_{j,m}$ is the monthly return of asset/factor j in month m. We denote the vector of the four cumulative factor returns (MKTRF, SMB, HML, UMD) by $\mathbf{F}_{t+1\to t+h}$.

Second, we obtain the vector of factor loadings for asset i at the end of month t, denoted by $\hat{\boldsymbol{\beta}}_{i,t} = (\hat{\beta}_{i,t}^{\mathrm{MKTRF}}, \hat{\beta}_{i,t}^{\mathrm{SMB}}, \hat{\beta}_{i,t}^{\mathrm{HML}}, \hat{\beta}_{i,t}^{\mathrm{UMD}})'$, by estimating the Carhart four-factor model using the 252 trading days of data up to and including the last trading day of month t:

$$r_{i,d} - \mathrm{r}_{f,d} = \alpha_i + \beta_i^{\mathrm{MKTRF}}\mathrm{MKTRF}_d + \beta_i^{\mathrm{SMB}}\mathrm{SMB}_d + \beta_i^{\mathrm{HML}}\mathrm{HML}_d + \beta_i^{\mathrm{UMD}}\mathrm{UMD}_d + \epsilon_{i,d}, \tag{A.30}$$

where $r_{i,d}$ is the daily return of asset i and $\mathrm{r}_{f,d}$ is the daily risk-free rate; for a fund, $r_{i,d}$ is its daily gross return.

Finally, we define the h-month factor-adjusted return of asset i, $Ret(FF4)_{i,t+h}$, as

$$Ret(FF4)_{i,t+h} = (R_{i,t+1\to t+h} - \mathrm{RF}_{t+1\to t+h}) - \hat{\boldsymbol{\beta}}_{i,t}' \mathbf{F}_{t+1\to t+h}. \tag{A.31}$$

We analogously construct the CAPM-adjusted returns, $Ret(CAPM)_{i,t+h}$, and the returns based on the Carhart four-factor model augmented with the return on the Global X Artificial Intelligence & Technology ETF (AIQ), $Ret(FF4 + AIQ)_{i,t+h}$.

A.8. Additional results on fund performance

Table A.9
All funds' performance drag

This table reports estimates from OLS regressions relating fund performance to buffer indicators:

$$\text{Ret(FF4)}_{f,t+h}(\%) = \delta_0 + \delta_1 D_{f,t}^{B<0} + \delta_2 D_{f,t}^{0\leq B<5} + \gamma_f + \varphi_{f,t+h}.$$

$\text{Ret(FF4)}_{f,t+h}$ is the cumulative Carhart four-factor risk-adjusted returns for fund f over horizons $h = 1, 2, 3, 4, 5, 6, 9,$ and 12 months following quarter t. The indicator $D_{f,t}^{B<0}$ equals one if $\text{Buffer}_{f,t} < 0$ and zero otherwise; $D_{f,t}^{0\leq B<5}$ is defined analogously. The regression sample consists of all funds. Fund fixed effects γ_f absorb time-invariant differences across funds. We cluster standard errors at the fund level and report t-statistics in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Return horizon							
	1M	2M	3M	4M	5M	6M	9M	12M
	Panel A: 2019-2024							
Buffer<0	-0.069	-0.082	-0.186	-0.164	-0.184	-0.174	0.312	1.875**
	(-0.36)	(-0.32)	(-0.56)	(-0.40)	(-0.38)	(-0.33)	(0.44)	(1.97)
0≤Buffer<5	-0.202	-0.244	-0.370*	-0.547**	-0.585**	-0.242	0.005	0.622
	(-1.59)	(-1.36)	(-1.67)	(-2.09)	(-2.06)	(-0.75)	(0.01)	(1.11)
Adjusted R-squared	-0.0125	-0.0122	-0.0112	0.0093	0.0275	0.0367	0.0737	0.1057
Observations	73,677	73,659	73,659	73,505	73,310	73,082	72,459	68,501
	Panel B: 2023-2024							
Buffer<0	-0.470**	-0.694*	-1.150**	-1.419***	-1.509**	-1.615***	-1.996**	-2.211*
	(-1.99)	(-1.87)	(-2.52)	(-2.71)	(-2.58)	(-2.65)	(-2.21)	(-1.92)
0≤Buffer<5	-0.405***	-0.551**	-0.825***	-0.947***	-1.119***	-0.969**	-1.116**	-0.904
	(-3.19)	(-2.32)	(-2.82)	(-2.78)	(-3.23)	(-2.47)	(-2.10)	(-1.40)
Adjusted R-squared	-0.0262	-0.0349	-0.0493	0.0087	0.0553	0.1024	0.2573	0.3891
Observations	28,166	28,158	28,163	28,096	28,013	27,952	27,706	24,091

Table A.10
Large-cap growth funds' performance drag (weighted least squares)

This table reports coefficients from weighted least squares regressions of

$$\text{Ret(FF4)}_{f,t+h}(\%) = \beta_0 + \beta_1 D_{f,t}^{B<0} + \beta_2 D_{f,t}^{0\leq B<5} + \gamma_f + \epsilon_{f,t+h}.$$

Regression weights are total assets of fund f in fiscal quarter t. The dependent variable $\text{Ret(FF4)}_{f,t+h}$ is the cumulative Carhart four-factor risk-adjusted returns for fund f over horizons $h = 1, 2, 3, 4, 5, 6, 9$, and 12 months following quarter t. The indicator $D_{f,t}^{B<0}$ equals one if $\text{Buffer}_{f,t} < 0$ and zero otherwise; $D_{f,t}^{0\leq B<5}$ is defined analogously. The regression sample consists of large-cap growth funds. Fund fixed effects γ_f absorb any time-invariant differences across funds within this segment. We cluster standard errors at the fund level and report t-statistics in parentheses. Significance levels are denoted by ***, **, and *, corresponding to 1%, 5%, and 10% significance, respectively.

	Return horizon							
	1M	2M	3M	4M	5M	6M	9M	12M
				Panel A: 2019-2024				
Buffer<0	-0.367	0.179	-0.048	-0.386	-0.773	-0.159	0.367	1.139
	(-0.88)	(0.43)	(-0.08)	(-0.43)	(-0.77)	(-0.12)	(0.22)	(0.45)
0≤Buffer<5	-0.647***	-1.042***	-0.690	-1.316***	-1.379***	-1.277***	-1.098*	-0.935
	(-5.09)	(-5.13)	(-1.48)	(-2.92)	(-4.36)	(-4.28)	(-1.93)	(-1.51)
Adjusted R-squared	-0.0046	-0.0133	-0.0281	-0.0020	-0.0066	-0.0004	0.0186	0.0469
Observations	5,866	5,861	5,862	5,858	5,845	5,828	5,786	5,469
				Panel B: 2023-2024				
Buffer<0	-1.004**	-0.713	-1.552***	-2.440***	-3.280***	-3.177***	-3.891***	-6.593***
	(-2.56)	(-1.24)	(-2.76)	(-3.92)	(-4.10)	(-3.58)	(-5.85)	(-8.01)
0≤Buffer<5	-0.724***	-1.252***	-1.124	-1.921**	-2.014***	-2.378***	-2.954***	-3.666***
	(-3.38)	(-4.00)	(-1.56)	(-2.57)	(-3.26)	(-4.78)	(-3.08)	(-3.42)
Adjusted R-squared	0.0323	0.0096	-0.0502	0.0237	0.0451	0.0693	0.0948	0.1664
Observations	2,229	2,226	2,228	2,227	2,221	2,216	2,198	1,901

Table A.11
Large-cap growth funds' performance drag (CAPM)

This table reports coefficients from OLS regressions of

$$\text{Ret(CAPM)}_{f,t+h}(\%) = \beta_0 + \beta_1 D_{f,t}^{B<0} + \beta_2 D_{f,t}^{0\leq B<5} + \gamma_f + \epsilon_{f,t+h}.$$

The dependent variable $\text{Ret(CAPM)}_{f,t+h}$ is the cumulative CAPM-adjusted returns for fund f over horizons $h = 1, 2, 3, 4, 5, 6, 9,$ and 12 months following quarter t. The indicator $D_{f,t}^{B<0}$ equals one if $\text{Buffer}_{f,t} < 0$ and zero otherwise; $D_{f,t}^{0\leq B<5}$ is defined analogously. The regression sample consists of large-cap growth funds. Fund fixed effects γ_f absorb any time-invariant differences across funds within this segment. We cluster standard errors at the fund level and report t-statistics in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Return horizon							
	1M	2M	3M	4M	5M	6M	9M	12M
				Panel A: 2019-2024				
Buffer<0	-0.996***	-0.805**	-1.188***	-1.061***	-1.430***	-1.147**	-1.270*	1.151
	(-4.35)	(-2.20)	(-3.67)	(-2.73)	(-3.02)	(-2.50)	(-1.93)	(1.19)
0≤Buffer<5	-0.571***	-1.100***	-1.103***	-1.133***	-1.281***	-1.062***	-0.633*	0.345
	(-4.27)	(-5.66)	(-5.52)	(-5.20)	(-5.23)	(-4.14)	(-1.69)	(0.59)
Adjusted R-squared	0.0008	-0.0106	-0.0216	-0.0095	-0.0065	0.0049	0.0259	0.0419
Observations	5,866	5,861	5,862	5,858	5,845	5,828	5,786	5,469
				Panel B: 2023-2024				
Buffer<0	-2.094***	-3.068***	-3.093***	-3.561***	-4.075***	-3.643***	-5.369***	-5.583***
	(-9.60)	(-7.53)	(-9.95)	(-9.43)	(-8.47)	(-8.11)	(-10.70)	(-7.70)
0≤Buffer<5	-0.949***	-2.064***	-1.787***	-2.138***	-2.325***	-2.197***	-2.983***	-3.163***
	(-5.74)	(-8.59)	(-7.71)	(-9.04)	(-9.21)	(-8.24)	(-8.75)	(-6.95)
Adjusted R-squared	-0.0040	0.0273	-0.0031	0.0550	0.0702	0.1016	0.1833	0.2801
Observations	2,229	2,226	2,228	2,227	2,221	2,216	2,198	1,901

Table A.12

Components of large-cap growth funds' performance drag

This table presents the sources of underperformance for constrained and negative-buffer large-cap growth funds. The exposure-adjustment effect captures the performance effect of adjusting total equity exposure while keeping the within-equity portfolio weights unchanged. The large-position rebalancing effect isolates the effect of rebalancing large positions ($\text{Weight}_{f,s,t} > 5\%$) while keeping both the total equity exposure and non-large positions fixed. The mean is the annualized equal-weighted average of performance drags across funds. The impact, measured in billions of USD, represents the dollar value of the performance drag, scaled by funds' total assets. For 2019–2024, the number of fund–quarter observations with $0 \leq \text{Buffer}_{f,t} < 5\%$ is 409, whereas the number of observations with $\text{Buffer}_{f,t} < 0$ is 115. For 2023–2024, the number of fund–quarter observations with $0 \leq \text{Buffer}_{f,t} < 5\%$ is 351, and the number of observations with $\text{Buffer}_{f,t} < 0$ is 107. We report t-statistics in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels.

	$0 \leq$ Buffer $< 5\%$		Buffer < 0	
	Mean (%)	Impact ($B)	Mean (%)	Impact ($B)
		Panel A: 2019-2024		
Exposure adjustment	-0.148***	-0.717	-0.036	-0.304
	(-4.29)		(-0.57)	
Large-position rebalancing	-0.018	0.866	0.082	0.248
	(-0.21)		(1.17)	
		Panel B: 2023-2024		
Exposure adjustment	-0.163***	-0.692	-0.060	-0.356
	(-4.47)		(-0.92)	
Large-position rebalancing	-0.129	0.149	0.022	0.150
	(-1.46)		(0.33)	

A.9. Additional results on return predictability

Table A.13
Stock return predictability (Driscoll-Kraay standard errors)

This table presents the ability of constrained ownership share $C_{s,t}$ to predict stock returns adjusted for the Carhart four risk factors. The dependent variable is the risk-adjusted cumulative return over 1, 3, 6, 9, and 12 months following month t. Each month t, we sort stocks into 2 groups: *High C* stocks with $C_{s,t} > 0$, and *Low C* stocks with $C_{s,t} = 0$. $C_{s,t}$ represents the proportion of stock shares held by funds with a buffer less than 5% and a position weight greater than 5%. We define $High\ Vol_{s,t}$ as an indicator equal to 1 if $Volatility_{s,t}$ exceeds the cross-sectional median across all stocks, and 0 otherwise. The regression sample includes stocks with prices above $5 and, within each month, the largest 50% of stocks by market capitalization, resulting in 2,806 stocks. We include year–month fixed effects and report t-statistics based on Driscoll-Kraay standard errors in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Return horizon					Return horizon				
	1M	3M	6M	9M	12M	1M	3M	6M	9M	12M
					Panel A: 2019-2024					
High C	0.112	0.337	0.805	1.546*	2.252**	0.091	0.359	0.549	1.044*	1.319**
	(1.05)	(1.10)	(1.21)	(1.98)	(2.64)	(0.92)	(1.54)	(1.21)	(1.79)	(2.26)
High C × High Vol						0.030	-0.182	0.578	1.258	2.630*
						(0.11)	(-0.35)	(0.58)	(1.15)	(1.82)
High Vol						-0.056	-0.181	-0.359	-0.511	-0.544
						(-0.22)	(-0.38)	(-0.38)	(-0.40)	(-0.40)
Adjusted R-squared	0.0097	0.0092	0.0078	0.0072	0.0064	0.0097	0.0092	0.0078	0.0072	0.0065
Observations	109,335	108,672	107,767	102,129	96,552	109,335	108,672	107,767	102,129	96,552
					Panel B: 2023-2024					
High C	0.309**	1.100***	2.301***	3.343***	4.391***	0.067	0.557*	0.835	1.591*	1.931*
	(2.29)	(3.06)	(3.48)	(4.16)	(4.12)	(0.55)	(1.96)	(1.59)	(1.91)	(1.75)
High C × High Vol						0.661*	1.473***	3.847***	4.416***	6.280***
						(1.75)	(2.81)	(5.26)	(4.18)	(4.95)
High Vol						-0.103	-0.247	-0.898	-1.467	-2.125
						(-0.33)	(-0.32)	(-0.60)	(-0.79)	(-1.12)
Adjusted R-squared	0.0077	0.0070	0.0039	0.0041	0.0025	0.0078	0.0072	0.0046	0.0048	0.0033
Observations	39,846	39,627	39,350	34,301	29,294	39,846	39,627	39,350	34,301	29,294

Table A.14
Stock return predictability ($0 \leq$ Buffer$_{f,t} < 5$)

This table presents the ability of constrained ownership share $C_{s,t}$ to predict stock returns adjusted for the Carhart four risk factors. The dependent variable is the risk-adjusted cumulative return over 1, 3, 6, 9, and 12 months following month t. Each month t, we sort stocks into 2 groups: *High C* stocks with $C_{s,t} > 0$, and *Low C* stocks with $C_{s,t} = 0$. $C_{s,t}$ represents the proportion of stock shares held by funds with a buffer in the range [0, 5)% and a position weight greater than 5%. We define *High Vol*$_{s,t}$ as an indicator equal to 1 if *Volatility*$_{s,t}$ exceeds the cross-sectional median across all stocks, and 0 otherwise. The regression sample includes stocks with prices above $5 and, within each month, the largest 50% of stocks by market capitalization, resulting in 2,806 stocks. We include year–month fixed effects, cluster standard errors at the stock level, and report t-statistics in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Return horizon					Return horizon				
	1M	3M	6M	9M	12M	1M	3M	6M	9M	12M
					Panel A: 2019-2024					
High C	0.074	0.215	0.605	1.012	1.288	0.012	0.036	-0.147	-0.016	-0.062
	(0.80)	(0.84)	(1.24)	(1.37)	(1.27)	(0.14)	(0.16)	(-0.37)	(-0.03)	(-0.08)
High C × High Vol						0.150	0.408	2.045*	2.818	3.866
						(0.65)	(0.67)	(1.67)	(1.53)	(1.52)
High Vol						-0.069	-0.251	-0.485	-0.661	-0.664
						(-1.18)	(-1.54)	(-1.53)	(-1.37)	(-1.02)
Adjusted R-squared	0.0097	0.0092	0.0077	0.0070	0.0061	0.0097	0.0092	0.0078	0.0072	0.0063
Observations	109,335	108,672	107,767	102,129	96,552	109,335	108,672	107,767	102,129	96,552
					Panel B: 2023-2024					
High C	0.319**	1.253***	2.431***	3.273***	4.057**	0.005	0.385	0.208	0.558	0.430
	(2.17)	(3.21)	(3.21)	(2.75)	(2.29)	(0.03)	(1.08)	(0.32)	(0.55)	(0.29)
High C × High Vol						0.847**	2.335***	5.875***	7.011***	9.428**
						(2.56)	(2.73)	(3.51)	(2.77)	(2.46)
High Vol						-0.101	-0.294	-0.990*	-1.640*	-2.322*
						(-0.99)	(-1.02)	(-1.76)	(-1.80)	(-1.79)
Adjusted R-squared	0.0077	0.0070	0.0036	0.0037	0.0018	0.0078	0.0073	0.0049	0.0048	0.0032
Observations	39,846	39,627	39,350	34,301	29,294	39,846	39,627	39,350	34,301	29,294

Table A.15
Stock return predictability ($\textbf{Buffer}_{f,t} < 0$)

This table presents the ability of constrained ownership share $C_{s,t}$ to predict stock returns adjusted for the Carhart four risk factors. The dependent variable is the risk-adjusted cumulative return over 1, 3, 6, 9, and 12 months following month t. Each month t, we sort stocks into 2 groups: *High C* stocks with $C_{s,t} > 0$, and *Low C* stocks with $C_{s,t} = 0$. $C_{s,t}$ represents the proportion of stock shares held by funds with a buffer less than 0% and a position weight greater than 5%. We define *High* $Vol_{s,t}$ as an indicator equal to 1 if $Volatility_{s,t}$ exceeds the cross-sectional median across all stocks, and 0 otherwise. The regression sample includes stocks with prices above $5 and, within each month, the largest 50% of stocks by market capitalization, resulting in 2,806 stocks. We include year–month fixed effects, cluster standard errors at the stock level, and report t-statistics in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Return horizon					Return horizon				
	1M	3M	6M	9M	12M	1M	3M	6M	9M	12M
Panel A: 2019-2024										
High C	0.118	0.381	1.241**	2.398***	3.683***	0.049	0.408*	1.110**	1.920***	2.289**
	(1.21)	(1.37)	(2.22)	(2.68)	(2.98)	(0.60)	(1.69)	(2.49)	(2.86)	(2.54)
High C × High Vol						0.185	-0.239	0.223	1.328	4.546
						(0.67)	(-0.31)	(0.15)	(0.53)	(1.31)
High Vol						-0.067	-0.195	-0.303	-0.440	-0.500
						(-1.15)	(-1.20)	(-0.97)	(-0.93)	(-0.78)
Adjusted R-squared	0.0097	0.0092	0.0078	0.0073	0.0066	0.0097	0.0092	0.0078	0.0073	0.0068
Observations	109,335	108,672	107,767	102,129	96,552	109,335	108,672	107,767	102,129	96,552
Panel B: 2023-2024										
High C	0.256*	0.804**	2.380***	3.763***	5.679***	0.073	0.648*	1.810***	3.174***	3.794***
	(1.84)	(2.11)	(3.21)	(3.22)	(3.33)	(0.62)	(1.90)	(2.79)	(3.02)	(2.62)
High C × High Vol						0.560	0.424	1.500	1.235	5.282
						(1.53)	(0.45)	(0.86)	(0.47)	(1.28)
High Vol						-0.066	-0.130	-0.542	-1.018	-1.696
						(-0.64)	(-0.45)	(-0.97)	(-1.12)	(-1.32)
Adjusted R-squared	0.0076	0.0066	0.0035	0.0038	0.0025	0.0076	0.0066	0.0035	0.0040	0.0030
Observations	39,846	39,627	39,350	34,301	29,294	39,846	39,627	39,350	34,301	29,294

Table A.16
Stock return predictability (excluding the Magnificent 7)

This table re-estimates the regressions of Table 8 on a sample that excludes the Magnificent 7 (Alphabet, Amazon, Apple, Meta, Microsoft, Nvidia, and Tesla). The dependent variable is the Carhart four-factor risk-adjusted cumulative return over 1, 3, 6, 9, and 12 months following month t. Each month, stocks are sorted into *High C* ($C_{s,t} > 0$) and *Low C* ($C_{s,t} = 0$) groups. $C_{s,t}$ represents the proportion of stock shares held by funds with a buffer less than 5% and a position weight greater than 5%. *High* $Vol_{s,t}$ equals 1 if $Volatility_{s,t}$ exceeds the cross-sectional median. The regression sample includes stocks with prices above \$5 that fall in the cross-sectional top 50% by market capitalization, yielding 2,799 unique stocks after excluding the Magnificent 7. We include year–month fixed effects, cluster standard errors at the stock level, and report t-statistics in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Return horizon					Return horizon				
	1M	3M	6M	9M	12M	1M	3M	6M	9M	12M
Panel A: 2019–2024										
High C	0.058	0.166	0.432	0.892	1.308	0.076	0.320	0.520	0.976*	1.203
	(0.78)	(0.81)	(1.09)	(1.49)	(1.61)	(1.05)	(1.60)	(1.39)	(1.76)	(1.61)
High C × High Vol						-0.091	-0.603	-0.510	-0.610	-0.031
						(-0.48)	(-1.25)	(-0.57)	(-0.48)	(-0.02)
High Vol						-0.056	-0.181	-0.358	-0.511	-0.540
						(-0.93)	(-1.09)	(-1.11)	(-1.04)	(-0.81)
Adjusted R-squared	0.0100	0.0095	0.0081	0.0075	0.0067	0.0100	0.0095	0.0081	0.0076	0.0067
Observations	108,889	108,226	107,321	101,704	96,149	108,889	108,226	107,321	101,704	96,149
Panel B: 2023–2024										
High C	0.265**	0.991***	2.104***	3.014***	3.815**	0.058	0.547*	0.873	1.641*	1.976
	(2.20)	(3.01)	(3.18)	(2.88)	(2.57)	(0.52)	(1.78)	(1.45)	(1.69)	(1.44)
High C × High Vol						0.564*	1.196	3.187**	3.311	4.409
						(1.96)	(1.61)	(2.19)	(1.53)	(1.44)
High Vol						-0.103	-0.247	-0.898	-1.467	-2.125
						(-0.98)	(-0.84)	(-1.57)	(-1.58)	(-1.61)
Adjusted R-squared	0.0079	0.0071	0.0038	0.0040	0.0022	0.0080	0.0072	0.0044	0.0045	0.0028
Observations	39,676	39,457	39,180	34,152	29,167	39,676	39,457	39,180	34,152	29,167

Table A.17
Stock return predictability (controlling for large position indicator)

This table presents the ability of constrained ownership share $C_{s,t}$ to predict stock returns adjusted for the Carhart four risk factors. The dependent variable is the risk-adjusted cumulative return over 1, 3, 6, 9, and 12 months following month t. Each month t, we sort stocks into 2 groups: *High C* stocks with $C_{s,t} > 0$, and *Low C* stocks with $C_{s,t} = 0$. $C_{s,t}$ represents the proportion of stock shares held by funds with a buffer less than 5% and a position weight greater than 5%. The indicator $D^{Large}_{s,t}$ equals one if a stock accounts for a weight greater than 5% in at least one fund's portfolio, and zero otherwise. The regression sample includes stocks with prices above $5 and, within each month, the largest 50% of stocks by market capitalization, resulting in 2,806 stocks. We include year–month fixed effects, cluster standard errors at the stock level, and report t-statistics in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Return horizon				
	1M	3M	6M	9M	12M
	Panel A: 2019-2024				
High C	0.112	0.207	0.468	1.051	1.377
	(1.21)	(0.81)	(0.95)	(1.39)	(1.34)
D^{Large}	0.000	0.175	0.453	0.662	1.175*
	(0.00)	(0.92)	(1.25)	(1.25)	(1.68)
Adjusted R-squared	0.0097	0.0092	0.0078	0.0072	0.0066
Observations	109,335	108,672	107,767	102,129	96,552
	Panel B: 2023-2024				
High C	0.286**	0.914**	1.820**	2.799**	3.660**
	(2.01)	(2.28)	(2.31)	(2.25)	(2.06)
D^{Large}	0.030	0.249	0.645	0.728	0.980
	(0.26)	(0.75)	(1.00)	(0.71)	(0.68)
Adjusted R-squared	0.0077	0.0070	0.0039	0.0042	0.0025
Observations	39,846	39,627	39,350	34,301	29,294

A.10. Controlling for the AI tech boom

Table A.18

Large-cap growth funds' performance drag (Carhart + AI-sector factor)

This table reports coefficients from OLS regressions of

$$\text{Ret(FF4+AIQ)}_{f,t+h}(\%) = \beta_0 + \beta_1 D^{B<0}_{f,t} + \beta_2 D^{0\leq B<5}_{f,t} + \gamma_f + \epsilon_{f,t+h}.$$

The dependent variable $\text{Ret(FF4+AIQ)}_{f,t+h}$ is the cumulative risk-adjusted return for fund f over horizons $h = 1, 2, 3, 4, 5, 6, 9,$ and 12 months following quarter t, computed from the Carhart four-factor model augmented with the return on the Global X Artificial Intelligence & Technology ETF (AIQ) as a fifth factor; the construction follows Appendix A.7. The indicator $D^{B<0}_{f,t}$ equals one if $\text{Buffer}_{f,t} < 0$ and zero otherwise; $D^{0\leq B<5}_{f,t}$ is defined analogously. The regression sample consists of large-cap growth funds. Fund fixed effects γ_f absorb any time-invariant differences across funds within this segment. We cluster standard errors at the fund level and report t-statistics in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Return horizon							
	1M	2M	3M	4M	5M	6M	9M	12M
				Panel A: 2019-2024				
Buffer<0	-0.224	0.002	-0.194	-0.403	-0.455	-0.308	-0.979	-0.486
	(-1.52)	(0.01)	(-0.72)	(-1.01)	(-1.00)	(-0.57)	(-1.25)	(-0.41)
0≤Buffer<5	-0.229***	-0.421***	-0.366***	-0.671***	-0.734***	-0.526***	-0.761**	-0.742*
	(-3.03)	(-3.80)	(-2.86)	(-4.44)	(-4.27)	(-2.60)	(-2.49)	(-1.68)
Adjusted R-squared	-0.0067	-0.0087	-0.0095	0.0103	0.0241	0.0410	0.0846	0.1273
Observations	5,866	5,861	5,862	5,858	5,845	5,828	5,786	5,469
				Panel B: 2023-2024				
Buffer<0	-0.805***	-0.916***	-1.567***	-2.084***	-2.554***	-2.706***	-4.812***	-6.369***
	(-5.62)	(-3.59)	(-6.79)	(-6.37)	(-6.58)	(-6.83)	(-10.37)	(-9.92)
0≤Buffer<5	-0.507***	-0.833***	-0.990***	-1.513***	-1.761***	-1.863***	-3.198***	-4.028***
	(-5.06)	(-5.47)	(-5.73)	(-7.70)	(-7.77)	(-7.22)	(-9.65)	(-8.69)
Adjusted R-squared	-0.0039	0.0005	-0.0178	0.0351	0.0636	0.0920	0.1750	0.2614
Observations	2,229	2,226	2,228	2,227	2,221	2,216	2,198	1,901

Table A.19
Stock return predictability (Carhart + AI-sector factor)

This table re-estimates the regressions of Table 8 after augmenting the Carhart four-factor model with the return on the Global X Artificial Intelligence & Technology ETF (AIQ) as a fifth factor. The dependent variable is the resulting five-factor risk-adjusted cumulative return over 1, 3, 6, 9, and 12 months following month t. Each month, stocks are sorted into *High C* ($C_{s,t} > 0$) and *Low C* ($C_{s,t} = 0$) groups. $C_{s,t}$ represents the proportion of stock shares held by funds with a buffer less than 5% and a position weight greater than 5%. *High Vol*$_{s,t}$ equals 1 if *Volatility*$_{s,t}$ exceeds the cross-sectional median. The regression sample includes stocks with prices above $5 that fall in the cross-sectional top 50% by market capitalization, yielding 2,806 unique stocks in total. We include year–month fixed effects, cluster standard errors at the stock level, and report t-statistics in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Return horizon					Return horizon				
	1M	3M	6M	9M	12M	1M	3M	6M	9M	12M
					Panel A: 2019–2024					
High C	0.134*	0.413*	0.931**	1.778***	2.596***	0.167**	0.556***	0.882**	1.500***	1.785**
	(1.71)	(1.88)	(2.13)	(2.62)	(2.78)	(2.36)	(2.85)	(2.41)	(2.74)	(2.42)
High C × High Vol						-0.133	-0.645	-0.346	-0.067	1.232
						(-0.67)	(-1.20)	(-0.32)	(-0.04)	(0.54)
High Vol						-0.050	-0.315*	-0.803**	-1.481***	-2.072***
						(-0.84)	(-1.88)	(-2.47)	(-3.02)	(-3.11)
Adjusted R-squared	0.0102	0.0101	0.0087	0.0084	0.0078	0.0102	0.0102	0.0089	0.0089	0.0084
Observations	109,335	108,672	107,767	102,129	96,552	109,335	108,672	107,767	102,129	96,552
					Panel B: 2023–2024					
High C	0.363***	1.237***	2.496***	3.657***	4.850***	0.122	0.683**	1.031*	1.938**	2.426*
	(3.02)	(3.76)	(3.76)	(3.48)	(3.20)	(1.12)	(2.26)	(1.75)	(2.04)	(1.80)
High C × High Vol						0.580**	1.264*	3.339**	3.598*	5.033
						(2.06)	(1.73)	(2.30)	(1.65)	(1.57)
High Vol						-0.239**	-0.672**	-1.797***	-2.692***	-3.931***
						(-2.30)	(-2.26)	(-3.12)	(-2.89)	(-2.96)
Adjusted R-squared	0.0091	0.0084	0.0054	0.0053	0.0036	0.0092	0.0087	0.0066	0.0068	0.0056
Observations	39,846	39,627	39,350	34,301	29,294	39,846	39,627	39,350	34,301	29,294

A.11. Implementability of trading strategies

Table A.20
Investment strategy: lagged C

This table reports annualized daily alphas (%) from the Carhart four-factor model. $C_{s,t}$ represents the proportion of stock shares held by funds with a buffer less than 5% and a position weight greater than 5%. The *Single-sort* column presents results from sorting stocks each month into two groups based on $C_{s,t-3}$: a High C group with C above 0, and a Low C group with C = 0. We form two value-weighted portfolios and hold them for one year. *Double-sort with volatility* columns present results from independently sorting stocks each month into two volatility groups and the same two C groups, forming 2×2 value-weighted portfolios held for one year. The sample includes stocks priced above $5 and, within each month, the largest 50% of stocks by market capitalization, resulting in 2,806 stocks. We report Newey–West t-statistics using a five-day lag in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Single-sort	Double-sort with volatility	
		High Vol	Low Vol
		Panel A: 2019-2024	
High C	1.65*	9.74**	-1.14
	(1.71)	(2.12)	(-0.70)
Low C	-1.60	-0.59	-1.92
	(-0.87)	(-0.19)	(-0.83)
		Panel B: 2023-2024	
High C	2.23**	10.93*	-1.31
	(2.19)	(1.84)	(-0.53)
Low C	-1.75	-1.27	-1.94
	(-0.78)	(-0.39)	(-0.63)

A.12. Active funds

Table A.21
Changes in active funds' large positions

This table presents coefficients from OLS regressions of

$$\Delta \text{Weight}_{f,s,t+1} = \beta_0 + \beta_1 D^{W>5}_{f,s,t} + \beta_2 D^{B<0}_{f,t} + \beta_3 D^{0\leq B<5}_{f,t} + \beta_4 (D^{W>5}_{f,s,t} \times D^{B<0}_{f,t}) + \beta_5 (D^{W>5}_{f,s,t} \times D^{0\leq B<5}_{f,t}) + \epsilon_{f,s,t+1}.$$

The weight indicator, D^W, is based on $\text{Weight}_{f,s,t}$ (%). Buffer indicators, D^B, are based on $\text{Buffer}_{f,t}$ (%). The regression sample focuses on active funds and includes stocks with prices above $5 and, within each fiscal quarter, the largest 50% of stocks by market capitalization, resulting in 2,806 stocks. Standard errors are clustered at the stock level, and t-statistics are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. Q denotes fiscal quarter.

			Panel A: 2019-2024		
5<W × Buffer<0	-0.071*	-0.072*	-0.041	-0.073***	-0.070**
	(-1.91)	(-1.92)	(-1.53)	(-2.87)	(-2.44)
5<W × 0≤Buffer<5	-0.044	-0.046	-0.016	-0.026	-0.021
	(-1.12)	(-1.15)	(-0.69)	(-1.17)	(-0.90)
5<W	-0.118***	-0.118***	-0.166***	-0.148***	-0.141***
	(-4.32)	(-4.30)	(-9.25)	(-9.36)	(-8.89)
Fixed Effects	No	Q	Q×Stock	Q×Stock + Fund	Q×Stock + Q×Fund
Adjusted R-squared	0.0024	0.0030	0.1484	0.1737	0.2104
Observations	5,528,105	5,528,105	5,528,105	5,528,105	5,528,105
			Panel B: 2023-2024		
5<W × Buffer<0	-0.070*	-0.071*	-0.040	-0.086***	-0.080***
	(-1.90)	(-1.91)	(-1.49)	(-3.44)	(-2.90)
5<W × 0≤Buffer<5	-0.033	-0.034	-0.017	-0.030	-0.024
	(-0.78)	(-0.81)	(-0.63)	(-1.12)	(-0.85)
5<W	-0.101***	-0.101***	-0.156***	-0.133***	-0.129***
	(-4.25)	(-4.21)	(-9.96)	(-8.88)	(-8.49)
Fixed Effects	No	Q	Q×Stock	Q×Stock + Fund	Q×Stock + Q×Fund
Adjusted R-squared	0.0022	0.0026	0.1550	0.1866	0.2146
Observations	2,106,250	2,106,250	2,106,250	2,106,250	2,106,250

Table A.22
Changes in active funds' positions and volatility

This table presents coefficients from OLS regressions of

$$\Delta \text{Weight}_{f,s,t+1} = \gamma_0 + \gamma_1 \text{Weight}_{f,s,t} + \gamma_2 \text{Volatility}_{s,t} + \gamma_3(\text{Weight}_{f,s,t} \times \text{Volatility}_{s,t}) + \varphi_{f,s,t+1}.$$

We define $\text{Volatility}_{s,t}$ (%) as the standard deviation of daily returns within the corresponding fiscal quarter. The regression sample focuses on active funds and includes stocks with prices above $5 and, within each fiscal quarter, the largest 50% of stocks by market capitalization, resulting in 2,806 stocks. Standard errors are clustered at the stock level, and t-statistics are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. Q denotes fiscal quarter.

	Panel A: 2019-2024				
Weight	-0.017***	-0.017***	-0.028***	-0.038***	-0.031***
	(-2.76)	(-2.68)	(-8.35)	(-7.21)	(-5.90)
Weight × Volatility	-0.008***	-0.008***	-0.009***	-0.007***	-0.009***
	(-3.66)	(-3.60)	(-6.70)	(-5.40)	(-5.36)
Fixed Effects	No	Q	Q×Stock	Q×Stock + Fund	Q×Stock + Q×Fund
Adjusted R-squared	0.0199	0.0206	0.1709	0.1880	0.2233
Observations	5,528,105	5,528,105	5,528,105	5,528,105	5,528,105
	Panel B: 2023-2024				
Weight	-0.026***	-0.026***	-0.024***	-0.032***	-0.030***
	(-2.88)	(-2.88)	(-5.38)	(-6.73)	(-6.55)
Weight × Volatility	-0.002	-0.002	-0.011***	-0.008***	-0.008***
	(-0.37)	(-0.36)	(-4.10)	(-3.06)	(-3.12)
Fixed Effects	No	Q	Q×Stock	Q×Stock + Fund	Q×Stock + Q×Fund
Adjusted R-squared	0.0158	0.0162	0.1765	0.1984	0.2254
Observations	2,106,250	2,106,250	2,106,250	2,106,250	2,106,250

Table A.23
Changes in constrained and negative-buffer active funds' positions and volatility

This table reports coefficients from OLS regressions run separately for active funds with $\text{Buffer}_{f,t} < 0$ and $0 \leq \text{Buffer}_{f,t} < 5\%$:

$$\Delta\text{Weight}_{f,s,t+1} = \delta_0 + \delta_1(D^{W>6}_{f,s,t} \times \text{Volatility}_{s,t}) + \delta_2(D^{5<W\leq 6}_{f,s,t} \times \text{Volatility}_{s,t}) + \delta_3(D^{4<W\leq 5}_{f,s,t} \times \text{Volatility}_{s,t}) + \delta_4 D^{W>6}_{f,s,t} + \delta_5 D^{5<W\leq 6}_{f,s,t} + \delta_6 D^{4<W\leq 5}_{f,s,t} + \delta_7\text{Volatility}_{s,t} + \eta_{f,s,t+1}.$$

Weight indicators are based on $\text{Weight}_{f,s,t}$ (%). $\text{Volatility}_{s,t}$ (%) is the standard deviation of daily returns within the corresponding fiscal quarter. The sample focuses on active funds and includes stocks with prices above \$5 and, within each fiscal quarter, the largest 50% of stocks by market capitalization, resulting in 2,806 stocks. Standard errors are clustered at the stock level, and t-statistics are reported in parentheses. ***, **, and * denote significance at 1%, 5%, and 10% levels. Q denotes fiscal quarter.

	Buffer < 0					0 ≤ Buffer < 5%				
	Panel A: 2019-2024									
6<W × Volatility	-0.040*	-0.041	-0.065*	-0.055	-0.055	0.019	0.021	-0.018	-0.009	-0.016
	(-1.68)	(-1.64)	(-1.77)	(-1.47)	(-1.37)	(0.68)	(0.71)	(-0.64)	(-0.33)	(-0.54)
5<W≤6 × Volatility	-0.015	-0.017	-0.071**	-0.067*	-0.048	-0.078***	-0.078***	-0.076***	-0.071***	-0.064**
	(-0.59)	(-0.67)	(-2.13)	(-1.78)	(-1.41)	(-3.59)	(-3.58)	(-2.72)	(-2.62)	(-2.11)
4<W≤5 × Volatility	-0.014	-0.017	-0.021	-0.001	0.004	-0.026*	-0.026*	-0.023	-0.015	-0.020
	(-0.66)	(-0.77)	(-0.60)	(-0.02)	(0.12)	(-1.82)	(-1.73)	(-1.17)	(-0.76)	(-0.99)
Fixed Effects	No	Q	Q×Stock	Q×Stock + Fund	Q×Stock + Q×Fund	No	Q	Q×Stock	Q×Stock + Fund	Q×Stock + Q×Fund
Adjusted R-squared	0.0265	0.0326	0.4927	0.5171	0.5666	0.0164	0.0189	0.3893	0.4137	0.4327
Observations	16,707	16,707	16,707	16,707	16,707	39,858	39,858	39,858	39,858	39,858
	Panel B: 2023-2024									
6<W × Volatility	0.030	0.032	-0.084*	-0.060	-0.083*	0.103***	0.105***	-0.009	0.011	0.008
	(0.87)	(0.93)	(-1.75)	(-1.18)	(-1.67)	(3.21)	(3.26)	(-0.22)	(0.27)	(0.19)
5<W≤6 × Volatility	-0.125**	-0.122**	-0.136***	-0.122**	-0.149***	-0.102***	-0.101***	-0.104**	-0.081*	-0.079*
	(-2.25)	(-2.23)	(-2.62)	(-2.32)	(-2.82)	(-2.95)	(-2.95)	(-2.46)	(-1.89)	(-1.70)
4<W≤5 × Volatility	-0.016	-0.013	-0.064	-0.067*	-0.088**	-0.006	-0.005	-0.001	0.004	-0.008
	(-0.41)	(-0.33)	(-1.60)	(-1.72)	(-2.32)	(-0.18)	(-0.17)	(-0.04)	(0.14)	(-0.29)
Fixed Effects	No	Q	Q×Stock	Q×Stock + Fund	Q×Stock + Q×Fund	No	Q	Q×Stock	Q×Stock + Fund	Q×Stock + Q×Fund
Adjusted R-squared	0.0249	0.0271	0.4997	0.5326	0.5560	0.0164	0.0176	0.3791	0.4071	0.4190
Observations	9,959	9,959	9,959	9,959	9,959	26,155	26,155	26,155	26,155	26,155

Table A.24
Changes in active funds' equity exposure

This table reports estimates from regressions relating active funds' buffers, $\text{Buffer}_{f,t}$, to changes in equity exposure. $\Delta\text{EE}_{f,t\to t+1}$ denotes the change in fund f's equity exposure between fiscal quarters t and $t+1$. Active-$\Delta\text{EE}_{f,t\to t+1}$ isolates the component of this change attributable to active portfolio rebalancing, after netting out passive changes driven by stock returns. The indicator $D^{B<0}_{f,t}$ equals one if $\text{Buffer}_{f,t} < 0$ and zero otherwise; $D^{0\leq B<5}_{f,t}$ is defined analogously. Control variables, measured at quarter t for each fund, include the log of the total net assets, the log of return standard deviation, net flow, and gross return. Standard errors are clustered by fiscal quarter and fund, and t-statistics are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels. Q denotes fiscal quarter.

	ΔEE (%)				Active-ΔEE (%)			
Panel A: 2019-2024								
Buffer<0	-0.656***	-0.667***	-1.467***	-1.429***	-0.629***	-0.630***	-1.514***	-1.481***
	(-3.59)	(-3.81)	(-4.50)	(-4.28)	(-3.74)	(-3.98)	(-5.24)	(-5.03)
0≤Buffer<5	-0.233***	-0.234***	-0.570***	-0.541***	-0.179**	-0.196**	-0.579***	-0.554***
	(-2.91)	(-3.44)	(-5.46)	(-4.72)	(-2.16)	(-2.50)	(-4.97)	(-4.49)
Fixed Effects	No	Q	Q+Fund	Q+Fund	No	Q	Q+Fund	Q+Fund
Controls	No	No	No	Yes	No	No	No	Yes
Adjusted R-squared	0.0004	0.0176	-0.0152	-0.0133	0.0004	0.0179	0.0005	0.0015
Observations	53,895	53,895	53,895	53,895	53,895	53,895	53,895	53,895
Panel B: 2023-2024								
Buffer<0	-0.467**	-0.473**	-1.409***	-1.332***	-0.344**	-0.346**	-1.161***	-1.188***
	(-2.52)	(-2.55)	(-3.27)	(-2.97)	(-2.23)	(-2.28)	(-4.11)	(-4.21)
0≤Buffer<5	-0.184**	-0.151**	-0.512***	-0.452***	-0.185**	-0.156*	-0.450***	-0.461***
	(-2.16)	(-2.16)	(-4.36)	(-3.25)	(-2.21)	(-1.94)	(-3.33)	(-3.21)
Fixed Effects	No	Q	Q+Fund	Q+Fund	No	Q	Q+Fund	Q+Fund
Controls	No	No	No	Yes	No	No	No	Yes
Adjusted R-squared	0.0003	0.0052	-0.0815	-0.0758	0.0003	0.0060	-0.0557	-0.0505
Observations	20,541	20,541	20,541	20,541	20,541	20,541	20,541	20,541

Table A.25
Active large-cap growth funds' performance drag

This table reports estimates from OLS regressions relating fund performance to buffer indicators:

$$\text{Ret(FF4)}_{f,t+h}(\%) = \delta_0 + \delta_1 D^{B<0}_{f,t} + \delta_2 D^{0\leq B<5}_{f,t} + \gamma_f + \varphi_{f,t+h}.$$

The dependent variable $\text{Ret(FF4)}_{f,t+h}$ is the cumulative Carhart four-factor risk-adjusted returns for fund f over horizons $h = 1, 2, 3, 4, 5, 6, 9,$ and 12 months following quarter t. The indicator $D^{B<0}_{f,t}$ equals one if $\text{Buffer}_{f,t} < 0$ and zero otherwise; $D^{0\leq B<5}_{f,t}$ is defined analogously. The regression sample consists of active large-cap growth funds. Fund fixed effects γ_f absorb time-invariant differences across funds within this segment. We cluster standard errors at the fund level and report t-statistics in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Return horizon							
	1M	2M	3M	4M	5M	6M	9M	12M
	Panel A: 2019-2024							
Buffer<0	-0.354*	-0.313	-0.461	-0.768*	-0.943**	-0.500	-0.863	-0.345
	(-1.82)	(-1.36)	(-1.63)	(-1.82)	(-2.18)	(-0.92)	(-1.20)	(-0.30)
0≤Buffer<5	-0.287***	-0.783***	-0.673***	-0.983***	-1.136***	-0.801***	-0.630	-0.624
	(-2.90)	(-5.53)	(-4.18)	(-4.82)	(-5.23)	(-3.00)	(-1.56)	(-1.03)
Adjusted R-squared	0.0001	-0.0034	-0.0140	0.0092	0.0146	0.0232	0.0602	0.0872
Observations	4,854	4,850	4,851	4,848	4,836	4,821	4,781	4,518
	Panel B: 2023-2024							
Buffer<0	-1.020***	-1.556***	-2.160***	-3.018***	-3.436***	-3.395***	-5.242***	-7.425***
	(-5.58)	(-6.06)	(-9.21)	(-9.16)	(-8.57)	(-7.48)	(-12.01)	(-9.51)
0≤Buffer<5	-0.664***	-1.511***	-1.661***	-2.425***	-2.666***	-2.753***	-3.879***	-5.221***
	(-4.91)	(-7.61)	(-7.98)	(-9.22)	(-9.37)	(-8.87)	(-9.78)	(-9.07)
Adjusted R-squared	-0.0276	-0.0003	-0.0165	0.0176	0.0300	0.0626	0.1337	0.2264
Observations	1,816	1,814	1,815	1,814	1,809	1,803	1,786	1,543

Table A.26
Components of active funds' performance drag

This table presents the sources of underperformance for constrained and negative-buffer active funds. The exposure-adjustment effect captures the performance effect of adjusting total equity exposure while keeping the within-equity portfolio weights unchanged. The large-position rebalancing effect isolates the effect of rebalancing large positions ($\text{Weight}_{f,s,t} > 5\%$) while keeping both the total equity exposure and non-large positions fixed. The mean is the annualized equal-weighted average of performance drags across funds. The impact, measured in billions of USD, represents the dollar value of the performance drag, scaled by funds' total assets. For 2019–2024, the number of fund–quarter observations with $0 \leq \text{Buffer}_{f,t} < 5\%$ is 1,075, whereas the number of observations with $\text{Buffer}_{f,t} < 0$ is 613. For 2023–2024, the number of fund–quarter observations with $0 \leq \text{Buffer}_{f,t} < 5\%$ is 621, and the number of observations with $\text{Buffer}_{f,t} < 0$ is 313. We report t-statistics in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels.

	$0 \leq$ Buffer $< 5\%$		Buffer < 0	
	Mean (%)	Impact ($B)	Mean (%)	Impact ($B)
		Panel A: 2019-2024		
Exposure adjustment	-0.067	-0.365	-0.066	0.009
	(-1.00)		(-0.77)	
Large-position rebalancing	-0.173**	-0.386	-0.269***	-0.065
	(-2.14)		(-2.87)	
		Panel B: 2023-2024		
Exposure adjustment	-0.115**	-0.428	-0.066	-0.325
	(-2.45)		(-0.72)	
Large-position rebalancing	-0.215**	-1.041	-0.098	0.032
	(-2.27)		(-1.46)	

Table A.27
Stock return predictability (active funds)

This table presents the ability of constrained active ownership share $C_{s,t}$ to predict stock returns adjusted for the Carhart four risk factors. The dependent variable is the risk-adjusted cumulative return over 1, 3, 6, 9, and 12 months following month t. Each month t, we sort stocks into 2 groups: *High C* stocks with $C_{s,t} > 0$, and *Low C* stocks with $C_{s,t} = 0$. $C_{s,t}$ represents the proportion of stock shares held by active funds with a buffer less than 5% and a position weight greater than 5%. We define $High\ Vol_{s,t}$ as an indicator equal to 1 if $Volatility_{s,t}$ exceeds the cross-sectional median across all stocks, and 0 otherwise. The regression sample includes stocks with prices above $5 and, within each month, the largest 50% of stocks by market capitalization, resulting in 2,806 stocks. We include year–month fixed effects, cluster standard errors at the stock level, and report t-statistics in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Return horizon					Return horizon				
	1M	3M	6M	9M	12M	1M	3M	6M	9M	12M
					Panel A: 2019-2024					
High C	0.138*	0.332	0.852*	1.384*	2.066**	0.083	0.223	0.275	0.485	0.704
	(1.65)	(1.41)	(1.81)	(1.86)	(2.01)	(1.08)	(1.08)	(0.71)	(0.84)	(0.90)
High C × High Vol						0.133	0.201	1.545	2.476	4.009
						(0.63)	(0.34)	(1.32)	(1.34)	(1.57)
High Vol						-0.065	-0.226	-0.448	-0.634	-0.662
						(-1.09)	(-1.37)	(-1.40)	(-1.31)	(-1.01)
Adjusted R-squared	0.0098	0.0092	0.0078	0.0071	0.0063	0.0097	0.0092	0.0079	0.0072	0.0065
Observations	109,335	108,672	107,767	102,129	96,552	109,335	108,672	107,767	102,129	96,552
					Panel B: 2023-2024					
High C	0.298**	1.087***	2.475***	3.262***	4.640***	0.031	0.438	0.652	1.090	1.311
	(2.35)	(3.14)	(3.50)	(2.90)	(2.86)	(0.27)	(1.43)	(1.08)	(1.11)	(0.93)
High C × High Vol						0.728**	1.762**	4.842***	5.620**	8.880**
						(2.44)	(2.26)	(3.12)	(2.40)	(2.57)
High Vol						-0.103	-0.271	-0.962*	-1.575*	-2.332*
						(-1.00)	(-0.93)	(-1.69)	(-1.70)	(-1.78)
Adjusted R-squared	0.0077	0.0069	0.0039	0.0039	0.0024	0.0078	0.0072	0.0049	0.0048	0.0038
Observations	39,846	39,627	39,350	34,301	29,294	39,846	39,627	39,350	34,301	29,294

A.13. Passive funds

Table A.28
Changes in passive funds' large positions

This table presents coefficients from OLS regressions of

$$\Delta \text{Weight}_{f,s,t+1} = \beta_0 + \beta_1 D^{W>5}_{f,s,t} + \beta_2 D^{B<0}_{f,t} + \beta_3 D^{0\leq B<5}_{f,t} + \beta_4 (D^{W>5}_{f,s,t} \times D^{B<0}_{f,t}) + \beta_5 (D^{W>5}_{f,s,t} \times D^{0\leq B<5}_{f,t}) + \epsilon_{f,s,t+1}.$$

The weight indicator, D^W, is based on $\text{Weight}_{f,s,t}$ (%). Buffer indicators, D^B, are based on $\text{Buffer}_{f,t}$ (%). The regression sample focuses on passive funds and includes stocks with prices above \$5 and, within each fiscal quarter, the largest 50% of stocks by market capitalization, resulting in 2,806 stocks. Standard errors are clustered at the stock level, and t-statistics are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. Q denotes fiscal quarter.

	Panel A: 2019-2024				
5<W × Buffer<0	-0.158***	-0.158***	-0.112***	-0.119***	-0.104***
	(-3.23)	(-3.24)	(-2.85)	(-3.24)	(-2.66)
5<W × 0≤Buffer<5	-0.152***	-0.153***	-0.114***	-0.115***	-0.114***
	(-3.58)	(-3.61)	(-3.68)	(-4.14)	(-3.77)
5<W	-0.119***	-0.119***	-0.159***	-0.155***	-0.150***
	(-3.65)	(-3.65)	(-6.96)	(-8.36)	(-8.03)
Fixed Effects	No	Q	Q×Stock	Q×Stock + Fund	Q×Stock + Q×Fund
Adjusted R-squared	0.0039	0.0045	0.1302	0.1836	0.2519
Observations	5,985,814	5,985,814	5,985,814	5,985,814	5,985,814
	Panel B: 2023-2024				
5<W × Buffer<0	-0.157***	-0.158***	-0.129***	-0.134***	-0.107**
	(-2.89)	(-2.90)	(-2.64)	(-2.78)	(-2.10)
5<W × 0≤Buffer<5	-0.155***	-0.155***	-0.134***	-0.139***	-0.144***
	(-3.17)	(-3.18)	(-3.59)	(-3.98)	(-4.10)
5<W	-0.106***	-0.106***	-0.137***	-0.139***	-0.133***
	(-5.58)	(-5.57)	(-7.79)	(-10.39)	(-10.05)
Fixed Effects	No	Q	Q×Stock	Q×Stock + Fund	Q×Stock + Q×Fund
Adjusted R-squared	0.0038	0.0044	0.1298	0.1924	0.2582
Observations	2,248,620	2,248,620	2,248,620	2,248,620	2,248,620

Table A.29
Changes in passive funds' positions and volatility

This table presents coefficients from OLS regressions of

$$\Delta \text{Weight}_{f,s,t+1} = \gamma_0 + \gamma_1 \text{Weight}_{f,s,t} + \gamma_2 \text{Volatility}_{s,t} + \gamma_3 (\text{Weight}_{f,s,t} \times \text{Volatility}_{s,t}) + \varphi_{f,s,t+1}.$$

We define $\text{Volatility}_{s,t}$ (%) as the standard deviation of daily returns within the corresponding fiscal quarter. The regression sample focuses on passive funds and includes stocks with prices above $5 and, within each fiscal quarter, the largest 50% of stocks by market capitalization, resulting in 2,806 stocks. Standard errors are clustered at the stock level, and t-statistics are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. Q denotes fiscal quarter.

	Panel A: 2019-2024				
Weight	-0.010**	-0.010**	-0.018***	-0.020***	-0.010***
	(-2.48)	(-2.43)	(-6.14)	(-5.17)	(-3.31)
Weight × Volatility	-0.010***	-0.010***	-0.011***	-0.011***	-0.014***
	(-5.12)	(-5.09)	(-11.65)	(-10.27)	(-9.62)
Fixed Effects	No	Q	Q×Stock	Q×Stock + Fund	Q×Stock + Q×Fund
Adjusted R-squared	0.0273	0.0279	0.1596	0.1985	0.2651
Observations	5,985,814	5,985,814	5,985,814	5,985,814	5,985,814
	Panel B: 2023-2024				
Weight	-0.017**	-0.017**	-0.012**	-0.011**	-0.009*
	(-2.00)	(-1.99)	(-2.36)	(-2.43)	(-1.93)
Weight × Volatility	-0.006	-0.006	-0.015***	-0.015***	-0.015***
	(-1.03)	(-1.02)	(-4.77)	(-4.17)	(-4.13)
Fixed Effects	No	Q	Q×Stock	Q×Stock + Fund	Q×Stock + Q×Fund
Adjusted R-squared	0.0219	0.0223	0.1577	0.2047	0.2685
Observations	2,248,620	2,248,620	2,248,620	2,248,620	2,248,620

Table A.30

Changes in constrained and negative-buffer passive funds' positions and volatility

This table reports coefficients from OLS regressions run separately for passive funds with $\text{Buffer}_{f,t} < 0$ and $0 \leq \text{Buffer}_{f,t} < 5\%$:

$$\Delta\text{Weight}_{f,s,t+1} = \delta_0 + \delta_1(D^{W>6}_{f,s,t} \times \text{Volatility}_{s,t}) + \delta_2(D^{5<W\leq 6}_{f,s,t} \times \text{Volatility}_{s,t}) + \delta_3(D^{4<W\leq 5}_{f,s,t} \times \text{Volatility}_{s,t}) + \delta_4 D^{W>6}_{f,s,t} + \delta_5 D^{5<W\leq 6}_{f,s,t} + \delta_6 D^{4<W\leq 5}_{f,s,t} + \delta_7 \text{Volatility}_{s,t} + \eta_{f,s,t+1}$$

Weight indicators are based on $\text{Weight}_{f,s,t}$ (%). $\text{Volatility}_{s,t}$ (%) is the standard deviation of daily returns within the corresponding fiscal quarter. The sample focuses on passive funds and includes stocks with prices above $5 and, within each fiscal quarter, the largest 50% of stocks by market capitalization, resulting in 2,806 stocks. Standard errors are clustered at the stock level, and t-statistics are reported in parentheses. ***, **, and * denote significance at 1%, 5%, and 10% levels. Q denotes fiscal quarter.

	Buffer < 0					0 ≤ Buffer < 5%				
	Panel A: 2019-2024									
6<W × Volatility	-0.109***	-0.113***	-0.281***	-0.319***	-0.315***	-0.027	-0.028	-0.071	-0.089	-0.109**
	(-2.75)	(-2.80)	(-4.43)	(-4.49)	(-4.50)	(-0.94)	(-0.95)	(-1.30)	(-1.58)	(-2.39)
5<W≤6 × Volatility	-0.067**	-0.073***	0.146**	0.137	0.136*	-0.055*	-0.052	-0.213***	-0.233***	-0.236***
	(-2.43)	(-2.88)	(1.99)	(1.61)	(1.68)	(-1.73)	(-1.59)	(-3.24)	(-2.89)	(-2.92)
4<W≤5 × Volatility	-0.035	-0.032	0.059	0.076	0.074	-0.061***	-0.056***	-0.064**	-0.065*	-0.073**
	(-0.92)	(-0.83)	(1.05)	(1.11)	(1.11)	(-3.21)	(-3.01)	(-2.16)	(-1.96)	(-2.10)
Fixed Effects	No	Q	Q×Stock	Q×Stock + Fund	Q×Stock + Q×Fund	No	Q	Q×Stock	Q×Stock + Fund	Q×Stock + Q×Fund
Adjusted R-squared	0.0670	0.0858	0.6613	0.6866	0.6847	0.0556	0.0584	0.4509	0.4704	0.5097
Observations	4,972	4,972	4,972	4,972	4,972	40,459	40,459	40,459	40,459	40,459
	Panel B: 2023-2024									
6<W × Volatility	-0.009	-0.012	-0.825	-1.339**	-1.306**	0.025	0.023	-0.224**	-0.234***	-0.234***
	(-0.11)	(-0.14)	(-1.62)	(-2.05)	(-2.19)	(0.53)	(0.49)	(-2.48)	(-2.64)	(-2.87)
5<W≤6 × Volatility	-0.034	-0.048	-0.160	-0.037	-0.051	-0.178*	-0.179*	-0.247***	-0.268***	-0.263***
	(-0.42)	(-0.59)	(-0.54)	(-0.10)	(-0.14)	(-1.83)	(-1.87)	(-2.70)	(-2.82)	(-2.78)
4<W≤5 × Volatility	-0.053	-0.057	2.036***	1.405	0.900	-0.104***	-0.104***	-0.094**	-0.108***	-0.118***
	(-0.68)	(-0.72)	(3.55)	(1.65)	(0.96)	(-3.73)	(-3.77)	(-2.55)	(-2.68)	(-3.03)
Fixed Effects	No	Q	Q×Stock	Q×Stock + Fund	Q×Stock + Q×Fund	No	Q	Q×Stock	Q×Stock + Fund	Q×Stock + Q×Fund
Adjusted R-squared	0.0543	0.0952	0.7439	0.7600	0.7576	0.0526	0.0540	0.4027	0.4262	0.4564
Observations	2,313	2,313	2,313	2,313	2,313	28,387	28,387	28,387	28,387	28,387

Table A.31
Changes in passive funds' equity exposure

This table reports estimates from regressions relating passive funds' buffers, $\text{Buffer}_{f,t}$, to changes in equity exposure. $\Delta\text{EE}_{f,t\rightarrow t+1}$ denotes the change in fund f's equity exposure between fiscal quarters t and $t+1$. Active-$\Delta\text{EE}_{f,t\rightarrow t+1}$ isolates the component of this change attributable to active portfolio rebalancing, after netting out passive changes driven by stock returns. The indicator $D^{B<0}_{f,t}$ equals one if $\text{Buffer}_{f,t} < 0$ and zero otherwise; $D^{0\leq B<5}_{f,t}$ is defined analogously. Control variables, measured at quarter t for each fund, include the log of the total net assets, the log of return standard deviation, net flow, and gross return. Standard errors are clustered by fiscal quarter and fund, and t-statistics are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels. Q denotes fiscal quarter.

	ΔEE (%)				Active-ΔEE (%)			
Panel A: 2019-2024								
Buffer<0	-1.349**	-1.415**	-2.534***	-2.537***	-0.932***	-0.995***	-1.831***	-1.832***
	(-2.46)	(-2.61)	(-3.30)	(-3.29)	(-2.91)	(-3.12)	(-4.07)	(-4.06)
0≤Buffer<5	-0.425***	-0.447***	-0.907***	-0.900***	-0.321**	-0.341***	-0.717***	-0.716***
	(-2.96)	(-3.19)	(-4.03)	(-4.04)	(-2.61)	(-2.78)	(-3.45)	(-3.46)
Fixed Effects	No	Q	Q+Fund	Q+Fund	No	Q	Q+Fund	Q+Fund
Controls	No	No	No	Yes	No	No	No	Yes
Adjusted R-squared	0.0010	0.0193	-0.0219	-0.0219	0.0006	0.0218	-0.0034	-0.0035
Observations	21,859	21,859	21,859	21,859	21,859	21,859	21,859	21,859
Panel B: 2023-2024								
Buffer<0	-0.694	-0.767	-2.379*	-2.377*	-0.431	-0.481	-1.546*	-1.543*
	(-0.95)	(-1.03)	(-1.81)	(-1.81)	(-0.88)	(-0.97)	(-1.75)	(-1.75)
0≤Buffer<5	-0.377*	-0.375*	-0.864***	-0.888***	-0.217	-0.215	-0.608***	-0.617***
	(-1.96)	(-2.04)	(-3.95)	(-4.09)	(-1.50)	(-1.52)	(-3.21)	(-3.28)
Fixed Effects	No	Q	Q+Fund	Q+Fund	No	Q	Q+Fund	Q+Fund
Controls	No	No	No	Yes	No	No	No	Yes
Adjusted R-squared	0.0005	0.0068	-0.0885	-0.0877	0.0001	0.0064	-0.0656	-0.0644
Observations	8,380	8,380	8,380	8,380	8,380	8,380	8,380	8,380

Table A.32
Passive large-cap growth funds' performance drag

This table reports estimates from OLS regressions relating fund performance to buffer indicators:

$$\text{Ret(FF4)}_{f,t+h}(\%) = \delta_0 + \delta_1 D^{B<0}_{f,t} + \delta_2 D^{0\leq B<5}_{f,t} + \gamma_f + \varphi_{f,t+h}.$$

The dependent variable $\text{Ret(FF4)}_{f,t+h}$ is the cumulative Carhart four-factor risk-adjusted returns for fund f over horizons $h = 1, 2, 3, 4, 5, 6, 9,$ and 12 months following quarter t. The indicator $D^{B<0}_{f,t}$ equals one if $\text{Buffer}_{f,t} < 0$ and zero otherwise; $D^{0\leq B<5}_{f,t}$ is defined analogously. The regression sample consists of passive large-cap growth funds. Fund fixed effects γ_f absorb time-invariant differences across funds within this segment. We cluster standard errors at the fund level and report t-statistics in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Return horizon							
	1M	2M	3M	4M	5M	6M	9M	12M
	Panel A: 2019-2024							
Buffer<0	-0.932**	-2.070***	-1.671***	-2.428***	-3.546***	-2.772***	-3.871***	-3.769***
	(-2.55)	(-3.00)	(-6.18)	(-4.13)	(-3.87)	(-6.40)	(-5.76)	(-5.33)
0≤Buffer<5	-0.325*	-0.280	-0.252	-0.621**	-0.777**	-0.049	-0.518	-0.299
	(-1.90)	(-1.25)	(-1.06)	(-2.46)	(-2.43)	(-0.14)	(-1.31)	(-0.55)
Adjusted R-squared	0.0023	0.0097	-0.0097	0.0269	0.0450	0.0422	0.0746	0.1040
Observations	1,012	1,011	1,011	1,010	1,009	1,007	1,005	951
	Panel B: 2023-2024							
Buffer<0	-0.954*	-2.298**	-2.356***	-3.286***	-3.982***	-3.162***	-5.139***	-4.915***
	(-1.98)	(-2.10)	(-4.29)	(-4.16)	(-3.45)	(-4.16)	(-4.21)	(-7.53)
0≤Buffer<5	-0.213	-0.243	-0.375	-0.709**	-0.677	-0.103	-0.892*	-0.618
	(-0.94)	(-0.83)	(-1.21)	(-2.12)	(-1.63)	(-0.22)	(-1.78)	(-1.07)
Adjusted R-squared	0.0476	0.0125	-0.0632	0.0280	0.0752	0.0670	0.1333	0.2737
Observations	413	412	413	413	412	413	412	358

Table A.33
Components of passive funds' performance drag

This table presents the sources of underperformance for constrained and negative-buffer passive funds. The exposure-adjustment effect captures the performance effect of adjusting total equity exposure while keeping the within-equity portfolio weights unchanged. The large-position rebalancing effect isolates the effect of rebalancing large positions ($\text{Weight}_{f,s,t} > 5\%$) while keeping both the total equity exposure and non-large positions fixed. The mean is the annualized equal-weighted average of performance drags across funds. The impact, measured in billions of USD, represents the dollar value of the performance drag, scaled by funds' total assets. For 2019–2024, the number of fund–quarter observations with $0 \leq \text{Buffer}_{f,t} < 5\%$ is 497, whereas the number of observations with $\text{Buffer}_{f,t} < 0$ is 120. For 2023–2024, the number of fund–quarter observations with $0 \leq \text{Buffer}_{f,t} < 5\%$ is 254, and the number of observations with $\text{Buffer}_{f,t} < 0$ is 50. We report t-statistics in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels.

	$0 \leq$ Buffer $< 5\%$		Buffer < 0	
	Mean (%)	Impact ($B)	Mean (%)	Impact ($B)
		Panel A: 2019-2024		
Exposure adjustment	0.103	0.079	-0.727*	-0.214
	(1.07)		(-1.71)	
Large-position rebalancing	-0.405***	-0.963	-0.246	-0.117
	(-3.01)		(-1.59)	
		Panel B: 2023-2024		
Exposure adjustment	-0.001	0.017	-0.639	0.042
	(-0.01)		(-0.92)	
Large-position rebalancing	-0.365***	-0.471	-0.279*	0.030
	(-2.67)		(-1.80)	

Table A.34
Stock return predictability (passive funds)

This table presents the ability of constrained passive ownership share $C_{s,t}$ to predict stock returns adjusted for the Carhart four risk factors. The dependent variable is the risk-adjusted cumulative return over 1, 3, 6, 9, and 12 months following month t. Each month t, we sort stocks into 2 groups: *High C* stocks with $C_{s,t} > 0$, and *Low C* stocks with $C_{s,t} = 0$. $C_{s,t}$ represents the proportion of stock shares held by passive funds with a buffer less than 5% and a position weight greater than 5%. We define *High Vol*$_{s,t}$ as an indicator equal to 1 if *Volatility*$_{s,t}$ exceeds the cross-sectional median across all stocks, and 0 otherwise. The regression sample includes stocks with prices above $5 and, within each month, the largest 50% of stocks by market capitalization, resulting in 2,806 stocks. We include year–month fixed effects, cluster standard errors at the stock level, and report t-statistics in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Return horizon					Return horizon				
	1M	3M	6M	9M	12M	1M	3M	6M	9M	12M
						Panel A: 2019-2024				
High C	0.021	0.243	1.136	2.681**	3.390**	-0.053	0.197	0.541	1.415	1.266
	(0.16)	(0.62)	(1.49)	(2.28)	(2.12)	(-0.48)	(0.62)	(0.94)	(1.64)	(1.11)
High C × High Vol						0.200	0.005	1.721	3.843	6.728
						(0.53)	(0.01)	(0.81)	(1.18)	(1.56)
High Vol						-0.068	-0.223	-0.386	-0.555	-0.581
						(-1.20)	(-1.40)	(-1.25)	(-1.18)	(-0.90)
Adjusted R-squared	0.0097	0.0092	0.0077	0.0072	0.0063	0.0097	0.0092	0.0078	0.0073	0.0066
Observations	109,335	108,672	107,767	102,129	96,552	109,335	108,672	107,767	102,129	96,552
						Panel B: 2023-2024				
High C	0.197	1.022*	2.474**	4.647**	5.510**	-0.054	0.465	0.751	2.194	2.090
	(1.00)	(1.79)	(2.13)	(2.55)	(2.04)	(-0.28)	(0.86)	(0.74)	(1.34)	(0.93)
High C × High Vol						0.795	1.739	5.277*	7.269*	10.238
						(1.56)	(1.21)	(1.88)	(1.66)	(1.48)
High Vol						-0.064	-0.180	-0.698	-1.300	-1.913
						(-0.64)	(-0.64)	(-1.27)	(-1.47)	(-1.51)
Adjusted R-squared	0.0076	0.0066	0.0031	0.0036	0.0017	0.0076	0.0067	0.0036	0.0043	0.0026
Observations	39,846	39,627	39,350	34,301	29,294	39,846	39,627	39,350	34,301	29,294

A.14. 75/5/10 rule

Table A.35

Diversified funds' performance drag

This table reports estimates from OLS regressions relating fund performance to buffer indicators:

$$\text{Ret(FF4)}_{f,t+h}(\%) = \beta_0 + \beta_1 D_{f,t}^{20\leq B<25} + \beta_2 D_{f,t}^{25\leq B<30} + \gamma_f + \epsilon_{f,t+h}.$$

The dependent variable $\text{Ret(FF4)}_{f,t+h}$ is the cumulative Carhart four-factor risk-adjusted returns for fund f over horizons $h = 1, 2, 3, 4, 5, 6, 9,$ and 12 months following quarter t. The indicator $D_{f,t}^{20\leq B<25}$ equals one if $\text{Buffer}_{f,t} \in [20, 25)\%$, and zero otherwise. $D_{f,t}^{25\leq B<30}$ is defined analogously. The regression sample consists of diversified funds with $\text{Buffer}_{f,t} \geq 20\%$. Fund fixed effects γ_f absorb any time-invariant differences across funds within this segment. We cluster standard errors at the fund level and report t-statistics in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Return horizon							
	1M	2M	3M	4M	5M	6M	9M	12M
				Panel A: 2019-2024				
20≤Buffer<25	0.048	0.140	0.111	-0.054	-0.073	0.038	-0.188	-0.145
	(0.68)	(1.40)	(0.88)	(-0.34)	(-0.38)	(0.18)	(-0.65)	(-0.39)
25≤Buffer<30	-0.020	0.150**	0.183*	0.170	0.191	0.103	0.055	0.039
	(-0.41)	(2.14)	(1.92)	(1.49)	(1.42)	(0.69)	(0.26)	(0.13)
Adjusted R-squared	-0.0149	-0.0063	-0.0020	0.0215	0.0447	0.0551	0.0962	0.1332
Observations	54,903	54,886	54,892	54,769	54,608	54,454	53,989	51,118
				Panel B: 2023-2024				
20≤Buffer<25	0.080	-0.075	-0.227	-0.276	-0.420	-0.485	-0.860**	-1.814***
	(0.71)	(-0.40)	(-1.02)	(-0.99)	(-1.21)	(-1.38)	(-2.00)	(-3.30)
25≤Buffer<30	-0.007	0.070	-0.011	-0.147	-0.464***	-0.678***	-1.117***	-1.852***
	(-0.10)	(0.65)	(-0.08)	(-0.90)	(-2.59)	(-3.67)	(-4.86)	(-6.07)
Adjusted R-squared	-0.0333	-0.0417	-0.0495	0.0101	0.0578	0.1090	0.2600	0.4019
Observations	20,456	20,449	20,453	20,407	20,342	20,306	20,133	17,528

Table A.36
Non-diversified funds' performance drag

This table reports estimates from OLS regressions relating fund performance to buffer indicators:

$$\text{Ret(FF4)}_{f,t+h}(\%) = \beta_0 + \beta_1 D_{f,t}^{20\leq B<25} + \beta_2 D_{f,t}^{25\leq B<30} + \gamma_f + \epsilon_{f,t+h}.$$

The dependent variable $\text{Ret(FF4)}_{f,t+h}$ is the cumulative Carhart four-factor risk-adjusted returns for fund f over horizons $h = 1, 2, 3, 4, 5, 6, 9,$ and 12 months following quarter t. The indicator $D_{f,t}^{20\leq B<25}$ equals one if $\text{Buffer}_{f,t} \in [20, 25)\%$, and zero otherwise. $D_{f,t}^{25\leq B<30}$ is defined analogously. The regression sample consists of non-diversified funds with $\text{Buffer}_{f,t} \geq 20\%$. Fund fixed effects γ_f absorb any time-invariant differences across funds within this segment. We cluster standard errors at the fund level and report t-statistics in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Return horizon							
	1M	2M	3M	4M	5M	6M	9M	12M
				Panel A: 2019-2024				
20≤Buffer<25	0.027	0.267	0.279	0.141	0.254	0.293	0.351	0.138
	(0.17)	(1.12)	(0.88)	(0.38)	(0.63)	(0.67)	(0.57)	(0.17)
25≤Buffer<30	0.297**	0.334*	0.364	0.524*	0.754**	0.516	0.618	0.601
	(2.05)	(1.75)	(1.50)	(1.84)	(2.38)	(1.51)	(1.31)	(0.99)
Adjusted R-squared	-0.0102	-0.0045	-0.0100	0.0262	0.0517	0.0672	0.1121	0.1436
Observations	9,159	9,162	9,152	9,142	9,129	9,080	8,989	8,556
				Panel B: 2023-2024				
20≤Buffer<25	-0.049	0.119	0.355	0.317	0.575	0.359	-0.188	-1.485
	(-0.18)	(0.27)	(0.69)	(0.48)	(0.87)	(0.57)	(-0.17)	(-0.96)
25≤Buffer<30	0.059	-0.003	0.305	0.410	0.889	0.853	0.724	0.052
	(0.23)	(-0.01)	(0.62)	(0.70)	(1.56)	(1.58)	(0.90)	(0.05)
Adjusted R-squared	-0.0378	-0.0420	-0.0784	-0.0181	0.0381	0.0926	0.2291	0.3816
Observations	3,243	3,245	3,243	3,231	3,221	3,206	3,165	2,775

Table A.37
Stock return predictability (75/5/10 rule)

This table presents the ability of constrained ownership share $C_{s,t}$ to predict stock returns adjusted for the Carhart four risk factors. The dependent variable is the risk-adjusted cumulative return over 1, 3, 6, 9, and 12 months following month t. Each month t, we sort stocks into 2 groups: *High C* stocks with $C_{s,t} > 0$, and *Low C* stocks with $C_{s,t} = 0$. $C_{s,t}$ represents the proportion of stock shares held by diversified funds with a buffer $\in [20, 30)\%$ and a position weight greater than 5%. We define $High\ Vol_{s,t}$ as an indicator equal to 1 if $Volatility_{s,t}$ exceeds the cross-sectional median across all stocks, and 0 otherwise. The regression sample includes stocks with prices above $5 and, within each month, the largest 50% of stocks by market capitalization, resulting in 2,806 stocks. We include year–month fixed effects, cluster standard errors at the stock level, and report t-statistics in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Return horizon					Return horizon				
	1M	3M	6M	9M	12M	1M	3M	6M	9M	12M
					Panel A: 2019-2024					
High C	0.165	0.734***	1.313**	1.664**	2.147*	0.000	0.439	0.613	0.958	1.407
	(1.61)	(2.59)	(2.38)	(1.97)	(1.84)	(0.00)	(1.61)	(1.28)	(1.28)	(1.37)
High C × High Vol						0.416*	0.708	1.746	1.719	1.840
						(1.76)	(1.13)	(1.48)	(0.96)	(0.77)
High Vol						-0.084	-0.252	-0.431	-0.559	-0.498
						(-1.43)	(-1.55)	(-1.36)	(-1.16)	(-0.76)
Adjusted R-squared	0.0097	0.0093	0.0078	0.0071	0.0062	0.0098	0.0093	0.0079	0.0072	0.0063
Observations	109,335	108,672	107,767	102,129	96,552	109,335	108,672	107,767	102,129	96,552
					Panel B: 2023-2024					
High C	0.327*	0.779*	1.946**	2.737**	4.019**	0.029	0.457	0.998	1.505	2.655
	(1.95)	(1.66)	(2.28)	(2.06)	(1.98)	(0.17)	(0.99)	(1.24)	(1.19)	(1.42)
High C × High Vol						0.774**	0.803	2.311	2.853	3.038
						(2.05)	(0.80)	(1.30)	(1.06)	(0.73)
High Vol						-0.083	-0.178	-0.674	-1.281	-1.784
						(-0.81)	(-0.62)	(-1.19)	(-1.41)	(-1.38)
Adjusted R-squared	0.0077	0.0066	0.0032	0.0032	0.0016	0.0077	0.0066	0.0034	0.0036	0.0021
Observations	39,846	39,627	39,350	34,301	29,294	39,846	39,627	39,350	34,301	29,294

Table A.38
Investment strategy (75/5/10 rule)

This table reports annualized daily alphas (%) based on the Carhart four-factor model. The *Single-sort* column presents results from sorting stocks each month into two groups based on $C_{s,t}$: a High C group with C above 0, and a Low C group with C = 0. $C_{s,t}$ represents the proportion of stock shares held by diversified funds with a buffer $\in [20, 30)$% and a position weight greater than 5%. We form two value-weighted portfolios and hold them for one year. *Double-sort with volatility* columns present results from independently sorting stocks each month into two volatility groups and the same two C groups, forming 2×2 value-weighted portfolios held for one year. The sample includes stocks priced above $5 and, within each month, the largest 50% of stocks by market capitalization, resulting in 2,806 stocks. We report Newey–West t-statistics using a five-day lag in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Single-sort	Double-sort with volatility	
		High Vol	Low Vol
		Panel A: 2019-2024	
High C	2.56*	10.20**	-0.35
	(1.74)	(2.04)	(-0.20)
Low C	-1.68	-0.38	-2.28
	(-1.01)	(-0.13)	(-1.01)
		Panel B: 2023-2024	
High C	3.64*	14.62**	-1.43
	(1.90)	(2.07)	(-0.51)
Low C	-1.68	-1.63	-1.60
	(-0.75)	(-0.49)	(-0.50)

Table A.39
Investment strategy: lagged C (75/5/10 rule)

This table reports annualized daily alphas (%) from the Carhart four-factor model. The *Single-sort* column presents results from sorting stocks each month into two groups based on $C_{s,t-3}$: a High C group with C above 0, and a Low C group with C = 0. $C_{s,t}$ represents the proportion of stock shares held by diversified funds with a buffer $\in [20, 30)\%$ and a position weight greater than 5%. We form two value-weighted portfolios and hold them for one year. *Double-sort with volatility* columns present results from independently sorting stocks each month into two volatility groups and the same two C groups, forming 2×2 value-weighted portfolios held for one year. The sample includes stocks priced above $5 and, within each month, the largest 50% of stocks by market capitalization, resulting in 2,806 stocks. We report Newey–West t-statistics using a five-day lag in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Single-sort	Double-sort with volatility	
		High Vol	Low Vol
		Panel A: 2019-2024	
High C	2.56	10.26*	-0.59
	(1.62)	(1.86)	(-0.32)
Low C	-1.30	0.24	-2.01
	(-0.76)	(0.08)	(-0.87)
		Panel B: 2023-2024	
High C	2.76	13.90**	-2.02
	(1.46)	(1.97)	(-0.72)
Low C	-1.28	-0.95	-1.42
	(-0.57)	(-0.29)	(-0.45)