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Diversification driven demand for large stock☆

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ABSTRACT

I show that as a portfolio's value concentration increases, actively managed portfolios predictably trim large positions, maintaining a level of practical diversification. This rebalancing channel is concentrated at thresholds implied by regulatory guidelines and by a fund's own risk management histories. Since larger stocks are typically held widely and in large weights, they experience a coordinated contrarian trading demand that originates from this form of risk management. Diversification driven demand captures a novel return-reversal pattern in the large stock portfolios. Compensating this source of demand accentuates momentum returns during the modern sample period (1990 to 2022).

1. Introduction

Institutional risk management typically involves limiting the concentrations of individual issuers and establishing a practical form of portfolio diversification.[1] Trading to maintain these practices can be meaningful to the liquidity and pricing of stocks as more assets are now institutionally held than in any prior period. Amplifying this concern of liquidity demand from institutions, the largest stocks have also substantially increased their share of the equity market value through returns and outperformance, driving portfolio concentrations mechanically to conflict with these same diversification principles. Stocks such as Apple and Microsoft have benchmark weights that surpass the most common risk-management thresholds in active portfolios.[2]

An equity market that increasingly concentrates its value toward a handful of issuers is at odds with an expanding asset management sector that seeks to diversify away from concentrated idiosyncratic risks.

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[1] For instance, a mutual fund advertising as *diversified* is mandated by the Investment Company's Act to hold less than 5 % of its assets is in any single issuer for 75 % of their AUM. According to Morningstar (2023), less than 30 % of funds have elected to be *non-diversified* in the most concentrated Large-Growth Morningstar category, where the largest 3 stocks exceed 20 % of the benchmark index. In other main US Equity Morningstar Categories, the fraction of funds marketed as *non-diversified* are substantially less- between 23 % and 3 %.

[2] As of 2024, Apple and Microsoft both surpass the 5 % of the S&P 500. I find that 67 % of funds that are marketed as *diversified* keep their largest single issuer concentration at a level well below the 5 % limit.

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Institutions are shown to persistently underweight the largest stocks (Blume and Keim, 2017), despite such stocks' perceived benefit to liquidity management and pricing (Falkenstein, 1996; Gompers and Metrick, 2001). How does the conflict between practical diversification and the market driven changes in equity concentration reflect in portfolio management, asset demand, and what are its consequences on stock returns?

In this paper, I examine the typical equity mutual fund portfolio and find that active funds conduct a form of contrarian trading that is consistent with a diversification driven investment process- that is, trading to mechanically reduce the concentration of stocks within a portfolio. As returns drive up value concentrations, active portfolios predictably trim their nominally outsized positions. Unlike the typical behavioral channels of contrarian trading, this quarterly rebalancing is not associated with liquidations, intensifies near a common regulatory threshold, and is related to portfolio characteristics such as historical holdings concentration and diversification mandates. Consistent with composition management, the magnitude of the trading actions indicates trimming, rather than significant whole-sale scale downs or asset rotations. This tendency of active managers to re-diversify against the market driven changes in stock concentration forms a separate, quantitatively impactful, and unexplored, channel of trade predictability distinct from the extensive existing literature on the benchmarking demands of institutions (Buffa et al., 2022; Chang et al., 2014; Greenwood, 2005; Harris and Gurel, 1986; Kaul et al., 2002; Pavlova and Sikorskaya, 2023; Shleifer, 1986).[3]

The drive to diversify concentrated positions aggregates to form net demand from active mutual funds to other market participants on a value-weighted basis. While fund families minimize net trades within their managed portfolios, stocks that are often held widely and in large weights are difficult to net by active funds. An aggregation that predicts this excess demand forecasts trading and stock returns on the largest capitalization stocks[4] - the main foci of this conflict between portfolio diversification and value-concentration- during the modern sample period. I discover a return-reversal pattern that is consistent with this diversification driven demand in the large capitalization stock portfolio during the modern sample period (Q1 1990 to Q4 2022).

In summary, this paper shows that preferences for diversification and risk management from institutional portfolios have substantial effects on trading patterns and return dynamics. Therefore, it is organized into two parts. First, it tests the hypothesis that correlated risk management drives contrarian trading in asset managers. This rebalancing channel by asset managers provides contrast to the standard behavioral channels of contrarian trading in retail investors; and demonstrates the trading effects of pervasive institutional risk management in practice. The second part of the paper then investigates the effect of this asset demand on the pricing of the cross-section of equities; showing the consequences of the preference for practical diversification on return predictability and asset selection.

To test the hypothesis that institutional risk management drives contrarian rebalancing in asset managers, I establish the following facts about predictable trading from institutional portfolios.

The predictable trading based on composition management is asymmetrically related to increases in pre-existing portfolio weights- which are directly increasing in a stock's market capitalization. Active fund managers trim stocks based on compositional changes mainly if these stocks were already relatively large within their portfolios, and- as average weight is directly increasing in market capitalization- this contrarian trading is ends up concentrating in the large capitalization stocks (stocks whose size exceed the 80th percentile of NYSE firms).

This concentration driven rebalancing coincides with common regulatory and institutional guidelines for risk management. The most predictable trading pattern occurs in positions with portfolio weights in the range of 4–6 % of a fund's total AUM- exactly at a range that contains the pervasive 5 % issuer concentration limit prescribed in the asset management industry. Statistical tests of density discontinuities (McCrary, 2008) show that active diversified portfolios manage positions weights to cluster asymmetrically below the 5 % threshold- a feature that is absent for funds not exposed to such guidelines. Larger fund families, presumably with tighter risk management practices, drive the asymmetry at this 5 % threshold.

Lastly, diversified funds with a history of managing their largest positions trade the most against return driven compositional changes, maintaining a tight constraint on the number of outsized positions and keeping these portfolios from mechanically becoming more concentrated. In contrast, variables that proxy lower levels of fund manager bias, such as higher managerial skills and longer tenure length have little explanatory power to these effects. Speculative motives for investing in a stock, as measured by a position's recent initiation, doesn't indicate more contrarian behavior.

The trades to diversify do not net out for large capitalization stocks- stocks whose market values exceed 80 % of firms in the NYSE. While asset management families minimize net trades by reallocating positions across their own funds, this rebalancing channel generates excess demand for stocks that are held widely in large pre-existing weights across funds.[5] Consequently, certain stocks must be sold outside of the fund family and the asset management industry to non-asset managers. A one standard deviation increase (decrease) of 0.22 % of the portfolio weight on average in fund portfolios forecasts a 0.08 % difference in the share of the stock held by active mutual funds.[6]

The second portion of this paper relates this excess demand from risk management and diversification to return predictability. I show that the large stock portfolios during the sample period exhibit a novel return-reversal pattern that exemplifies this resulting tension from portfolio diversification to market returns and can be forecasted by predictors of this excess demand.

Measuring the tendency to rebalance compositional changes, *Rebalancing Demand* is the average return driven change in a stock's portfolio weight across observable mutual funds. A one standard deviation of *Rebalancing Demand* each quarter (as a tendency to sell) predicts -0.44 % ($t = -3.21$) returns within the first 35 trading days and 0.27 % ($t = 2.60$) positive returns during the rest of the trading quarter. Controlling for past momentum and extreme negative past returns, the abnormal return and reversal patterns occur over a longer horizon. A one standard deviation of the predictor variable, while controlling for the past quarter's returns, forecasts -0.56 % ($t = -3.71$) returns within a quarter and a subsequent reversal of 0.67 % ($t = 2.16$) over the rest of the year. While these effects are temporary and modest in magnitudes, they center on the larger stocks in the equity universe (these regressions use market cap weighting, and calendar time portfolios are made using stocks that exceed the 80th percentile breakpoint of the NYSE values) - in stark contrast to the patterns of the extant asset return anomaly literature that centers on smaller and harder to arbitrage stocks (See Muravyev et al.,

[3] Using value-weighted benchmarks as risk-minimizing target portfolios doesn't appear to be implemented in practice (Blume and Keim, 2017), nor is it always practical for active managers. DeMiguel et al. (2009) finds that 1/N portfolio consistently outperforms an assortment of allocation models, including the market portfolio.

[4] Stocks whose values exceed 80th percentile of NYSE firms.

[5] I also find that passive funds to exhibit significant contrarian trading; much of which can be explained by their mechanical mandates. However, the mandated strategies of the passive funds may be designed so that their rebalancing tend to net out within the fund family. This aspect of passive funds is explored in Section II.D.

[6] Given that the median percentage of a stock held in active fund was 7.66 % in the sample period, a standard deviation increase of rebalancing demand decreases the net proportion of shares held by about 1–0.08 % divided by 7.66 %.

2025 for a review). Alternative measurements of the diversification driven demand channel are also constructed and give similar results.

In fact, further analysis shows that these patterns of return reversals can be observed in the simple size and momentum sorted portfolios. This is because a position's average return driven weight change in a sizeable equity portfolio effectively captures the interaction of its past return and market size. In the factor portfolios provided by Ken French, Winner and Loser portfolios constructed from the stocks whose size surpass the top quintile of NYSE market equity exhibit the same evident pattern of return reversals. Controlling for both the traditional momentum signal and the forecasted rebalancing demand increases the predictive power of both channels.

Overall, these results show how the institutional preference for practical diversification relates to the pattern of return predictability in momentum and large capitalization stocks. It is natural to speculate whether and how such a channel might have affected other areas of modern finance- for instance, the drive for diversification may contribute significantly to the rise of alternative assets, the timing of equity offerings, and the large share of international equity for target date funds. This paper's thesis that the institutional preference to re-diversify concentrated portfolios drives asset demand and affect prices will hopefully charter explanations for a gamut of modern finance phenomenon.

The paper is organized as follows. Section 1 reviews the related literature. Section 2 describes the data used. Section 3 establishes risk management and diversification as the primary channel that drives contrarian mutual fund trading. Section 4 aggregates the rebalancing trades, describes the predictable price patterns, and records the returns of calendar-time strategies. Section 5 concludes.

2. Relevant literature

That risk management and diversification underlie institutional preferences and affects asset holdings was proposed in Blume and Keim (2017), which finds a pervasive underweighting of the level of mega capitalization stocks held by institutional portfolios. Extending their analysis of levels to trades, this paper shows evidence that such preferences also underlie the quarter-to-quarter rebalancing of institutionally managed portfolios. This re-diversification channel for large stocks provides a novel underpinning for the disposition effect in mutual fund portfolios and documents a new form of return predictability in certain large capitalization stocks.

Therefore, this paper first offers an institutional/risk management explanation of the disposition effect of Shefrin and Statman (1985) in active asset managers. Empirical works of the disposition effect include those of Ben-David and Hirshleifer (2012, Frazzini (2006), Odean (1998), Thaler and Johnson (1990)), and Hartzmark (2014). However, the channel of empirical rebalancing in this paper is consistent with a risk management channel. We observe that the tendency to sell winners in active fund portfolios intensifies near a regulatory threshold, is stronger in longer serving asset managers, and can be explained by ex-ante measures of diversification practices.

There is also a relevantly nascent body of literature on asset rebalancing. This literature typically examines rebalancing across asset classes by various investor classes (Calvet and Campbell, 2009; Chien et al., 2012; Gabaix et al., 2022; Parker et al., 2023). Using Target Date Funds as the source of rebalancing demand, Parker et al. (2023) find a similar inelastic demand curve for the average equity fund dollar as Gabaix and R (2021). Camanho et al. (2022) examine rebalancing of currency portfolios. In terms of the aggregate rebalancing demand, Chinco and Fos (2021) argue that diverse non-coordinated rebalancing demand is computationally difficult to aggregate and effectively generates noise. Other works on mutual fund level trading include Jiang et al. (2007), and Sammon and Shim (2024). As this paper will demonstrate, the current form of rebalancing is predictably coordinated across active funds, and an extremely predictable source of net trading demand.

The second part of the paper investigates how the institutional preference for diversification affects asset prices. Diversification as a mutual fund behavior is used in Pollet and Wilson (2008) to show the consequences of increased size in the mutual fund industry. The under-diversification of retail portfolios is explained theoretically in Roussanov (2010) as an outcome of preference for idiosyncratic risks over systematic ones. The main thesis of the current empirical work is that the preference for certain diversification by active funds generates trading demand.

As such, this investigation parallels a large literature on benchmarking demands. Pavlova and Sikorskaya (2023) show that benchmarking popularity can generate pricing demand, extending the prior works on index reconstitutions (Chang et al., 2014; Greenwood, 2005; Harris and Gurel, 1986; Kaul et al., 2002; Shleifer, 1986). Koijen and Yogo (2019) and its demand system analyze the institutional preference for certain stock characteristics. Buffa et al. (2022) investigates the tension between active managed portfolios and their benchmarks. Jiang et al. (2022) shows excess returns on small capitalization stocks within the S&P 500 from the large capitalization demand of index-weighted mutual funds. Unlike these pre-existing works, I show the preference against concentrated positions reflect pervasive active portfolio management practices and is a different source of trading predictability from benchmarking.

There are several arguments for why large stocks can exhibit certain return predictability originating from risk-management mandates. While the largest stocks are typically assumed to be the most liquid and well-priced securities in the financial literature,[7] they are also widely held in positions by most asset management portfolios. Therefore, these stocks are the most susceptible to correlated portfolio constraints across mutual funds- if most asset managers already hold a certain stock in large weights, they will be constrained in their ability to increase their positions as a means of liquidity provision. As prior evidence for this possible mechanism, Koch et al. (2016) documents commonality in liquidity due to common mutual fund ownership. Second, in terms of potential price impact, a growing demand-based asset pricing literature argues that equities- as a class of assets- exhibits a high degree of inelasticity, despite the perceived liquidity of the largest stocks.[8] The majority of the value within equities tend to be in large capitalization stocks. The current paper provides evidence that significant predictability can even exist within this specific cross-section of large equities.

The two facts that market participants rebalance in response to the same shock (changes in position size) and that most investors are constrained in their ability to absorb this rebalancing demand form a basis for possible limits to arbitrage (Shleifer, 1986; Shleifer and Vishny, 1992; Shleifer and Vishny, 1997).

Beyond the central theme of the disposition effect and its effect on prices, this paper is related to literature that explores the non-fundamental risks that result from ownership structures. These papers typically argue that idiosyncratic flows to institutions lead to stock volatility. Greenwood and Thesmar (2011) explore fragility from the ownership concentration in mutual funds. Ben-David et al. (2021) find that stocks with concentrated institutional ownership tend to be accompanied by increased idiosyncratic volatilities. Massa et al. (2021) observe that there are substantial changes to institutional portfolios after the merger of BlackRock and Barclays Global Investors due to the risks involved in concentrated ownership. Lines (2022) shows distortions caused by volatility managed portfolios in asset prices. In a similar vein, but from an alternative channel to investor flows, this paper shows that return driven compositional changes to portfolios have predictable

[7] See Falkenstein (1996), Gompers and Metrick (2001), Bennett et al. (2003), and Lewellen (2011) for evidence of large to medium capitalization liquidity.

[8] See Gabaix and R (2021), Gabaix et al. (2022), and Bretscher et al., 2025 for the literature on demand systems.

power over stocks prices and holding preference within the mutual fund sector.

This discussion of flows leads to other works exploring the mutual fund industry's collective effects on demand and flows (Ben-David et al., 2022a; Ben-David et al., 2022b; Bretscher et al., 2025; Chen, 2024,; Christoffersen and Simutin, 2017,; Coval and Stafford, 2007; Edmans et al., 2012; Evans and Sun, 2021; Hartzmark and Solomon, 2022; Lou, 2012; Schmickler and Tremacoldi-Rossi, 2022; Wardlaw, 2020). Wardlaw (2020) shows that certain flow-based measures of price impact loads on traditional return factors such as small size and momentum. The price reversals on large-cap stocks observed in this paper found on a cross-section of stocks that oppose the normal size and momentum factors.

Prior literature also explores other trading behavior of mutual funds. Related to the current paper, Grinblatt et al. (1995) document that mutual funds appear to chase stocks that have high historical returns. Extrapolative behaviors are found in works including Greenwood and Shleifer (2014) and Barberis et al. (2018). Cici (2012) explores tax-loss strategies as the counterpoint to the disposition effect Frazzini (2006) in explaining the trades of asset managers. Controls used to capture these effects have no qualitative effect on the findings in this paper.

Finally, there is also an empirical literature on momentum and reversal returns (Ben-David et al., 2024; Daniel and Moskowitz, 2016; Grinblatt and Han, 2005; Huang, 2022; Jegadeesh and Titman, 1993). Recent works find that intermediate lagged past returns, from seven to 12 months ago, tend to forecast future returns (Novy-Marx, 2012). In contrast, recent past returns, from one to six months ago, do not significantly generate such predictability in stock returns. Huang (2022) finds that when the cross-sectional dispersion in returns is the highest, momentum strategies have the lowest returns- a fact that is consistent with the reversal of momentum returns documented in this paper.

This paper shows that quarterly rebalancing by professional investors generates predictable price impact in the opposite direction of short-term momentum. Once an econometrician accounts for this missing mechanism in the cross-sectional predictability regressions, recent stock performance gain additional power to forecast future returns. These results show that the underlying mechanisms that create momentum (see (Goetzmann and Huang, 2018) for a review) are still extant in the modern history of the financial markets.

3. Data section

The Thomson-Reuters CDA/Spectrum database provides the quarterly fund holdings information. This database was originally taken from the fund's common quarterly securities filings (N-Q, N-CSR, and NCSRS forms) with the Security Exchange Commission (SEC). The CRSP mutual fund files are used for fund characteristics and returns. The two databases are connected using MFLinks. The construction of the final linked database follows Lou (2012) but is extended to Q4 2022.

The definition of diversified funds comes from Morningstar Direct and is matched using tickers to the underlying equity portfolios. Index funds and ETF flags come from the CRSP database. An index fund is designated by the index fund flag ("D") in the CRSP mutual fund database at any time in the sample. Active mutual funds are any other non-ETF/ETN flagged fund.

Factor portfolio returns are taken from Ken French's website. The standard CRSP stock and Compustat accounting files provide monthly stock returns and characteristics. The universe of equity studied consists of common stocks from the AMEX, NASDAQ, and NYSE exchanges. The sample period is between Q1 1990 and Q4 2022.[9] For the discontinuity density tests of section III.C, which requires precise portfolio weights, I limit funds to only those without implied leverage or short-positions through their equity holdings value to observed quarter-end TNA ratios.

Summary statistics for stock-portfolio-quarter observations and the active mutual funds that own them are reported in Table 1.

4. Diversification and risk management as the drivers of mutual fund contrarian behavior

This section tests the hypothesis that portfolio risk management drives the trading behavior of active mutual fund managers. I show that contrarian rebalancing from active mutual fund managers is 1) upward sloping in portfolio weights, 2) asymmetrically driven by increases in stock weights, 3) concentrated at a common risk management threshold, and 4) explained, at least in part, by variations in risk management characteristics for mutual funds. These tests are designed to provide diversification driven rebalancing as the explanatory channel of contrarian trading for institutional investors and set the stage for dissecting the pricing tension between institutional investors and the equity market.

Section III.A establishes the primary measures of discretionary rebalancing and shifts in stock concentration. Section III.B applies these metrics to analyze the re-diversification channel of mutual fund behavior. Sections III.C shows that different weights align with an increased propensity to trim the largest positions, and that the resultant density of portfolio weights cluster below a common regulatory threshold. Section III.D examines the varying degrees of contrarian rebalancing by interacting *Passive* with fund characteristics. Section III.E then discusses the rebalancing patterns of passive mutual fund portfolios and the families that run them.

4.1. Rebalancing measures

I begin the analysis by decomposing the quarterly changes in mutual fund compositions into *Active* discretionary and *Passive* return-driven components. The change in the total weight of a position *i*, in fund *j*, between quarters *t* and *t-1* can be represented as:

$$w_{i,j,t} - w_{i,j,t-1} = \underbrace{w_{i,j,t} - \widehat{w}_{i,j,t}}_{Active_{i,j,t}} + \underbrace{\widehat{w}_{i,j,t} - w_{i,j,t-1}}_{Passive_{i,j,t}}, \tag{1}$$

where

$$\widehat{w}_{i,j,t} = \frac{(1 + r_{i,t})\, w_{i,j,t-1}}{\sum (1 + r_{i,t})\, w_{i,j,t-1}}. \tag{2}$$

Here, $\widehat{w}$ is the projected weight of stock *i* in quarter *t* as driven by returns using the previous quarter's observed weights. *r* is the stock's quarterly returns. If fund *j* does not trade and simply holds its portfolio from the previous quarter to the present quarter end, then $\widehat{w}$ would be the resultant stock weight.[10] Therefore, *Passive*- the difference between $\widehat{w}$ and the initial weight- is the market returns driven change in a position's concentration- assuming that there were no trades during the current quarter.

Mechanically, *Passive* is likely high if the position had high initial weights and obtained high returns within the quarter, but the projected weight, $\widehat{w}$, is scaled by the returns of all the initial positions. If a portfolio has equally many positions of similar return magnitudes, then the *Passive* change in portfolio weights will be close to zero. In contrast, a single large position with a positive return in a portfolio replete with negative returning stocks will likely have a high *Passive* due to the scaling effect in the denominator.

[9] Portfolio holdings are examined through Q1 1990 to Q4 2022. Trading portfolios are formed using holding information from Q1 1990 to Q2 2022. The predicted returns are from Q3 1990 to Q4 2022.

[10] The measure is calculated using total returns, which assumes that dividend income is reinvested into the same stock. Alternatively, measurement using simple price returns and assuming that dividend income is reinvested proportionally to all stocks within a portfolio will give similar results.

Table 1
Summary statistics.

Panel A. Individual Holdings of Actively Managed Portfolios

	N	Mean	Std	5th Pctl	25th Pctl	Median	75th Pctl	95th Pctl
Sell	14,979,727	36.05 %	48.01 %	0	0	0	1	1
Buy	14,979,727	23.73 %	42.54 %	0	0	0	0	1
Liquidation	14,979,727	10.04 %	30.06 %	0	0	0	0	1
Passive (equal-weighted)	14,979,727	0.00 %	0.21 %	−0.26 %	−0.03 %	−0.00 %	0.03 %	0.26 %
Passive (value-weighted)	14,979,727	0.00 %	0.44 %	−0.55 %	−0.14 %	−0.00 %	0.12 %	0.56 %
Active (equal-weighted)	14,871,485	−0.09 %	0.51 %	−0.88 %	−0.07 %	−0.00 %	0.03 %	0.36 %
Active (value-weighted)	14,871,485	−0.23 %	0.96 %	−1.81 %	−0.31 %	−0.01 %	0.09 %	0.61 %
Weight (equal-weighted)	14,979,727	0.89 %	1.15 %	0.01 %	0.10 %	0.50 %	1.26 %	3.08 %
Weight (value-weighted)	14,979,727	2.39 %	2.25 %	0.34 %	1.06 %	1.85 %	3.07 %	5.93 %

Panel A summarizes the stock by fund by time observations panel used for analyzing the trading activities of mutual funds on average. *Sell* (*Buy*) indicates a net decrease (increase) in the number of shares owned by a fund portfolio over the quarter. *Passive* is the percentage change in quarterly holdings driven by returns for a position within a mutual fund each quarter. That is, if a fund doesn't trade and reinvests the dividends from each respective stock, *Passive* would be the resultant change in a position's weight. *Active* is the residual discretionary change in weight between quarters. *Weight* is the size of a position relative to the total position reported in a fund portfolio. The value-weighting represent the *Passive* and *Weight* experienced by the average dollar within a portfolio. The sample period of the holdings is from Q1 1990 to Q4 2022.

Panel B. Individual Actively Managed Mutual Funds

	N	Mean	Std	5th Pctl	25th Pctl	Median	75th Pctl	95th Pctl
Number of Stocks	133,057	113	193	29	45	67	103	325
Max Size	70,667	4.68 %	2.33 %	1.60 %	3.05 %	4.37 %	5.78 %	9.09 %
Non-Diversified	88,798	7.63 %	26.6 %	0	0	0	0	1
TNA ($Millions)	133,057	1160	4060	8.616	60.70	226	822	4770

Panel B summarizes the *Number of Stocks* and the *Total Net Assets* of the fund by time observations. *Number of Stocks* is the number of stocks (with matching identifiers) observable in portfolio at a quarter end. *Max Size* is the average size of the largest stock position over the past 4 quarters. *Non-Diversified* is an indicator of a non-diversified fund from a single cross-section available from Morningstar Direct. *Total Net Assets* is the total value of the holdings within a fund portfolio. The sample period of the holdings is from Q1 1990 to Q4 2022.

Panel C. Stock Characteristics

	N	Mean	Std	5th Pctl	25th Pctl	Median	75th Pctl	95th Pctl
Rebalancing Demand (equal-weighted)	221,733	−0.000 %	0.219 %	−0.300 %	−0.083 %	−0.002 %	0.077 %	0.309 %
Rebalancing Demand (value-weighted)	221,733	0.001 %	0.301 %	−0.412 %	−0.128 %	−0.004 %	0.121 %	0.431 %
Threshold Demand (equal-weighted)	221,733	0.000 %	0.149 %	−0.160 %	−0.013 %	0.000 %	0.010 %	0.157 %
Threshold Demand (value-weighted)	221,733	0.000 %	0.254 %	−0.330 %	−0.070 %	0.000 %	0.066 %	0.333 %
Fitted Demand (equal-weighted)	221,733	0.000 %	0.031 %	−0.044 %	−0.011 %	−0.000 %	0.010 %	0.045 %
Fitted Demand (value-weighted)	221,733	−0.000 %	0.041 %	−0.060 %	−0.019 %	−0.000 %	0.018 %	0.063 %
Quarterly Returns	221,733	2.635 %	22.26 %	−31.68 %	−8.859 %	2.186 %	13.28 %	37.07 %
Change in Ownership	221,733	−0.097 %	1.910 %	−2.699 %	−0.564 %	−0.002 %	0.477 %	2.229 %
Book-to-Market	219,429	0.589	0.632	0.0754	0.273	0.484	0.773	1.389
Log Size	221,728	14.258	1.702	11.698	13.038	14.135	15.328	17.276

Panel C summarizes the stock by time observations used to examine returns and net trading behavior. Value-weighted summary statistics is weighed by the stock's market share of the total observed equity portfolio each quarter. *Rebalancing Demand* is the average percentage change in quarterly holdings as driven by returns over all observed active portfolios. *Threshold Demand* is the return driven change in the portfolio weight for only positions with 2 % or more weights scaled by the total observed mutual fund shares. *Fitted Demand* is the average return driven change in the portfolio weight of a stock scaled. The *Quarterly Returns* is the quarterly return measured. *Change in Ownership* is the difference in the percent of a stock owned by equity funds between two observed quarters. *Book-to-Market* is the book to market ratio. Log *Size* is the log of a stock's total aggregate market capitalization in thousands. The sample period is from Q1 1990 to Q4 2022

Active is the residual of each position's quarterly weight change after deducting the mechanical changes. This component captures the discretionary rebalancing of a position by a portfolio manager, scaled by the manager's actions to the rest of his portfolio. For instance, *Active* will be positive if a manager increases the relative weight of stock *i* by scaling down every other stock in his portfolio, even without trading- informing an analyst his preference to keep stock *i* concentrated. Furthermore, the magnitude of *Active* captures relative degrees of a trading action. A *Sell* or a *Buy* indicator makes no distinction between liquidations, large scale-downs, or trimmings of positions, whereas *Active* distinguishes such actions by capturing their quantitative size. An *Active* rebalancing of −0.1 % for a 4 % weight position indicates that a manager is trimming this position, whereas −2 % *Active* would indicate a quasi-liquidation by the manager and potential asset rotation by the fund.

One concern about the *Active* and *Passive* measures is that they are constructed by decomposing the quarterly change in a position's weight into two separate components, and such decomposition may drive a degree of mechanical negative correlation if quarterly weight changes are random or noisily measured. I provide alternative tests that use indicators of simple trading directions as the left-hand side variables in Appendix A1, which display broadly similar results. Similarly, placebo tests on value-weighted index funds in Appendix A2 show no such dependency of *Active* to *Passive* on exactly the funds that have no discretion or mechanical rebalancing strategies beyond benchmarking.

The following trading tests also split stock positions into spline-wise bins by weight and decompose *Passive* measurement into positive and negative sides. All these piece-wise measures should be equally affected by noise, but the difference between the observed coefficients shows increasing risk management to the larger, positive changes in weights. Furthermore, distribution of portfolio weights each quarter shows that funds obey certain threshold guidelines on issuer concentration. Lagging *Passive* by one quarter, which breaks any possible relationship that may be driven by noise, predicts future *Active* discretionary trading. Holistically, these results indicate low noise in the measured outcome variable.

4.2. Active rebalancing to passive changes in position weights

Starting off, I regress contemporaneous and subsequent trading activity to *Passive*. The sample panel consists of changes in stock positions held by mutual fund portfolios between an initial quarter-end snapshot and the subsequent two quarter-end snapshots.

Table 2 regresses contemporaneous trading and future *Active* rebalancing on *Passive* and its components, after accounting for a gamut of different multivariate specifications. These regressions control for initial weights, raw quarterly stock returns, portfolio/time-fixed effects, stock/time-fixed effects, and other variables. The *Rank Effect* variable indicates stocks with the highest and lowest returns within each portfolio (Hartzmark, 2014). Similarly, I include the cumulative unrealized gains and losses (*Unrealized Profits*) using the First-In-First-Out (FIFO) accounting of a fund's position calculated from each fund's first observation divided by the total fund size in order to account for potential unrealized gain/losses and tax-treatment effects (Cici, 2012; Frazzini, 2006). In all the specifications, I observe that funds trim positions that became more concentrated due to returns.

Active rebalancing by active mutual funds is consistently negatively related to *Passive*, indicating a preference for weight management. Under the fully specified model without stock time fixed effects (thereby capturing possible coordinated action on individual stocks) in Column (2), a fund manager counters a 1% change in *Passive* weight of a position by 0.23 % *Active* in the contemporaneous quarter.[11] Such actions continue into the subsequent quarter, as they trim another 0.17 % from the initial 1 % change.

This effect is asymmetric and is entirely driven by increases in position sizes. I decompose *Passive* into positive and negative components. That is

$$Passive^{+}_{i,j,t} = Passive_{i,j,t} \cdot I\left(Passive_{i,j,t} > 0\right), \tag{3}$$

and

$$Passive^{-}_{i,j,t} = Passive_{i,j,t} \cdot I\left(Passive_{i,j,t} < 0\right). \tag{4}$$

Ideally, only increases in position weights should increase the concentration of a portfolio – driving a position toward risk-management constraints like the 5 % rule. Decreases in weights mechanically diversify a portfolio- this should not be met with active rebalancing.

Columns (3), (5), (8) and (10) repeat the multivariate regressions using $Passive^{+}$ and $Passive^{-}$ separately. We see that the tendency to rebalance is predominantly driven by the mechanical increase in position concentrations. Consistent with re-diversifying positions whose concentrations increased mechanically, $Passive^{+}$ is significantly related to discretionary *Active* both contemporaneously and in the subsequent quarter, but $Passive^{-}$ has zero effect on contemporaneous activity and very little magnitude in forecasting future *Active*. For the same 1 % change in portfolio weight due to *Passive*, a fund manager would trim the position down by 0.46 % if it were an increase but leave the position essentially unchanged if it were a decrease. In the following quarter, the manager trims down the increase by another 0.28 %; and marginally scales up some positions whose concentrations had decreased to returns (i.e. they must buy assets somewhere to replace the existing ones). Overall, fund managers rebalance in a manner that is consistent with re-diversifying the increases in portfolio concentration.

The magnitudes of these coefficients indicate trimming concentrated positions instead of whole-sale scale downs and asset rotations. None of the trading reactions to *Passive* suggest that this variable captures a channel where a portfolio manager would increase their speculation tendencies or make large corrections in his portfolio after realizing large bets.

Similarly, these tests are not driven by the decomposition of weight changes into active and passive components. Appendix A1 records alternative tests that use indicators of simple trading directions (*Sell* and *Buy*) as the left-hand side variables. We see largely similar results on the forecast of trading directions by the *Passive* coefficients.

Appendix A2 conducts placebo tests of rebalancing coefficients on value-weighted index funds. These index funds have no active discretion in portfolio management, nor do they follow trading strategies that require specific mechanical contrarian trading. The investment principle behind these funds is to replicate the performance of their respective benchmarks, either by holding their components in proportion, or by implementing a strategy that minimizes tracking error. Appendix Table A2 produces the same regressions as Table 2 for these value-weighted entities. In them, I find no significantly negative correlation (neither contemporaneously nor between quarters) between *Passive* and *Active* components. There is even a slight positive relation between *Passive* and next quarter *Active*, potentially accounting for patterns in issuances. These placebo results indicate that neither noise nor mechanical rebalancing drive my findings.

Lastly, the coefficients in Table 2 are not driven by averaging potentially different channels of behavioral bias. It could be that funds either scale down positions significantly or don't sell at all. For a 4 % sized position that experiences a 1 % *Passive*, the portfolio manager may partially liquidate- by selling off 50 % of the position- or not trade at all. Mixing these two patterns would average the coefficient on *Passive* into a "trimming" range, despite that one of the trading patterns indicates speculative behavior by the asset manager.

In Appendix A3, I focus only on the subset of positions that funds do sell. These conditional regressions are still consistent with trimming rather than partial liquidations. The magnitude on $Passive^{+}$ is essentially unchanged from -0.46 to -0.53, indicating stability in the trimming behavior by asset managers. Further tests on trading directions against flows and stock size are included in Appendix A4 and A5 respectively to show the diversification effect of scale (similar to Pollet and Wilson (2008), and that stocks of varying equity size characteristics exhibit different contrarian trading by funds.

4.3. Rebalancing across weights and threshold management

Presumably, the risk management practices constrain managers at specific position ranges. Under the Investment Company's Act and Internal Revenue Code's Rule for Regulated Investment Companies, the most common risk management practice is to limit individual issuers concentration at 5 % (5 % of 75 % and 5 % of 50 % of a fund's AUM by the two regulations respectively).[12] In Fig. 1, I plot the distribution of the largest position (left) and all positions above 1 % (right) within portfolios over my sample.

From the left graph, it appears that most mutual funds have asset concentrations that are well within what is required by the 5 % rule. 67 % of active portfolio observations do not have a single asset position that exceeds 5 %. Funds may choose to stay- potentially with a sizable buffer- within limits. The modal peak of the largest positions is at 4.5 %, which is consistent with some buffering against the 5 % threshold.

Furthermore, from the right graph, we see that position weights typically follow a zipf- inverse power-law distribution. The shape of this distribution decreases exponentially, essentially disappearing after 6 %.

Fig. 1 suggests that funds have varying levels of internal risk management limits and mandates. For example, Dimensional Fund Advisors reports that it follows the 5 % of 75 % AUM limit in their SEC documents, but their portfolios' largest positions are consistently below 2–3

[11] A 1% magnitude *Passive* occurs with probability 0.64 % in all stock by fund by time observations. On a dollar of portfolio value-weighted basis, it occurs more frequently with the probability 3.23 %. Furthermore, 34.5 % of active portfolios experience a position with 1 % or more magnitude *Passive* at any given quarter.

[12] Appendix B1 discusses several risk management thresholds in more detail.

Table 2
Regression of *Active* Rebalancing on *Passive* for Actively Managed Funds.

	Contemporaneous Active					Next Quarter Active				
	1	2	3	4	5	6	7	8	9	10
Passive	−0.124***	−0.234***		−0.294***		−0.140***	−0.171***		−0.197***	
	(−16.75)	(−14.68)		(−15.89)		(−22.57)	(−20.92)		(−26.46)	
Passive$^+$			−0.461***		−0.522***			−0.282***		−0.309***
			(−20.88)		(−23.37)			(−25.13)		(−26.55)
Passive$^-$			0.0138		−0.0340**			−0.0498***		−0.0695***
			(1.068)		(−2.068)			(−3.622)		(−6.165)
Weight		−0.108***	−0.0862***	−0.128***	−0.104***		−0.0689***	−0.0584***	−0.0863***	−0.0750***
		(−23.30)	(−18.93)	(−29.38)	(−23.45)		(−28.06)	(−22.79)	(−32.37)	(−26.85)
Return		0.0004***	0.0004***				0.0001***	0.0002***		
		(10.54)	(12.64)				(4.631)	(5.705)		
Unrealized Profit		0.112***	0.107***	0.105***	0.101***		0.0232***	0.0207***	0.0188***	0.0164***
		(6.052)	(5.714)	(5.121)	(4.816)		(5.219)	(4.749)	(4.075)	(3.653)
Rank Effect		−0.001***	−0.0004***	−0.0008***	−0.0004***		−0.0005***	−0.0001***	−0.0004***	−0.0002***
		(−29.03)	(−10.05)	(−19.46)	(−9.827)		(−14.60)	(−3.661)	(−13.36)	(−6.233)
Time-Fixed Effects	Yes	No	No	No	No	Yes	No	No	No	No
Time X Fund Fixed Effects	No	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes
Time X Stock Fixed Effects	No	No	No	Yes	Yes	No	No	No	Yes	Yes
Adj. R^2	0.007	0.131	0.135	0.170	0.172	0.006	0.078	0.079	0.125	0.126
N	14,406,577	14,405,149	14,405,149	14,343,582	14,343,582	14,402,568	14,401,142	14,401,142	14,339,663	14,339,663

This table shows the regressions of contemporaneous and next quarter *Active* change in portfolio weights on *Passive*, various controls, and fixed effects due to time/fund and time/stock for actively managed mutual funds. *Active* is the discretionary change in the weight of a position. *Passive* is the return driven change in the weight of a stock in the portfolio from its initial portfolio weight. *Passive+* is *Passive* · I(*Passive* > 0), while *Passive-* is *Passive* · I(*Passive* < 0). *Return* is the total quarterly returns. *Unrealized Profit* is the cumulative unrealized gains and losses using First-In-First-Out accounting divided by the fund's total size. *Rank Effect* is 1 if the stock had either the highest or the lowest return within the portfolio each quarter. The t-statistics reported in parentheses are clustered quarterly. *, **, *** indicates statistical significance at the 90 %, 95 %, and 99 % level respectively.

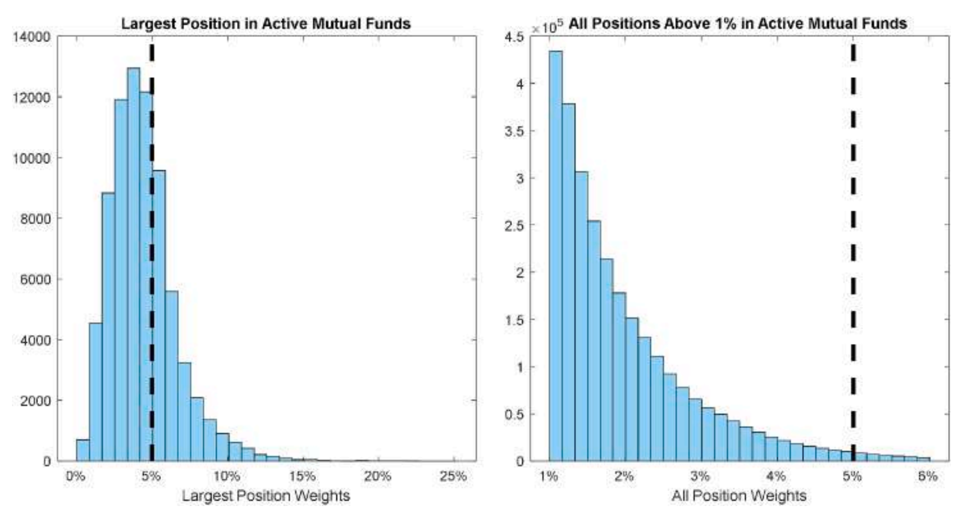


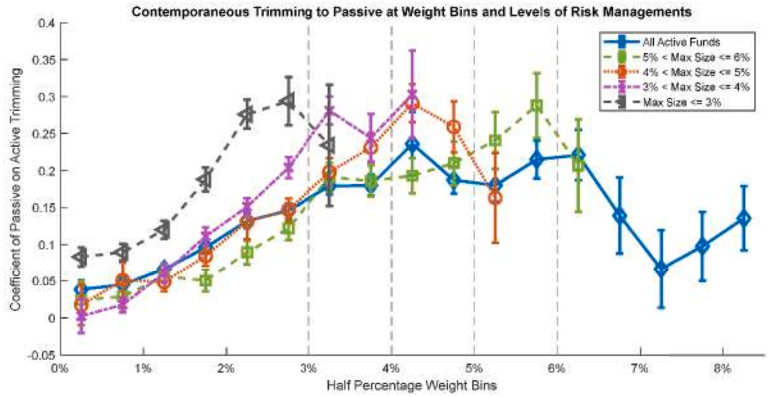
Fig. 1. Histogram of the largest position weight (left) and all positions with weights above 1 % (right) in actively managed mutual fund portfolios. The dashed line indicates the 5 % weight threshold.

%. I examine the average degree of trading actions across positions with different weight ranges.

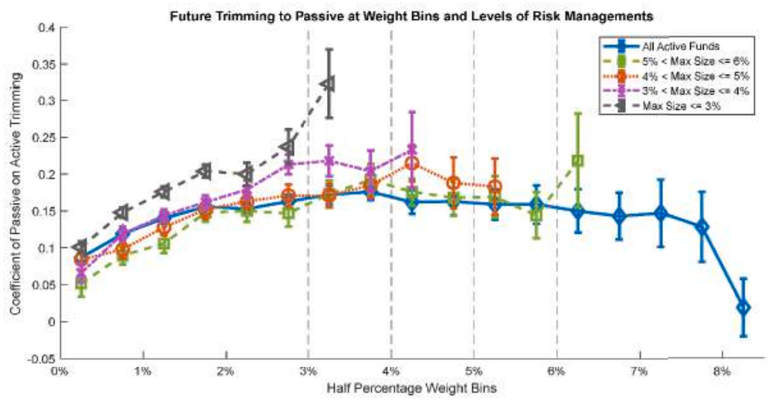
I divide up the whole sample of mutual funds into groups with varying historic degrees of risk management practices. Specifically, I average a fund's maximum holding size over the past year (*Max Size*), which approximates the level of concentration management at the fund level. The funds with the most restrictive concentration management practices will have the lowest *Max Size*. I use integer % to separate *Max Size* groups for interpretation. Dividing portfolio observations into categories of funds with *Max Size* greater than 6 %, 5 % to 6 %, 4 % to 5 %, 3 % to 4 %, and below 3 % results in roughly equally divided groups of 20 %.

Fig. 2 plots the negative regression coefficients on *Active* rebalancing against *Passive* in the same quarter for different half percentage bins of ex ante weights. The blue line is the sample of all actively managed mutual funds. The top figure plots the spline-wise *Passive* coefficients to contemporaneous *Active* rebalancing, whereas the bottom figure plots it for next quarter's *Active*. The bins are divided by 50 basis points (0 to 0.5 %, 0.5 % to 1 %, etc.) ending in the upper limit of *Max Size* (6 %, 5 %, 4 %, and 3 %), and then one additional bin for observed weights that exceed *Max Size* (above 6 %, above 5 %, etc.) in the current quarter (*Max Size* is constructed using average rolling data prior to the trading quarter, so it doesn't limit position weights outside of the *Max Size* limit). For the blue line, which uses all actively managed mutual funds, the last bin consists of positions with 8 % or more in ex ante weights.

That is, the figure displays the β coefficients from the following regression:



(a) Contemporaneous trimming across 0.5% weight bins and different levels of historic risk management.



(b) Future trimming across 0.5% weight bins and different levels of historic risk management.

Fig. 2. Piecewise regressions of active rebalancing on passive changes using the following specifications:
$Active_{i,j,t} = \alpha - \sum_b \beta_b \cdot Passive \cdot I(w_{i,j,t-1} \in Bin_b) + \gamma \cdot w_{i,j,t-1} + \epsilon_{t+1,i,j}$
$Active_{i,j,t+1} = \alpha - \sum_b \beta_b \cdot Passive \cdot I(w_{i,j,t-1} \in Bin_b) + \gamma \cdot w_{i,j,t-1} + \epsilon_{t+1,i,j}$
for stock *i* in portfolio *j* at time *t. Active* is the active rebalancing of stock *i* by portfolio *j* between *t* and $t+1$. *Passive* is the market return driven change in the weight of stock *i* between *t-1* and *t. w* is the weight of asset *i* in portfolio *j* at *t-1. Bins* are ranges of weights separated by 50 basis points. Bin_1 contains positions with weights from 0 % to 0.5 %, Bin_2 contains positions with weights above 0.5 % and below 1 %, and so forth. The last *Bin* holds positions with weights above 8 %, 6 %, 5 %, 4 %, and 3 % for the varying sample of funds respectively. The figures plot the estimated beta coefficients of the contemporaneous (top) and subsequent (bottom) period's trimming actions on returns for positions of different initial weights. The standard errors of the coefficients are reported by the horizontal band for each bin. The blue line represents all actively managed funds. The green, red, purple, and black are for the sample of funds with varying levels of historic risk management as indicated by the size of the largest position over the past year.(For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.).

$$Active = \alpha - \beta_1 \cdot Passive_{i,j,t} \cdot I(w_{i,j,t-1} \leq 0.5\%) - \beta_2 \cdot Passive_{i,j,t} \cdot I(w_{i,j,t-1} \in (0.5\%,\ 1\%]) - \ldots - \beta_n \cdot Passive_{i,j,t} \cdot I(8\% < w_{i,j,t-1}) + \gamma \cdot w_{i,j,t-1} + error_{i,j,t} \tag{5}$$

We see that in the case where all active funds are pooled (blue line), the magnitude trimming by *Passive* increases as we increase position weight up to a point. Such rebalancing begins to decrease significantly after a position crosses the 5 % to 6.5 % range. This decrease captures the non-diversified funds and the positions that had switched into a regime where the 5 % threshold doesn't matter (e.g. the non-75 % of AUM regime if the fund strictly obeys the 75-5-10 rule).

The other regression coefficients end with 6 %, 5 %, 4 %, and 3 % and above spline of weights respectively. For the other lines, we see that the rebalancing to *Passive* consistently increases as positions near a fund's historic concentration thresholds. The horizontal error bar lines are standard errors. We observe that an actively managed mutual fund's history of risk management practices captures the intensity to which they trade against the compositions changes as driven by returns.

The closer a position is to a fund's historic thresholds, the more intensely the fund trims. A fund is likely to trim much more (relative to the original position size) of a 4 % position that had 1 % *Passive* than a 1 % position that had 0.25 % *Passive*. The overall increase in the trimming intensity is consistent with threshold and size management.

The actual regression table for this figure is also presented in Table 3. It should be noted that Fig. 2(a), if scaled by the standard deviation of *Passive* in each of the bins, will be even more convex (up to the 5 to 6.5 % range). By construction, positions that start with larger weights will change more to returns and exhibit bigger dispersion in *Passive*. The predictable action in trading and pricing occurs at the upper ranges of portfolio weights. The accelerating coefficients in the current quarter regressions shows an immediacy to rebalance positions that come near a fund's upper limits of issuer concentrations.

Fig. 2(b) plots the piece-wise coefficients for regressions with the next quarter *Active* as the left-hand side variable. We see that the coefficients indicate a continuation of trimming into the following quarter. The magnitudes are lower and are less convex to increases in weights. As the positions closer to the thresholds are already trimmed in the contemporary quarter, there is a slight decline in the measured impulse to manage these positions further.

Table 3
Piecewise Regressions of Active Rebalancing on Passive Changes for Funds with Varying *Max Size*.

	Contemporaneous Active				
	All Active Funds 1	*Max Size between* 5 % to 6 % 2	*Max Size between* 4 % to 5 % 3	*Max Size between* 3 % to 4 % 4	*Max Size between* 0 % to 3 % 5
Passive x I(0 < Weight≤ 0.5 %)	−0.0384***	−0.0240	−0.0174	−0.00229	−0.0832***
	(−3.167)	(−0.935)	(−0.640)	(−0.101)	(−6.471)
Passive x I(0.5 % < Weight≤ 1 %)	−0.0449***	−0.0287*	−0.0510**	−0.0178*	−0.0894***
	(−4.666)	(−1.725)	(−2.090)	(−1.689)	(−8.160)
Passive x I(1 % < Weight≤ 1.5 %)	−0.0662***	−0.0561***	−0.0487***	−0.0606***	−0.120***
	(−8.124)	(−3.660)	(−3.852)	(−4.757)	(−10.03)
Passive x I(1.5 % < Weight≤ 2 %)	−0.0961***	−0.0505***	−0.0845***	−0.111***	−0.188***
	(−11.37)	(−3.406)	(−6.225)	(−9.245)	(−11.64)
Passive x I(2 % < Weight≤ 2.5 %)	−0.132***	−0.0891***	−0.131***	−0.151***	−0.276***
	(−13.24)	(−5.512)	(−5.405)	(−13.05)	(−14.15)
Passive x I(2.5 % < Weight≤ 3 %)	−0.146***	−0.122***	−0.147***	−0.204***	−0.294***
	(−14.54)	(−7.467)	(−9.709)	(−14.27)	(−9.103)
Passive x I(3 % < Weight≤ 3.5 %)	−0.179***	−0.191***	−0.198***	−0.281***	
	(−15.69)	(−9.768)	(−10.47)	(−14.81)	
Passive x I(3.5 % < Weight≤ 4 %)	−0.180***	−0.186***	−0.231***	−0.244***	
	(−12.71)	(−8.705)	(−12.10)	(−7.489)	
Passive x I(4 % < Weight≤ 4.5 %)	−0.236***	−0.193***	−0.291***		
	(−5.497)	(−8.262)	(−11.35)		
Passive x I(4.5 % < Weight≤ 5 %)	−0.187***	−0.210***			
	(−10.24)	(−7.236)			
Passive x I(5 % < Weight≤ 5.5 %)	−0.180***	−0.241***			
	(−8.124)	(−6.291)			
Passive x I(5.5 % < Weight≤ 6 %)	−0.215***	−0.288***			
	(−8.313)	(−6.567)			
Passive x I(6 % < Weight≤ 6.5 %)	−0.221***				
	(−6.499)				
Passive x I(6.5 % < Weight≤ 7 %)	−0.139***				
	(−2.696)				
Passive x I(7 % < Weight≤ 7.5 %)	−0.0664				
	(−1.258)				
Passive x I(7.5 % < Weight≤ 8 %)	−0.0974**				
	(−2.099)				
Passive x I(Max Size < Weight)	−0.135***	−0.207***	−0.163***	−0.303***	−0.234***
	(−3.107)	(−3.327)	(−2.681)	(−5.090)	(−2.863)
Weight	−0.0832***	−0.0864***	−0.0908***	−0.104***	−0.120***
	(−26.06)	(−26.65)	(−28.26)	(−33.81)	(−33.81)
Adj. R^2	0.043	0.040	0.038	0.043	0.065
N	7754,483	800,567	1096,972	1229,133	3636,892

This table shows the regressions of contemporaneous *Active* change in portfolio weights on *Passive* for positions of different initial weights for funds with differing measures of historic diversification (*Max Size*). *Active* is the discretionary change in the weight of a position. *Passive* is the return driven change in the weight of a stock in the portfolio from its initial portfolio weight. *Weight* is the initial size of the stock position relative to the total value of the portfolio. The interaction of *Passive* and indicators of ranges of weights are reported in the first set of regressors. For example, if a position representing 3.4 % of a portfolio had a *Passive* of 1 %, then *Passive x I (3 % < Weight≤3.5 %)* would be 1 %, and the other interaction variables 0. There are no fixed effects. The t-statistics reported in parentheses are clustered quarterly. *, **, *** indicates statistical significance at the 90 %, 95 %, and 99 % level respectively.

This set of tests indicates that funds manage positions more strictly at possible risk management thresholds. Such rebalancing actions can result in specific distributional effects on the density of position concentrations, especially for those that are near the 5 % threshold.

To observe this consequence from concentration management, I examine the positions that are predicted to end up with weights around the 5 % threshold. Fig. 3 plots the bin frequencies and density estimate for actual quarter-end weights ($w_{i,j,t}$) in stocks whose $\widehat{w}_{i,j,t}$ (the projected position weight by returns and prior weights) are between 4.5 % and 5.5 %. If this threshold comes to play in investment decisions, then these will be the sample that are affected.

Fig. 3 uses the McCrary (2008) discontinuity test to group the position samples into bins and to estimate probability densities to the right and left of the 5 % threshold. The estimated log difference in density between the right and left of the distribution detects possible selection, manipulation, or self-sorting. The circles are grouped histogram bins, and the solid lines are the estimated locally smooth densities to the left and right of the threshold for actual quarter-end weights.

Fig. 3(a) visualizes the discontinuity between the left and the right of the 5 % threshold for all positions from diversified funds predicted to be in the 4.5 % to 5.5 % range. Plots (b) and (c) visualize only such positions that experience more than 10 % and 20 % absolute returns respectively. The bin size and bandwidth of the local densities are chosen by the McCrary (2008) DCdensity package's default parameters. The logarithmic jump size in the estimated density and its standard error are drawn to the upper right corner of each plot.

We see very distinctive patterns. The distribution of actual weights is left skewed, and the densities decay fast on the right side of the threshold- implying more dramatic position management when positions are likely to exceed the 5 % threshold. In all three cases the fall in the estimated densities from the left to the right of this threshold is statistically significant, and the magnitude of such drops increases as individual stock volatility increases. The bigger the absolute returns, the bigger the gap; indicating that funds do manage around the 5 % threshold, and more dramatically when returns are volatile.

Fig. 3(d) and (e) examine this threshold with respect to family size, as indicated by the number of funds they operate. Larger fund families tend to have tighter risk management practices and give less discretion to an individual fund manager. The sample of all positions is divided into ones belonging to the funds of large (d) and those of small fund families (e). We observe that most of the discontinuity occurs in large fund families- consistent with family level risk awareness.

This empirical strategy of looking only at positions that are predicted to hit the 4.5–5.5 % range has the benefit of creating counterfactuals.

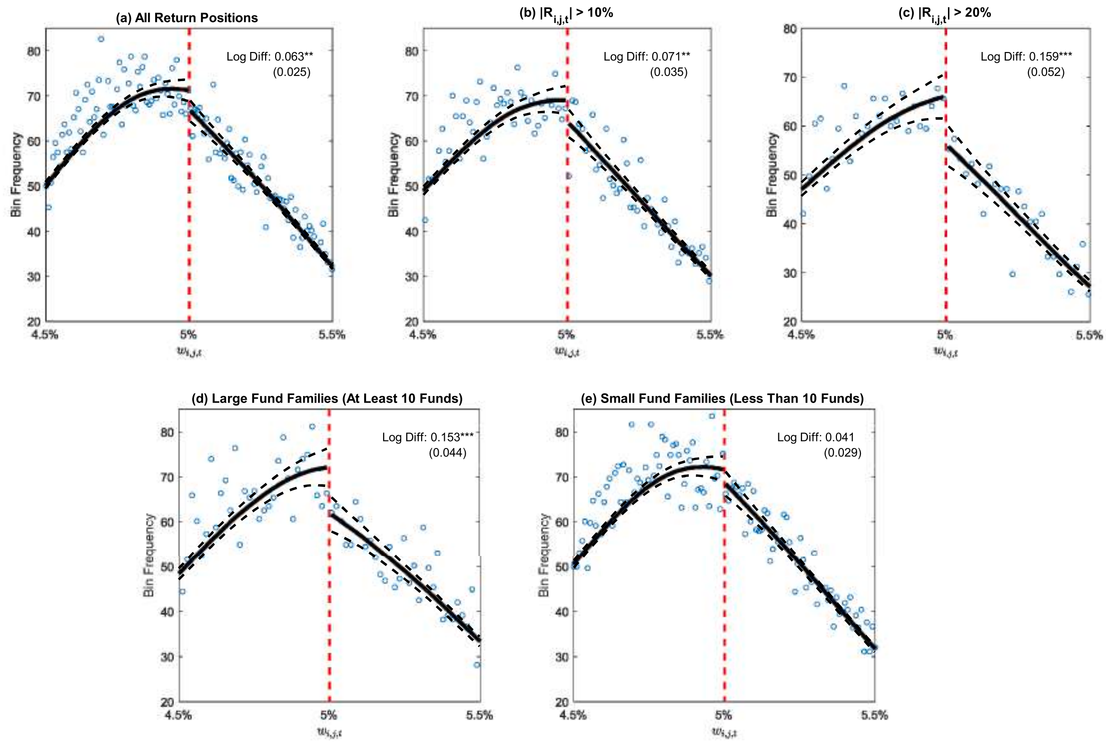


Fig. 3. Distributional Discontinuity of Actual Weights for Actively Managed Mutual Funds. This figure uses the McCrary (2008) discontinuity test to group samples into bins and to estimate probability densities to the right and left of the 5 % threshold for positions with predicted weights between 4.5 % and 5.5 %. The circles are grouped histogram bins, and the solid lines are the estimated locally smooth densities to the left and right of the threshold for actual quarter-end weights. The bin size and bandwidth of the local densities are chosen by the McCrary (2008)'s DCdensity package's default parameters. Plot (a) visualizes the discontinuity between the left and the right of the 5 % threshold for all positions from actively managed funds predicted to be in the 4.5 % to 5.5 % range. (b) and (c) visualize only such positions that experience more than 10 % and 20 % absolute returns respectively. (d) plots only the positions of active funds from large fund families. (e) plots only the positions of active funds from smaller fund families. The estimated log difference in density between the right and left of the distribution and its standard error are displayed to the top right of each plot. The red dashed line signifies a 5 % threshold. *, **, *** indicates significance at 90 %, 95 %, and 99 % levels.(For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.).

Appendix B2 plots the predicted weights ($\widehat{w}_{i,j,t}$) for the same samples of mutual funds and portfolio positions. The counterfactual distribution of predicted weights is locally smooth, and the locally fitted densities do not visually or statistically exhibit any jumps. Some tests using other placebo thresholds are also included in the Appendix B3.

Importantly, the discontinuity in the density of positions exists mainly in funds that are mandated to manage risk and issuer concentrations. Fig. 4 plots the actual holding weights of all positions predicted to end up between 4.5 % and 5.5 % for Non-Diversified Funds[13], Index Funds, Index ETFs, and Actively Managed ETFs. We observe that this discontinuity at 5 % doesn't appear for non-diversified funds (a), index funds (b), or index ETF's (c); but it reappears for actively managed ETF's- (d) which likely have similar, if not more binding, risk management practices/awareness of issuer concentration as actively managed mutual funds.

The degree of *Active* rebalancing and the resultant densities of mutual fund positions across ranges of portfolio weights indicate pervasive and binding consequences from active mutual funds' management of large positions.

4.4. Characteristics of active funds and risk management

This subsection contrasts the risk management related characteristics against characteristics that typically capture behavioral channels of contrarian trading.

First, we observe that rebalancing trades are not associated with liquidations. This was the original Odean (1998) test on the behavioral patterns of the disposition effect- the tendency to sell to gains and not losses. Panel A of Table 4 regresses *Passive* on *Liquidation* in the following quarter as the target left-hand side variable. We observe that in these simple specifications, *Passive* isn't associated with liquidations, failing to indicate a distinctive behavioral aspect to the rebalancing phenomenon. While this fact does not reject behavioral models of contrarian trading or say that asset managers do not exhibit behavioral biases; it shows that behavioral models may not be necessary to explain the documented incremental contrarian trading that rises with position size.

Further tests take advantage of the mutual funds setting, where performances and portfolios characteristics are observed for long periods. These tests examine the degree of contrarian trading as amplified by risk-management and behavioral limitations. Specifically, I interact measures of manager sophistication and measures of portfolio risk management on *Passive*.

If contrarian trading behaviors are associated with risk management and diversification, then funds that have prior measurable indicators of these preferences likely will conduct more contrarian trading. If contrarian trading by asset managers is rooted in behavioral biases, then we expect to see more activities coming from managers that are less skilled and less experienced.

In Panel B of Table 4, we observe that non-diversified active portfolios with low historic issuer concentrations tend to conduct more rebalancing to *Passive*- preventing these portfolios from becoming more concentrated due to returns. In column (1), I interact *Passive* with *Max*

13 The categorization of a non-diversified fund comes from Morningstar Direct. The limitation of using this definition is that it is extracted from fund prospectuses at a single recent cross-section. There is likely some misplacement of diversified funds into this category in earlier samples.

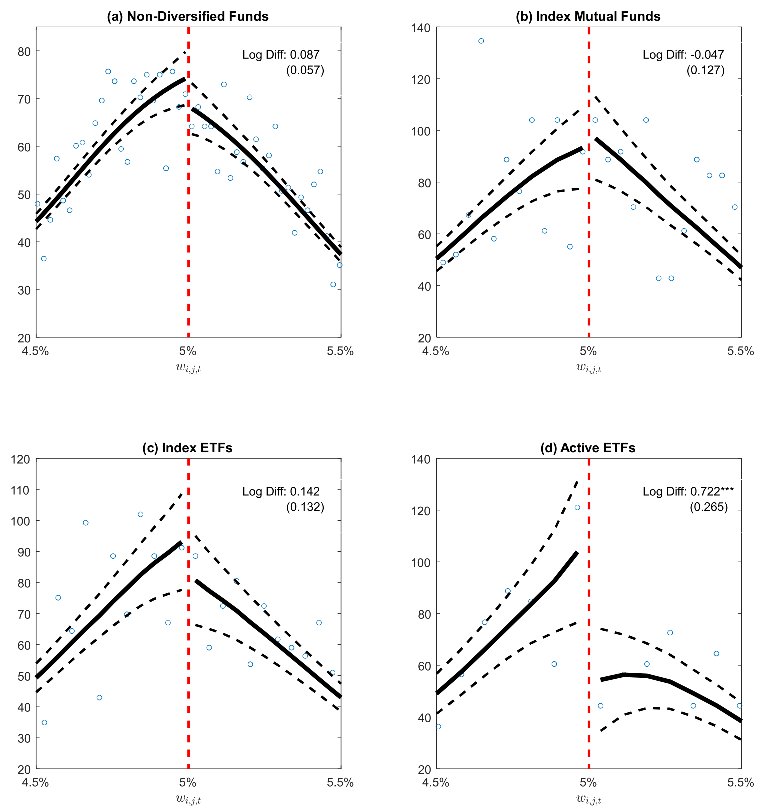


Fig. 4. Distributional Discontinuity of Actual Weights for Other Fund Types. This figure uses the McCrary (2008) discontinuity test to group samples into bins and to estimate probability densities to the right and left of the 5 % threshold for positions with predicted weights between 4.5 % and 5.5 %. The circles are grouped histogram bins, and the solid lines are the estimated locally smooth densities to the left and right of the threshold for actual quarter-end weights. The bin size and bandwidth of the local densities are chosen by the McCrary (2008)'s DCdensity package's default parameters. The distributional discontinuity plot for Non-Diversified Funds, Index Mutual Funds, Index ETFs, and Actively Managed ETFs are plotted in (a), (b), (c), and (d) respectively. The estimated log difference in density between the right and left of the distribution and its standard error are displayed to the top right of each plot. The red dashed line signifies a 5 % threshold. *, **, *** indicates significance at 90 %, 95 %, and 99 % levels.(For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.).

Size as an additional variable used in the panel regression. Recall *Max Size* is the size of the largest positions for each portfolio averaged over the past year. This interaction shows up as significantly positive in predicting *Active* by fund managers. Portfolios with an ex-ante history of highly concentrated portfolios tend to be less likely to exhibit contrarian rebalancing effect; instead, the funds with the most contrarian behavior have the most ex-ante diversified and least concentrated portfolios.

A self-declared indicator of a fund's diversification practices shows similar results. Column (2) interacts with whether the fund categorizes itself as a "non-diversified" portfolio within the equity fund sector. We observe that the non-diversified funds display significantly less contrarian rebalancing to return drifts. Non-diversified funds- presumably ones that allow for the most risk-taking and managerial discretion- show lower degrees of contrarian trading. This further supports the hypothesis that the portfolios, which are constrained by concentration and risk-oversight, rebalance more aggressively against the concentrating effects of market returns.

In contrast, portfolios that exemplify typical behavioral biases- the ones with low past performance and inexperienced managers- tend not to display significantly more trimming trading against *Passive*. Furthermore, contrasting speculation explanation of this rebalancing behavior, portfolio managers typically increase their holdings of recently initiated positions after experiencing holding-gains. Column (3) interacts a fund's 5-year performance ranking (*Skill Quintile*) within the mutual fund sector. We observe that this interaction is marginally negative, but not statistically significant, and also pales in comparison to the first two variables in terms of magnitudes. Column (4)'s interaction is with the length of a fund manager's tenure; we see a slight decrease in the degree of contrarian behavior. Finally, Column (5) interacts *Passive* with an indicator of a position's age (one indicates a position initiated over the past year, zero otherwise). The interaction between *Passive* and the indicator of a short-term position is marginally negative but such a coefficient pales in magnitude in comparison to direct measures of fund strategy and concentrations in columns (1) and (2). We see that these measures of potential behavioral bias as well as speculation indicate no significant difference to the compositional rebalancing at the fund level.

In sum, the findings point to institutional diversification as the foundation of this specific form of contrarian trading by active asset managers. The varying degrees of a fund's trading patterns are related to risk management variables rather than variables designed to capture degrees of behavioral biases. While I cannot reject all behavioral explanations of this phenomenon (for instance, a combination of anchoring, salience for positions near regulatory thresholds, and selection based on large fund families can potentially reconcile the findings), a simple channel of coordinated risk management practices is able to explain the novel empirical facts about quarterly institutional trading

Table 4
Diversification vs Behavioral Bias.

Panel A. Liquidation Patterns to *Passive*

	Liquidation		
	1	2	3
Passive	−4.387***	−0.235	−0.888***
	(−17.64)	(−0.716)	(−2.849)
Other Controls	No	Yes	Yes
Time-Fixed Effects	Yes	Yes	No
Time X Fund Fixed Effects	No	No	Yes
Adj. R^2	0.007	0.010	0.089
N	14,409,570	14,405,149	14,405,149

This panel shows the regressions of *Liquidation* in the following quarter on *Passive*, controls, and fixed effects due to time/fund and time/stock. Other Controls are initial portfolio weight, quarterly return, *Unrealized Profit*, and *Rank Effects*.

Panel B. Characteristics and Rebalancing Patterns

	Contemporaneous Active				
	1	2	3	4	5
Passive	−0.312***	−0.265***	−0.246***	−0.245***	−0.253***
	(−13.44)	(−16.27)	(−12.08)	(−15.72)	(−15.03)
Passive X Max Size	0.949***				
	(3.453)				
Passive X Non-Diversified		0.0892***			
		(6.418)			
Passive X Skill Quintile			−0.00181		
			(−0.300)		
Passive X Mgr Tenure				0.000254	
				(0.522)	
Passive X Short-term Position					−0.0245*
					(−1.944)
Other Controls	Yes	Yes	Yes	Yes	Yes
Time X Fund Fixed Effects	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.132	0.136	0.132	0.136	0.136
N	8021,236	10,010,122	9202,348	2841,701	10,010,122

This panel regresses contemporaneous *Active* rebalancing by *Passive* interacted with portfolio characteristics. *Active* is the discretionary change in the weight of a position. *Passive* is the return driven change in the weight of a stock in the portfolio from its initial portfolio weight. *Max Size* is the average size of the portfolio's largest position in the past 4 quarters. *Non-Diversified* indicates a non-diversified fund. *Skill Quintile* is the quintile rank of a fund's 5-year total performance. *Mgr Tenure* is the working length of the longest serving manager for the portfolio. *Short-term Position* is an indicator for whether the position was initiated in the past year. Other Controls are initial portfolio weight, quarterly return, *Unrealized Profit*, and *Rank Effects*. The t-statistics reported in parentheses are clustered quarterly. *, **, *** indicates statistical significance at the 90 %, 95 %, and 99 % level respectively.

documented in this section.

4.5. Net demand from families and passive fund vehicles

This section contrasts the contrarian rebalancing activities that arise from active and passive fund vehicles. Passive fund vehicles had tremendous growth during the sample period and rival the active managers in their sheer size. These passive funds also display contrarian trading at the individual level, mainly because they use certain equal-weighted and style-weighted strategies. However, at the family level, passively managed funds tend to net their rebalancing trades within the family (at least for larger stocks); this is in extreme contrast to actively managed mutual funds. This is likely due to the security design of these vehicles: growth funds are designed to take the opposite positions to value and balanced funds, and vice versa.

In Panel A Table 5, I regress the contrarian trading activities of passive funds[14] in the same fashion as Table 2. We observe that the rebalancing coefficients are extant but tend to be smaller in magnitude for these index funds. Passive funds counter a *Passive* change of 1 % by a −12.3 % *Active* compared to −23.4 % in active funds. These relationships are significantly weaker than those in actively managed mutual funds. Furthermore, as indicated before, these relationships do not exist for value-weighted index funds (Appendix A2).

Panel B of Table 5 shows that passively managed funds tend to exchange their rebalancing activities with other funds of the same family for large capitalization stocks (stocks with market capitalization exceeding the 80th percentile of the NYSE breakpoint). Here, I combine the *Passive* variable together for passively managed fund (1) through (3), and actively managed funds (4) through (6) within fund families. Rebalancing trades to compositional changes could ideally dissipate if there are enough other funds within the fund family taking the opposite position. The net selling of a stock due to large *Passive* from one fund could be met by another fund that had only a small or non-existent position on the same stock.

We observe that once aggregated, fund families that specialize in passively managed vehicles typically net their transactions for larger commonly owned stocks, implying that *Passive* changes in these index funds are met by other index funds of the same family. While certain value-style and unorthodox weighed funds trade mechanically against returns, their total net demand is balanced by growth and momentum funds that typically take the opposite direction- minimizing the excess demand for shares, and presumably price pressure, within fund families.

In contrast, from columns (4) to (6) of Panel B, the active fund families tend to trade large capital stocks in the opposite direction of average *Passive*, indicating that their rebalancing trades generate net demand for the equity market. The subsequent section focuses on its pricing consequences.

[14] A passive fund is any non-ETF/ETN fund that has the index fund flag ("D") in the CRSP mutual fund database at any time in the sample. Active funds are any other non-ETF/ETN funds.

Table 5
Net Demand from Passively Managed Funds.

Panel A. Predictive Regression of Active Rebalancing on *Passive* for Passively Managed Funds

	Contemporaneous Active			*Next Quarter Active*		
	1	2	3	6	7	8
Passive	−0.0629***	−0.123***	−0.138***	−0.0295*	−0.0262	−0.0628***
	(−4.922)	(−6.780)	(−5.942)	(−1.791)	(−1.412)	(−3.774)
Weight		−0.0431***	−0.0570***		−0.0259***	−0.0399***
		(−9.242)	(−8.738)		(−10.61)	(−10.87)
Return		3.3e-05***			−1.26e-05	
		(3.705)			(−1.066)	
Unrealized Profit		0.0684***	0.0646***		0.000609	−0.00740
		(6.061)	(4.636)		(0.0830)	(−0.884)
Rank Effect		−0.0002***	−0.0002***		−0.0002***	−0.0002***
		(−4.970)	(−4.098)		(−4.180)	(−4.292)
Time-Fixed Effects	Yes	No	No	Yes	No	No
Time X Fund Fixed Effects	No	Yes	Yes	No	Yes	Yes
Time X Stock Fixed Effects	No	No	Yes	No	No	Yes
Adj. R^2	0.002	0.144	0.184	0.001	0.084	0.144
N	3284,410	3284,248	3216,545	3283,480	3283,319	3215,655

This panel shows the regressions of contemporary and future *Active* rebalancing on *Passive*, various controls, and fixed effects due to time/fund and time/stock for passively managed mutual funds. *Sell* (*Buy*) is 1 if the fund sold (bought) the stock in net in the subsequent quarter. *Passive* is the return driven change in the weight of a stock in the portfolio from its initial portfolio weight. *Return* is the total quarterly returns. *Unrealized Profit* is the cumulative unrealized gains and losses using First-In-First-Out accounting divided by the fund's total size. *Rank Effect* is 1 if the stock had either the highest or the lowest return within the portfolio each quarter. The t-statistics reported in parentheses are clustered quarterly. *, **, *** indicates statistical significance at the 90 %, 95 %, and 99 % level respectively.

Panel B. Net selling to *passive* by passively and actively managed fund families for top quintile stocks.

	Net sell by fund family					
	Passive fund families			Active fund families		
	1	2	3	6	7	8
Avg Passive	0.831	2.105	0.394	3.551***	7.110***	6.396***
	(0.518)	(1.229)	(0.237)	(10.51)	(15.64)	(13.99)
Avg Weight		0.352	−0.501		0.701***	−0.230***
		(0.673)	(−1.119)		(11.11)	(−4.279)
Return		−0.0194	−0.0114		−0.0963***	−0.0823***
		(−0.836)	(−0.487)		(−11.75)	(−9.769)
Time-Fixed Effects	Yes	Yes	No	Yes	Yes	No
Time X Family Fixed Effects	No	No	Yes	No	No	Yes
Adj. R^2	0.116	0.116	0.459	0.003	0.004	0.096
N	128,344	128,344	128,344	1392,265	1392,265	1392,178

This panel aggregates *Passive* (by share) for positions within fund portfolios to the fund family level. Passively managed funds and actively managed funds are aggregated separately for large capitalization stocks (stocks whose value exceed the 80th percentile of the NYSE firms). Net *Sell* in the following quarter by this stock, family, time panels are then regressed against this share weighted *Avg Passive, Avg Weight*, and past quarter *Return*. We observe that the average return driven change in weight of positions in passively managed fund families has no predictive power over future selling in net within a fund family. In contrast, this variable retains power over the selling activities of actively managed fund families. The t-statistics reported in parentheses are clustered quarterly. *, **, *** indicates statistical significance at the 90 %, 95 %, and 99 % level respectively.

5. Aggregating risk management trades

Given that the whole market is value-weighted and that these rebalancing schemes are aimed at reducing the asset concentrations of larger asset positions, these trades drive net demand in the cross-section of large-cap stocks.

This section aggregates the predictable trading attributable to *Passive* rebalancing into several measures of Diversification Driven Demand. I show that these measurements are associated with decreases in the percentage of total shares held by the mutual fund sector, as well as significant abnormal excess returns and reversals. The documented relationship among holdings, abnormal returns, and the measurement of forecastable trading is consistent with a demand-driven channel.

As shown in the previous section, between 1990 and 2022, a *Passive* change in portfolio weight corresponds to contrarian trading by individual active funds in the following quarter. The total dollar composition shifts attributable to concentration rebalancing by mutual funds, calculated for stock i, can be calculated as

$$Dollar\ Rebalancing\ Demand_{i,t} = \sum_j \underbrace{\left(\widehat{w}_{i,j,t} - w_{i,j,t-1}\right)}_{Passive} \cdot Holdings_{i,j,t-1}.$$

I numeraire the trading activities with the total observable mutual fund holdings of stock i. That is,

$$Rebalancing\ Demand_{i,t} = \frac{\sum_j \left(\widehat{w}_{i,j,t} - w_{i,j,t-1}\right) \cdot Holdings_{i,j,t-1}}{\sum_j Holdings_{i,j,t-1}}.$$

$$Rebalancing\ Demand_{i,t} = \frac{\sum_j \left(\widehat{w}_{i,j,t} - w_{i,j,t-1}\right) \cdot Shares_{i,j,t-1}}{\sum_j Shares_{i,j,t-1}}.. \tag{6}$$

Removing prices per share of stock i from both the top and the bottom of the fraction, the right-hand side of the previous equation can be reduced to:

That is, *Rebalancing Demand* for each stock over the quarter can be interpreted as the share-weighted *Passive* increase in the average owner mutual fund portfolio. A one standard deviation increase in *Rebalancing Demand* of 0.22 % for a stock indicates that the size of its relative proportion in the existing mutual fund portfolios has increased by 0.22 %

due to returns.

Eq. (5) describes the primary measurement of stock demand used in the analysis in this section. Summary statistics on *Rebalancing Demand* on both an equal and value-weighted basis are contained in Table 1 Panel C. I focus on actively managed mutual funds only for this source of aggregation.

Alternatively, diversification driven demand can be constructed by focusing on positions where risk management practices matter, that is positions of certain size. For example, a *Threshold Demand* variable can be constructed by just looking at positions that exceed 2 % of a fund's total AUM:

$$\mathit{Threshold\ Demand}_{i,t} = \frac{\sum_j \left(\widehat{w}_{i,j,t} - w_{i,j,t-1}\right) \cdot I\left(w_{i,j,t-1} > 2\%\right) \cdot \mathit{Shares}_{i,j,t-1}}{\sum_j \mathit{Shares}_{i,j,t-1}}. \tag{7}$$

This measure uses only 10 % of fund positions (90 % of fund positions are smaller than 2 %); which are the subset of portfolio positions where concentration and relative size end up mattering.

Alternatively, a fitted version of diversification driven demand can use the spline-wise coefficients plotted in Fig. 2. That is

$$\mathit{Fitted\ Demand}_{i,t} = \frac{\sum_j \left(\widehat{w}_{i,j,t} - w_{i,j,t-1}\right) \cdot \beta_{weight} \cdot \mathit{Shares}_{i,j,t-1}}{\sum_j \mathit{Shares}_{i,j,t-1}}, \tag{8}$$

where the β_{weight} is the betas for each respective bin plotted in Fig. 2. *Fitted Demand* uses the unconditional coefficients of the degree of rebalancing exhibited by actively managed mutual funds to *Passive* at varying holding sizes. This measurement, in practice, focuses on the subset of positions that have weights between 2 % and 6.5 % of a fund's AUM.

All these measurements give similar forecasts of future quarterly returns, and can be used as sorting variables. For the Fama-Macbeth Regressions, I use the percentile rank of these variables, which simply are the percentile of each stock's *Rebalancing Demand, Threshold Demand*, and *Fitted Demand* measurements within the stock universe each quarter.

The following subsections show that this stock/time panel measurement is robustly predictive of key features associated with stock demand— features such as changes in the aggregate holdings by equity portfolios and abnormal excess returns.

5.1. Total holdings by funds and portfolio managers

The counterparties to the documented trading in the previous section can be a combination of other institutional investors, and retail investors. Empirically, I find that these rebalancing activities by portfolio managers generate trade transactions between mutual funds and other unobserved portfolios. In the panel of quarterly stock observations between Q1 1990 and Q4 2022, *Rebalancing Demand* is associated with decreases in the total shares held by the observed equity funds. That is, rebalancing trades generate *net* demand from the observable asset managers.

Table 6 regresses the net trading of the observed mutual fund portfolios against *Rebalancing Demand, Threshold Demand*, and *Fitted Demand*. These panel regressions also include average weights in the observed portfolios and quarterly returns, as well as book-to-market ratio and log-market capitalization. Fixed effects are included to account for time and stock identity. In the first fives columns, diversification demand measures forecast net decrease of shares by equity mutual funds. For a single standard deviation increase of 0.22 % in the average equity fund portfolio, the probability that the stock would be sold in net by all equity funds increases by 3.15 %. Given that the unconditional probability that Mutual Funds as a sector will decrease their holdings of the outstanding share of a stock is 48.9 %; a standard deviation of *Rebalancing Demand* increases this probability by 6.44 %. Column (4) and (5) use *Threshold Demand* and *Fitted Demand* as measurements of diversification driven demand; widely confirming the results of column (3). The standard deviations of these measurements are 0.15 % and 0.03 % respectively giving a range of 1.28 % to 2.20 % increase in the probabilities of a sell by the mutual fund sector respectively.

Columns (6)–(10) take the percentage of change in the shares held by

Table 6
Change in net active mutual fund ownership.

	Net decrease by equity funds					Change in equity fund ownership				
	1	2	3	4	5	6	7	8	9	10
Rebalancing Demand	13.80***	13.25***	14.33***			−0.307***	−0.312***	−0.351***		
	(8.724)	(8.030)	(9.009)			(−6.672)	(−6.726)	(−7.682)		
Threshold Demand				8.572***					−0.234***	
				(8.201)					(−8.209)	
Fitted Demand					73.31***					−1.764***
					(10.47)					(−8.388)
Returns	−0.223***	−0.231***	−0.231***	−0.159***	−0.216***	0.00655***	0.00651***	0.00667***	0.00500***	0.00627***
	(−12.62)	(−12.53)	(−13.07)	(−14.47)	(−14.69)	(13.41)	(13.39)	(13.66)	(14.80)	(15.02)
Average Weight	5.320***	3.793***	4.378***	4.317***	4.338***	−0.0716***	−0.0909***	−0.110***	−0.109***	−0.109***
	(16.36)	(15.74)	(13.82)	(13.67)	(13.80)	(−12.11)	(−13.43)	(−12.51)	(−12.48)	(−12.47)
Book-to-Market Ratio		−0.0008	0.0196***	0.0196***	0.0198***		−8.66e-05	−0.0007***	−0.0007***	−0.000682***
		(−0.354)	(5.389)	(5.437)	(5.461)		(−1.552)	(−6.459)	(−6.567)	(−6.557)
Log-Market Value		0.0108***	0.0186***	0.0192***	0.0190***		0.0001***	−0.0001	−0.000147	−0.000143
		(7.059)	(5.715)	(5.843)	(5.829)		(3.148)	(−1.271)	(−1.394)	(−1.362)
Time-Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Stock-Fixed Effect	No	No	Yes	Yes	Yes	No	No	Yes	Yes	Yes
Adj. R^2	0.018	0.018	0.030	0.029	0.030	0.016	0.016	0.014	0.014	0.014
N	214,735	212,453	212,045	212,045	212,045	214,735	212,453	212,045	212,045	212,045

This table reports the regression coefficients of changes to Mutual Fund ownership on measures of Diversification Driven Demand and stock characteristics. *Net Decrease in Mutual Fund Ownership* is 1 if the stock was sold in net by the equity funds in the following quarter, and 0 otherwise. *Change in Equity Fund Ownership* is the change in the percentage of shares owned by equity funds over the quarter (% of shares held by funds at the end of the quarter - % of shares held by funds at the beginning of the quarter). *Rebalancing Demand* is the average return driven change in the portfolio weight of a stock over observed mutual funds. *Threshold Demand* is the return driven change in the portfolio weight for only positions with 2% or more weights scaled by the total observed mutual fund shares. *Fitted Demand* is the average return driven change in the portfolio weight of a stock scaled. The sample consists of all stock-quarter observations with at least $5 in price per share and held by more than 5 observed mutual funds each quarter between Q1 1990 and Q4 2022. The t-statistics reported in parentheses are clustered quarterly. *, **, *** indicates statistical significance at the 90 %, 95 %, and 99 % level respectively. See Appendix C for regressions that focus on only large capitalization stocks whose size exceeds 80th percentile of the NYSE breakpoint.

equity funds as the variable on the right side. We observe the same pattern as the one reported in Panel B. The added benefit of this regression is that it implies an aggregate demand schedule for the *Rebalancing Demand* variable. Using the specification in column (6), a standard deviation increase of 0.20 % in *Rebalancing Demand* in the mutual fund portfolios implies a 0.08 % total decrease of the stock's fraction of holdings in the aggregate active fund portfolio. Given that the average stock has 7.64 % of its value in active portfolios during the sample, this represents a proportional decrease of about 1 % in the total holding of a stock by active equity funds. Regressions using *Threshold Demand* and *Fitted Demand* in columns (9) and (10) indicate half to two third of a percent in proportional decrease respectively.

Consistent with trading demand originating from portfolio managers, I find that the predicted *Rebalancing Demand* tends to be negatively associated with the amount of assets held in institutional portfolios. That is, when realized returns drive an asset to large weights across active equity fund portfolios, mutual funds and other asset managers tend decrease their holdings of this asset in general- consistent with the findings of Blume and Keim (2017). These trades are not netted through the increases in portfolio holdings by other mutual funds, and the counterparty to these demands must be composed of retail and non-institutional investors.

5.2. Abnormal returns and rebalancing demand

The foreseeable rebalancing demand generates excess return predictability on the underlying stocks. The returns associated with high levels of rebalancing are negative in the short term but revert in longer-holding horizons—a pattern consistent with ex-post non-fundamental demand.

There are two principal sets of specifications used to document the return predictability associated with equity fund rebalancing. The first examines the return predictability of *Rebalancing Demand* without controlling past stock performance. Table 7 Panel A conducts value-weighted Fama and MacBeth (1973) regressions that show *Rebalancing Demand* forecasts negative returns in the near short term. Specifically, returns accumulated across a 35-trading day and post 35 trading day horizons are regressed on the percentile rank of *Rebalancing Demand* and other controls in each cross-section of stock observations weighted by their respective lag-market capitalizations in each quarter. These trading days cut-offs are chosen to describe the maximum points of cumulative return and subsequent reversals (See Fig. 3). The cross-sectional coefficients from these regressions are then averaged and reported.

Between one and 35 trading days in each quarter, one standard deviation of the key variable forecasts up to −0.44% ($t = -3.21$) returns. This negative return reverts in the rest of the quarter, forecasting a positive return of 0.27% ($t = 2.60$). Columns (2) and (4) control for book-to-market ratio and size, and the pattern of short-term returns predictability along with long-term reversal remains. The coefficients using *Threshold Demand* and *Fitted Demand* give widely similar short-term return predictability and subsequent reversals in columns (3) and (4), and (7) and (8) respectively.

Tabulated in Table 7 Panel B, a long-short calendar time portfolio formed by holding the highest quintile portfolio and shorting the lowest quintile portfolio sorted by *Rebalancing Demand* obtains a three-factor adjusted return of −1.16% ($t = -2.89$) by the 35th trading day. The same portfolio reverts during the rest of the quarter, with a cumulative

Table 7
Value-weighted Fama-Macbeth regressions of rebalancing demand and characteristics.

Panel A. This panel conducts value weighted Fama Macbeth Regressions of *Rebalancing Demand, Threshold Demand, Fitted Demand,* and controls. *Rebalancing Demand Rank*, *Threshold Demand Rank*, and *Fitted Demand Rank* are the cross sectional percentiles of the three demand measures respectively. The first stage cross sectional regressions are weighted by stock market cap, averaged, and then reported in the table. OLS t-statistics are reported in parentheses.

	Cumulative Returns Over the Quarter							
	1st to 35th Trading Date				36th to End of Quarter			
	1	2	3	4	5	6	7	8
Rebalancing Demand Rank	−0.438 %	−0.466 %			0.267 %	0.257 %		
	(−3.213)	(−3.575)			(2.604)	(2.594)		
Threshold Demand Rank			−0.348 %				0.178 %	
			(−3.719)				(2.508)	
Fitted Demand Rank				−0.460 %				0.253 %
				(−3.598)				(2.616)
Book-to-Market Ratio		−0.210 %	−0.226 %	−0.212 %		−0.237 %	−0.238 %	−0.235 %
		(−0.695)	(−0.746)	(−0.702)		(−1.000)	(−0.997)	(−0.992)
Log Market Value		0.058 %	0.059 %	0.056 %		−0.166 %	−0.169 %	−0.164 %
		(0.643)	(0.653)	(0.617)		(−2.557)	(−2.595)	(−2.518)
Avg. Adj. R^2	0.025	0.064	0.060	0.064	0.019	0.052	0.049	0.052
Avg. N	2900	2859	2859	2859	2900	2859	2859	2859

Panel B. This panel reports calendar time value weighted excess returns of quintile portfolios sorted by *Rebalancing Demand*. Stocks are sorted in equal numbers into 5 portfolios by *Rebalancing Demand*. The LS portfolio is formed by longing the top quintile portfolio and shorting the bottom quintile portfolio. OLS t statistics are reported in parentheses.

	1st to 35th Trading Date			36th to End of Quarter		
Rank	Excess Returns	CAPM Adjusted	3 Factors Adjusted	Excess Returns	CAPM Adjusted	3 Factors Adjusted
1	2.375 %	0.720 %	0.725 %	0.348 %	−0.282 %	−0.149 %
	(3.598)	(3.338)	(3.266)	(0.694)	(−1.530)	(−0.824)
2	2.029 %	0.607 %	0.440 %	0.976 %	0.393 %	0.430 %
	(3.468)	(2.559)	(1.989)	(2.096)	(2.256)	(3.059)
3	2.272 %	0.854 %	0.896 %	0.880 %	0.308 %	0.241 %
	(3.878)	(3.512)	(3.862)	(1.895)	(1.618)	(1.278)
4	1.465 %	0.077 %	−0.151 %	0.822 %	0.257 %	0.194 %
	(2.612)	(0.378)	(−0.858)	(1.863)	(1.867)	(1.542)
5	1.077 %	−0.389 %	−0.433 %	1.160 %	0.551 %	0.570 %
	(1.838)	(−1.990)	(−2.202)	(2.444)	(3.803)	(3.935)
LS	−1.298 %	−1.109 %	−1.158 %	0.812 %	0.833 %	0.718 %
	(−3.347)	(−2.823)	(−2.892)	(2.725)	(2.768)	(2.408)

holding return of 0.72% ($t = 2.41$) from the 36th trading date beyond.

Fig. 5 plots the cumulative returns of the long-short portfolio formed by longing the top quintile and shorting the bottom quintile portfolios sorted by *Rebalancing Demand* over the entire quarter. We see that there is a clear V-shaped pattern of abnormal returns and reversals. The cumulative return bottoms at 35 trading days into each quarter over our sample period. These peak and reversals are indicative of price pressure and non-fundamental demand. Furthermore, these patterns are not driven by any specific quarter within each year and are robust to the exclusion of any specific season. This pattern is different from the traditional January Effect in stocks.

This negative return and subsequent reversal pattern coincide with past returns. Large-cap stocks with low past quarter returns tend to perform poorly in the trading days toward the end of each quarter, and stocks with high past returns tend to perform well near the end, reverting the short-term predictability discussed in the previous section. Section IV.C describes the intra-quarterly pattern of large-cap momentum portfolios, which displays similar patterns and reflects the confounding effect of returns on portfolio concentration.

While these specifications indicate predictability in the short term, there are confounding effects with traditional past-return-based predictability, such as momentum and short-term reversal effects. The second main set of specifications explicitly controls for past returns of varying horizons in addition to the *Rebalancing Demand*. These specifications attempt to control for the confounding effects of past performance on rebalancing and filter the calendar time results by 1) explicitly controlling for momentum and short-term reversal factors and 2) excluding stocks with extreme negative past quarter returns- as evidence by the existing literature Stambaugh et al. (2012), momentum returns are highly related to its short-leg.

The goal of this exercise is to assume that the economic forces on which classical momentum operates are different from the rebalancing demand channel. If that were the case, as seemingly indicated by the difference in the trading sensitivity to return by equity funds for small and large weight positions, then calendar time strategies that explicitly control for past-returns and for its substantial short-leg should likely have clearer predictions on returns.

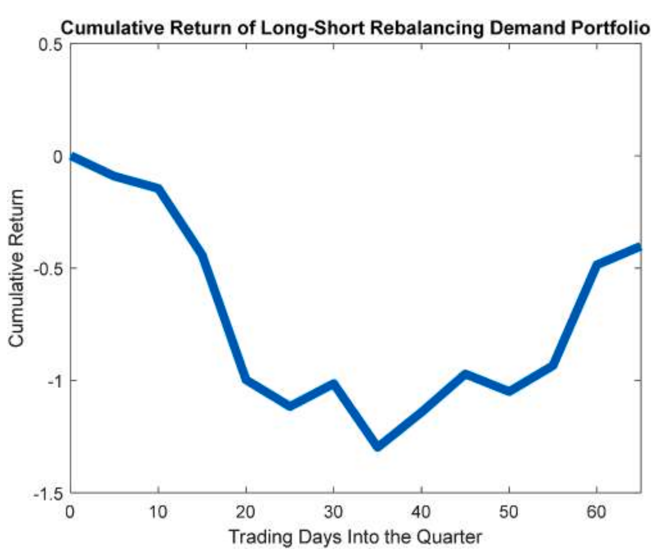


Fig. 5. Cumulative returns of a long-short value-weighted calendar portfolio sorted on *Rebalancing Demand* over every 5 trading days into each quarter. *Rebalancing Demand* is the average percentage change in quarterly holdings as driven by returns over all observed portfolios. The long-short portfolio is constructed by longing stocks sorted to the top quintile and shorting stocks sorted to the lowest quintile of *Rebalancing Demand*. The cumulative returns bottoms at the 35th trading date of each quarter. The returns are from Q3 1990 to Q4 2022.

Table 8 reports Fama-Macbeth regressions of future returns controlling for past returns of varying horizons. In this table, excess returns in individual stocks are regressed on their percentile *Rebalancing Demand*, past three-, six-, and 12-month returns, *Book-to-Market Ratio*, and Log-*Market Equity*. Again, the cross-sectional regressions each quarter are weighted by each stock's market capitalizations.

Rebalancing Demand, after controlling for short-term returns, negatively forecasts excess future stock returns. Controlling for past returns of varying horizons, as shown in Column 1, the regression indicates that a single standard deviation in the percentile *Rebalancing Demand* forecasts −0.56% ($t = -3.71$) return in the following quarter. *Threshold Demand* and *Fitted Demand* give widely comparable direct quarterly return predictability in columns (3) and (4).

This price effect is temporary. Additionally, I observe longer-term reversals of this price effect. In columns (5) through (8), I observe that these abnormal returns almost entirely disappear over the following four quarters. The same temporary price decreases are met with positive returns. One standard deviation of *Rebalancing Demand* is met with 0.67 % ($t = 2.16$) returns over this horizon, which subsumes the prior sell-driven price predictability; while *Threshold* and *Fitted Demand* predict similar levels of reversals at 0.52 % and 0.77 % over the 1 year respectively.

An interesting property of diversification driven demand measures is that the inclusion of these characteristics in a multivariate regression accentuates the positive correlation between recent momentum characteristics and future returns. In all the regression specifications, the coefficients of the past three-month returns on future excess returns switches show positive predictability in the bivariate regressions with *Rebalancing Demand*. The fact that the two variables tend to be related but capture differing mechanisms may explain the well-founded fact that momentum returns are driven mainly outside of recent past performances for US equities (Goyal and Wahal, 2015; Huang, 2022; Novy-Marx, 2012)- short-term returns tend to be confounded with the quarter-to-quarter rebalancing by equity mutual funds. Section III.C will further explore this relationship between momentum and diversification driven demand.

The Fama-Macbeth regression results naturally translate into calendar time trading strategies. Table 9 sorts large capitalization stocks (ones whose market cap exceed the 80th percentile of the NYSE size breakpoint) into portfolios using the *Rebalancing Demand* at the end of each quarter. In these specifications, the portfolio returns are explicitly adjusted using the Four-Factor Model (Carhart, 1997) and a Five-Factor Model that includes the two- to 12-month momentum and the one-month short run reversal factors.

To exclude potential momentum-driven effects, I also filter out stocks that had extremely poor returns- lower than −20 % returns- in the previous quarter (although removing this requirement still generates similar results). Column (1) reports the average value-weighted monthly returns, in excess of the risk-free rate, of these quintile portfolios during the following quarter. I observe that the stocks sorted at the top of the quintile portfolio have the lowest average excess returns, and the effect is not extremely significant. This follows closely with the univariate sort and the intra-quarterly returns reported in Tables 7 and 8, which typically revert within the same quarter. However, once I adjust for return-factor variables that account for momentum and reversals, as seen in Columns (4) and (5), the sorted portfolios begin to show a more monotonic pattern over the entirety of the quarter.

A calendar time strategy that accounts for momentum and reversal returns increases the significance of the rebalancing demand strategy. The portfolio that longs the highest quintile of *Rebalancing Demand* sorted stocks and shorts the bottom quintile yields a quarterly alpha of −1.15 % ($t = -2.51$). These effects may seem economically modest, but as we observe, they are centered in the largest, and supposedly most well priced stocks, in the equity universe.

The time series cumulative residuals of the top and bottom portfolios using the five-factor model are plotted in Fig. 6. I observe that the

Table 8
Value-weighted Fama-Macbeth regressions of rebalancing demand, characteristics, and stock returns.

	Next Quarter's Returns				Next 4 Quarter's Returns			
	1	2	3	4	5	6	7	8
Rebalancing Demand Rank	−0.557 %	−0.517 %			0.670 %	0.810 %		
	(−3.713)	(−3.498)			(2.161)	(3.025)		
Threshold Demand Rank			−0.292 %				0.520 %	
			(−3.261)				(3.315)	
Fitted Demand Rank				−0.487 %				0.768 %
				(−3.503)				(3.018)
Ret3m	4.134 %	3.238 %	1.830 %	3.023 %	−2.643 %	−2.999 %	−0.881 %	−2.738 %
	(2.311)	(2.036)	(1.298)	(1.952)	(−0.712)	(−0.902)	(−0.294)	(−0.835)
Ret4_6m		0.824 %	0.880 %	0.832 %		2.343 %	2.317 %	2.334 %
		(0.668)	(0.713)	(0.675)		(0.958)	(0.944)	(0.956)
Ret7_12m		1.246 %	1.258 %	1.245 %		−1.057 %	−1.040 %	−1.043 %
		(1.375)	(1.385)	(1.373)		(−0.758)	(−0.745)	(−0.747)
Book-to-Market Ratio		−0.152 %	−0.154 %	−0.158 %		−0.933 %	−0.940 %	−0.938 %
		(−0.473)	(−0.479)	(−0.492)		(−1.212)	(−1.218)	(−1.218)
Log Market Value		−0.086 %	−0.091 %	−0.086 %		−0.371 %	−0.374 %	−0.373 %
		(−0.812)	(−0.858)	(−0.811)		(−1.276)	(−1.287)	(−1.280)
Avg. Adj. R^2	0.033	0.107	0.105	0.106	0.029	0.097	0.096	0.097
Avg. N	2900	2855	2855	2855	2634	2612	2612	2612

The first-stage cross-sectional regressions are weighted by stock market cap and then the coefficients are averaged and reported in the table. *Rebalancing Demand Rank, Threshold Demand Rank, and Fitted Demand Rank* are the cross-sectional percentiles of *Rebalancing Demand, Threshold Demand, and Fitted Demand* respectively. *Rebalancing Demand* is the average return driven change in the portfolio weight of a stock over observed mutual funds. *Threshold Demand* is the return driven change in the portfolio weight for only positions with 2 % or more weights scaled by the total observed mutual fund shares. *Fitted Demand* is the average return driven change in the portfolio weight of a stock scaled. These measurements are standardized by their unconditional standard deviation for interpretation. *Ret3m* is the previous quarter's returns. *Ret4_6m* and *Ret7_12m* are the stock returns from the past four to six months and seven to 12 months past, respectively. *Book-to-Market Ratio* is the previous quarter's book-to-market ratio. Log *Size* is the log-market equity. OLS t-statistics are reported in parentheses.

Table 9
Calendar time sorted portfolios of "Large" Stocks (Quarterly).

Rank	Excess return	CAPM adjusted	3-factor adjusted	4-factor adjusted	5-factor adjusted
1	2.544 %	0.654 %	0.566 %	0.783 %	0.752 %
	(3.615)	(2.674)	(2.350)	(3.187)	(3.066)
2	2.854 %	0.900 %	0.756 %	0.903 %	0.869 %
	(3.827)	(2.962)	(2.714)	(3.111)	(2.994)
3	2.931 %	1.070 %	0.874 %	0.742 %	0.700 %
	(4.053)	(3.320)	(3.205)	(2.607)	(2.470)
4	1.850 %	−0.005 %	−0.219 %	−0.173 %	−0.166 %
	(2.660)	(−0.018)	(−1.007)	(−0.752)	(−0.717)
5	1.994 %	−0.170 %	−0.113 %	−0.467 %	−0.400 %
	(2.468)	(−0.593)	(−0.402)	(−1.687)	(−1.483)
LS	−0.550 %	−0.824 %	−0.678 %	−1.250 %	−1.153 %
	(−1.159)	(−1.713)	(−1.443)	(−2.680)	(−2.514)

This table reports the risk-adjusted excess returns of calendar time portfolios sorted on *Rebalancing Demand*. Common stocks with market capitalization greater than the 80 % breakpoint of NYSE size and past quarterly returns greater than −20 % are sorted equally into 5 portfolios. The following panel reports the value-weighted risk-adjusted excess return of these portfolios. The 3-Factor adjustment uses the Fama-French factor. The 4-Factor adjustment uses the Fama-French factor and the momentum factor. The 5-Factor adjustment adds an additional short-term reversal factor. OLS t-statistics are reported in parentheses.

returns occur through both legs of the portfolio strategy and that they tend to occur throughout the sample period[15].

5.3. Momentum portfolios

Given the prior results on univariate predictability from a variable that was constructed from holding weights and cross-sectional returns, it may not be too surprising that the documented pricing effects show up in momentum portfolios formed from the largest capitalization stocks. Such evidence, however, provides external validation of the predictability results. In this section, I show that similar evidences of return reversals can be observed in the large capitalization portfolio- formed using the stocks that exceed the 80th percentile of NYSE stocks and sorted using the standard past 1 to 12 month past returns, and that this reversal pattern can be explained by diversification driven demand channel.

Fig. 7 takes the momentum portfolios and plots the resultant cumulative long-short returns over the trading days of each quarter. These momentum portfolio returns are obtained from Ken French's website and are constructed by double-sorting the sample of US common stocks on size and then on past two- to 12-month returns. Specifically, this figure focuses on the portfolios formed from stocks sorted to the varying quintiles of Market Capitalization and then constructing the long/short portfolio by holding the stocks with the highest quintile and selling the lowest quintile of prior returns. The sample period focuses on the modern period of returns that match the timing of the *Rebalancing Demand* data.

From day 1 to near the 35th trading day, the average cumulative returns rise, extending to a maximum of −1.76 %. This coincides with the −1.16 % of returns formed in Table 7′s Panel B. Both cumulative negative returns revert over the quarter. The Fama-Macbeth regression of cross-sectional stocks based on past returns and *Rebalancing Demand* in Table 8 shows that this is no coincidence. Although momentum is known to forecast positive returns, I observe that in the modern finance period—a period that is dominated by professional asset managers—such positive predictability becomes intermingled with a reversal pattern.

From Table 9, we observed that stocks sorted into the bottom (top) quintile of diversification driven demand portfolios outperformed (underperformed) during the sample period. In other words, large capitalization stocks whose past quarterly returns mechanically increased (decreased) their mutual fund weights have low (high) forward returns. This reversal effect, where past returns are negatively related to future returns through their impact on portfolio weights, runs counter to the price-effects that are documented in momentum strategies during other sample periods.

This implies that the traditional momentum portfolios, which were

[15] Appendix A6 also controls for contemporaneous flow-induced price impact, which accentuate both the long and short-leg returns.

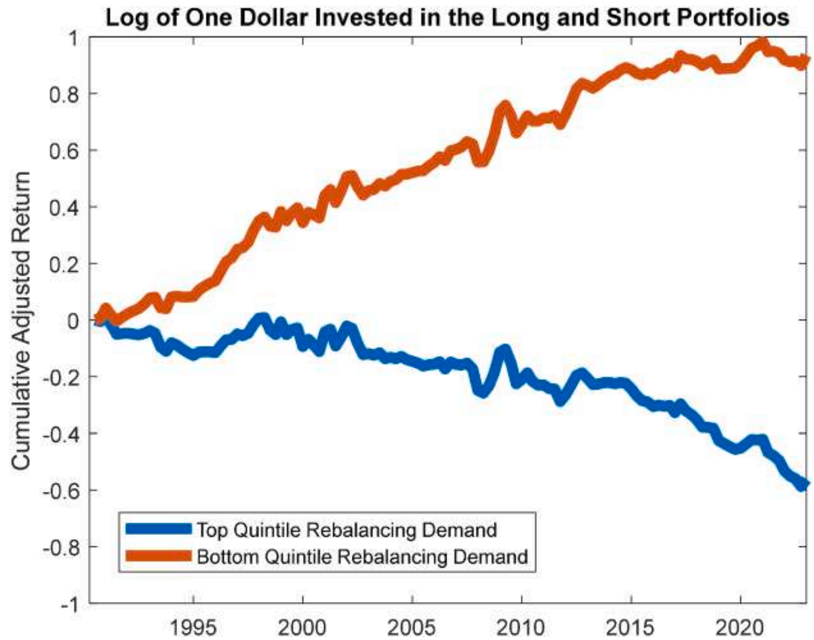


Fig. 6. Cumulative 5-factors adjusted returns of the top and bottom quintile value-weighted calendar portfolios for Large Stocks (stocks whose value exceed 80th percentile of NYSE value breakpoints) sorted by *Rebalancing Demand*. The blue (red) plots the investment value of a 1-dollar portfolio that longs stocks sorted to the top (bottom) quintile of *Rebalancing Demand* for the sample of common stocks with no more than a 20% loss in the previous quarter's stock returns. *Rebalancing Demand* is the average percentage change in quarterly holdings as driven by returns over all observed portfolios. These portfolios are rebalanced every quarter and held for 1 quarter.(For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.).

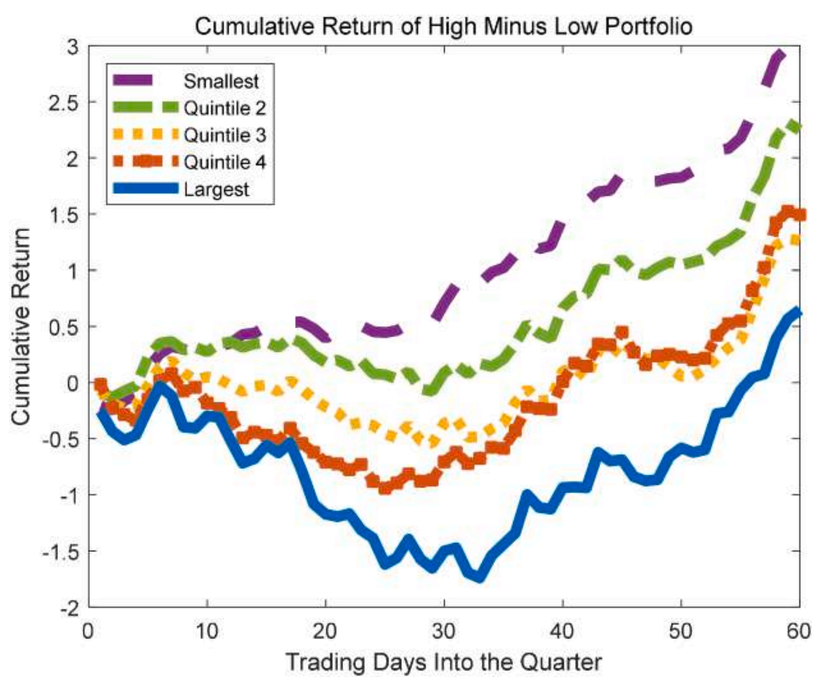


Fig. 7. Long-Short Portfolio Returns of the Standard Fama French Momentum and Size Portfolios. This portfolio is formed by using the 5 × 5 portfolios sorted by size and the past 2- to 12-month returns between Q3 1990 and Q4 2022 provided by Ken French. Specifically, the lines are strategies that longs High (stocks in the highest quintile of the past 2- to 12-month returns) and shorts Low (stocks in the lowest quintile of the past 2- to 12-month returns) return stocks within each size quintile (blue is the largest, purple is the smallest) are plotted. The pattern is robust to excluding any individual quarter of the year (See Appendix Fig. D).(For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.).

formed by longing/shorting stocks based on their past performance, may have had returns that were diminished by these price reversals. Indeed, the time series returns of the long-short *Rebalancing Demand* portfolio in Table 9 correlates at 29 % to the traditional momentum factor yet manifest in a negative return on average.

One question is whether momentum strategies would "work" better if the pricing effects of diversification driven demand can be removed. In Table 10, I simply regress the quarterly returns of momentum portfolios sorted by size (constructed from Ken French's data library) on the excess returns of the *Rebalancing Demand* portfolios (the rank 5 and rank 1

Table 10
Implementing momentum portfolios.

	Mom factor		Largest		Quintile 4		Quintile 3		Quintile 2		Smallest	
	1	2	3	4	5	6	7	8	9	10	11	12
Intercept	1.48 %	2.74 %	0.84 %	2.78 %	2.01 %	4.20 %	1.76 %	3.62 %	2.76 %	4.46 %	3.65 %	5.31 %
	(2.06)	(4.15)	(0.77)	(2.76)	(1.77)	(4.11)	(1.70)	(3.79)	(2.92)	(5.10)	(3.92)	(6.12)
Top Quintile Rebalancing Demand		0.38		0.49		0.37		0.51		0.28		0.19
		(3.22)		(2.76)		(2.03)		(3.01)		(1.80)		(1.22)
Bottom Quintile Rebalancing Demand		−0.79		−1.15		−1.15		−1.13		−0.89		−0.80
		(−5.89)		(−5.60)		(−5.53)		(−5.80)		(−4.98)		(−4.51)
Adj. R^2		0.236		0.231		0.264		0.237		0.225		0.218
N	130	130	130	130	130	130	130	130	130	130	130	130

This table regresses the quarterly returns of the various momentum strategies as related to size on *Rebalancing Demand* portfolio returns. *Mom Factor* is the quarterly momentum factor strategy returns. Columns 3 through 12 uses the momentum returns as partitioned by size quintiles in the NYSE. These are calculated using the 5 × 5 portfolios sorted by size and the past 2- to 12-month returns between Q3 1990 and Q4 2022 provided by Ken French. Specifically, each quintile size momentum return is the returns of a portfolio that longs High (stocks in the highest quintile of the past 2- to 12-month returns) and shorts Low (stocks in the lowest quintile of the past 2- to 12-month returns) return stocks within the size quintile (*Largest* is the by using stocks exceeding the 80th percentile of the NYSE market cap, *Quintile 4* is for those between 60 and 80 percentile, etc.). *Top Quintile Rebalancing Demand* is excess returns of the Rank 5 *Rebalancing Demand* portfolio from Table 9, while the *Bottom Quintile Rebalancing Demand* is that of the Rank 1 *Rebalancing Demand* portfolio.

portfolio excess returns in Table 9). This linear regression represents an ex-post hedging of the pricing effects of diversification driven demand on the momentum portfolios.[16] The resultant regression intercepts can be interpreted as the average quarterly return of momentum portfolio strategies after implementing hedging adjustments for *Rebalancing Demand* portfolios.

We observe that during this sample period, all the momentum portfolios become more profitable after adjusting for *Rebalancing Demand* returns. Comparing column 1 to column 2, the average quarterly momentum factor returns increased from 1.48 % ($t = 2.06$) to 2.74 % ($t = 4.15$). This adjustment also increased all the momentum portfolio returns that were first sorted on size.

Columns 3 through 12 uses the returns of the portfolios sorted on both Size and Momentum as the left-hand side variable. That is, long-short portfolios are formed by using the 5 × 5 portfolios sorted by size and the past 2- to 12-month returns between Q3 1990 and Q4 2022. Specifically, Largest is the returns of a portfolio that that longs High (stocks in the highest quintile of the past 2- to 12-month returns) and shorts Low (stocks in the lowest quintile of the past 2- to 12-month returns) return stocks only for stocks that are within the top size quintile. *Quintile 4* is the returns for the long-short momentum return within the second highest size quintile, etc., down to the *Smallest* quintile cross-section.

Adjusting for *Rebalancing Demand* increases the average return across all the size-sorted momentum strategies, but its most drastic effect concentrates on the large-size portfolios. For large capitalization stocks, adjusting for *Rebalancing Demand* produces an average momentum return of 2.78 % ($t = 2.76$) per quarter. This is a 230 % increase from the unconditional average of 0.84 % ($t = 0.77$); whereas this adjustment increases the smallest size quintile momentum return by 45 % from its unconditional mean.

Overall, the results here show that momentum returns were attenuated by this modern diversification mechanism arising from actively managed portfolios. By adjusting for *Rebalancing Demand*, the traditional momentum strategies that long and short stocks by their past performance have significantly stronger predictive power over future returns. This indicates that the fundamental mechanisms that underly momentum strategies are extant even during the modern period of financial history.[17]

6. Conclusion

The active asset management industry's treatment of large positions is consistent with diversification for risk management. This channel of rebalancing predictability forms a novel complement to the vast literature on predictable benchmarking. Such rebalancing motives drive coordination in investors and affect prices for stocks whose values exceed 80th percentile of NYSE breakpoints (the largest drivers of total equity market values).

Ultimately, large positions are an inherent feature of the equity market and investor portfolios. While theory assumes that the market portfolio is mean-variance efficient, when investors re-optimize their portfolios for diversification, strategic, and regulatory mandates, there is a common predictable component in their trading behavior- they seek to limit large, concentrated positions. Such trading patterns originate from even the most sophisticated- longer tenured- asset managers; is related to ex ante measures of portfolio diversification; and concentrates on regulation guided thresholds.

Such institutional preferences are consequential for asset pricing. This paper shows diversifying against increasing concentration of certain stocks for risk management and portfolio strategies is a persistent, widespread, and economically meaningful channel of stock return predictability.

CRediT authorship contribution statement

Huaizhi Chen: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

I have no conflicts of interest to declare for the submission of "Diversification Driven Demand for Large Stocks" to the Journal of Financial Economics

[16] Daniel and Moskowitz (2016) argues that hedging momentum against market returns using such an ex-post regression analysis is difficult to interpret and implement. In the case of hedging diversification driven demand, the regression in Table 10 has a straightforward interpretation. The momentum portfolio strategies hold stocks with high past returns and short stocks with low past returns. The betas in Table 10 shows that hedging momentum against diversification driven demand can be accomplished by not longing high return stocks that has high *Rebalancing Demand* (the positive coefficient on Top Quintile Rebalancing Demand) and not shorting low returns stocks that has low Rebalancing Demand (the negative coefficient on Bottom Quintile Rebalancing Demand).

[17] Appendix Table A7 conducts the same analysis as in Table 10 after removing periods of momentum crashes (the years 2001, 2002, and 2009).

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