Portfolio Rebalancing of Granular Stocks*

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ABSTRACT

I demonstrate that in order to diversify asset positions and track certain indices, the average mutual fund predictably trades against the return driven changes in their largest positions, resulting in an underweighting of large "granular" stocks. These trades lag behind asset returns and are forecastable. Because they are widely held by investors and still form large portions of an average portfolio, large-cap stocks exhibit price patterns that reflect this source of rebalancing trading demand. A variable that captures these rebalancing trades can predict and explain return reversals in the momentum portfolios formed from the largest US companies.

JEL Classification: G10, G11, G14, G40, and G41

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The stocks of the largest firms, which dominate the US economy (Gabaix (2011)), form the basis of most modern portfolios. By market capitalization, the top 1% of US publicly traded companies make up an outsized 45% of their total value.[1] The large granular stocks are more likely to be held by most market participants, and thereby command outsized influence over many portfolios' compositions and risks.

Table 1 summarizes the 10 largest stocks and their respective sizes within the aggregate market and the equity mutual fund industry at the end of June 2021. While collectively representing 23.3% of the total equity market value, each stock in this table had lower weights in the mutual fund industry. Collectively, they form only 19.4% of the total equity fund portfolio—reducing their market weights by 16.7%. Beyond this snapshot, Blume and Keim (2017) reports that the underweighting of large-cap stocks has been a persistent feature throughout the modern period of the asset management industry. It appears that notwithstanding a variety of possible individual investment strategies and benchmarking mandates, asset managers collectively maintain the underweighting of the largest companies.

What drives this preference to underweight the most important firms in the equity universe? Moreover, how does this prominent preference fit into asset pricing dynamics and demand for investible stocks? Although there are renewed interests in the finance literature on how institutional preferences drive demand for assets (Koijen and Yogo (2019), Pavlova and Sikorskaya (2022), and Gabaix and Koijen (2022), among others), the reasons that certain characteristics- in particular, size-matter to the weighting of portfolios are not well understood. This paper examines how the risk

[1] This was calculated using CRSP common stocks that are traded in the AMEX, NYSE, and NASDAQ exchanges in December 2021.

management practices and investment mandates that are integral to the pervasive asset management industry translate to portfolio choice and, in turn, stock pricing.

I use the setting of portfolio rebalancing by asset managers to investigate why institutions prefer to underweight the largest firms, how such preferences are maintained through portfolio rebalancing, and how the resultant demand affects stock prices.

Stocks price are not static. Although funds can always initiate their portfolios with fixed holding weights, the largest firms became large over periods of high past returns. If the underweighting of granular stocks is rooted in risk management and strategic mandates, as argued by the existing literature, then institutional investors must actively rebalance positional changes caused by returns in order to achieve these weighting goals. Large positions must be sold on high past returns so that portfolios do not become even more concentrated. I show that the management practices and investment mandates of the average funds widely and persistently affect their portfolio choice and trading behavior. A 1% increase in portfolio weight due to returns forecasts a 20.43% higher chance that a stock will be sold and a 14.87% lower chance that it would be bought over the next quarter.

Furthermore, I demonstrate that this underweighting preference matters to prices. Since changes to portfolio concentrations forecast active rebalancing among the average equity fund, and because many institutions often already hold granular stocks in large concentrations, the aggregation of these trades cannot be absorbed within the mutual fund sector. Consequently, the mutual fund sector is constrained in its ability to absorb this source of demand. A 1% increase of the portfolio weight among all equity funds (as driven by returns) decreases the percentage of a stock held by all equity funds by 0.182%.

This rebalancing demand from equity funds is related to return reversals in the momentum portfolios formed by the largest US stocks. Univariately, a one standard deviation a stock's percentile rank of *Rebalancing Demand* each quarter (as a tendency to sell) predicts -0.489% (t = *-2.908*) returns within 35 trading days and 0.286% (t = *2.539*) positive returns during the rest of the trading quarter. Controlling for past momentum, the abnormal return and reversal patterns occur over a longer horizon. A one standard deviation of the predictor variable, while controlling for the quarter's returns, forecasts -0.523% (t = *-3.580*) returns within a quarter and a subsequent reversal of 0.563% (t = *1.984*) over the rest of the year. Due to the inherent mechanical connection between passive changes to portfolio concentrations and quarterly returns, these return patterns are also evident in the largest capitalization momentum portfolios.

In summary, this paper analyzes how large-cap stocks are rebalanced by mutual fund companies, as well as presenting evidence that such practices lead to return predictability and inelastic demand. The contributions of this paper are as follows: 1) I show that the treatment of granular stocks explains the quarter-to-quarter rebalancing trades of the average mutual fund. 2) I describe the types of fund portfolios that are most likely to mechanically rebalance. This provides evidence that institutional and strategic constraints are driving the collective underweighting preference. 3) Finally, I show that granular stocks have predictable returns that coincide with rebalancing demand.

The mutual funds whose trades tend to be most predictable are the active mutual funds of particular asset management families, and passive funds that are using certain strategic weighting schemes. Variables that proxy for other trading behaviors, such as for the classical form of the disposition effect, tax-loss harvest, and rank effects, do not subsume the rebalancing predictability. Individual actively managed mutual funds' rebalancing of large granular positions can be explained at the family level. Index funds' mechanical investment strategies and mandates also drive forecastable contrarian trading.

This analysis of granular portfolio positions is novel for the finance literature. Although there is a growing interest in understanding how large firms affect aggregate fluctuations (Gabaix (2012) and Gabaix and Koijen (2022)), the literature has only started exploring the mechanisms of how exactly large stocks propagate shocks. Given their prominence in the modern market, institutional portfolios likely affect the demand for granular assets through their asset management practices. Rebalancing to the risk practices in the professionally managed portfolios naturally identifies a source of predictable weighting constraint and trading demand.[2] This paper proposes a new channel for how investors absorb shocks to granular stocks.

Second, large-cap stocks form a setting where there are the fewest possible trading frictions. The large body of literature on institutional demand for assets (Coval and Stafford (2005), Lou (2010), Chen (2022), Pavlova and Sikorskaya (2022), among others) show that investment demand affects stock-return predictability. Criticisms of this literature point out that the documented predictability centers on certain types of stocks (Wardlaw (2020)). An even larger body of literature points to the similar issues in stock return predictability in general. In contrast, large-cap stocks have the highest investor attention and daily volumes exceeding billions of dollars. The resultant return predictability must be a first-order effect in the financial markets.

In the subsequent sections, I show that the average mutual fund consistently reacts to changes in its granular positions by trimming and rebalancing its portfolio. For a 1% passive increase in an

[2] Rebalancing of asset classes for target date funds is explored in (Parker, Schoar, and Sun (2022)), and Camanho, Hau, and Rey (2022) study the rebalancing of exchange rate portfolios. The current paper instead focuses on granular positions and shows that patterns of rebalancing tend to be significantly diminished for smaller positions.

asset's portfolio weight, a fund manager is 15.28% more likely to sell the stock in net in the contemporaneous quarter, and is 20.43% times more likely to do so in the subsequent quarter. This relationship between passive positional changes and trading activity exists after controlling for actual returns, unrealized holding profits, and rank effects. This tendency to rebalance predictably can be linked to the fund family level practices and individual investment mandates. Fund families explain 10% of the variation in rebalancing predictability in active funds, but they do not explain the variation in index funds. Implicitly inverse-weighted and explicitly equal-weighting portfolios top the list of index funds that rebalance intensely.

Additionally, these trades do not clear within observable mutual fund portfolios. Because large-cap stocks are held widely, fewer asset managers initiate new positions to absorb the rebalancing demand. Given an average passive increase of 1% in weight among mutual fund portfolios due to returns, I forecast a 0.182% decrease in the percentage of the asset owned by all funds, indicating that the ability of fund managers to initiate new positions to absorb the excess demand is also constrained.

The two facts that market participants form an aggregate demand due to rebalancing and that many investors are also constrained in their ability to buy granular stocks form a basis for possible limits to arbitrage (Shleifer (1986), Shleifer and Vishny (1992), and Shleifer and Vishny (1997)). I show that the returns of large-cap stocks reflect an inelastic pricing demand. A constructed demand variable that forecasts these rebalancing trades can predict and explain return reversals in the largest US stocks. This demand variable can also be observed separately in the largest momentum portfolios, as they are formed by stocks within the top percentile.

The paper is organized as follows. Section I reviews the relevant literature on portfolio demand. Section II describes the data used. Section III examines how individual trading by mutual funds are shaped by managing portfolio drifts, the various funds whose rebalancing tends to be the most predictable, and the costs to rebalancing. Section III aggregates the rebalancing trades, describe the predictable price patterns, and the returns certain calendar-time strategies. Section V concludes.

I. Relevant Literature

How asset managers' prefer to underweight large firms affects asset prices, to my understand, this has not been explored in the finance literature. The analysis of these underweighted positions extends across several strands of the finance literature.

Foremost, the paper is related to the literature on how the asset management industry, because of its institutional requirements, affects the trading and the pricing of financial assets. Related to the content of this paper, Pavlova and Sikorskaya (2022) show that benchmarking popularity can generate pricing demand. Koijen and Yogo (2019) and their demand system analyze the institutional preference for certain stock characteristics, including size. In this demand system, the portfolio weights are determined by characteristics, whereas in this paper I use the apparent wired-in institutional preferences for weights. I show the preference against large weights reflect family level portfolio management practices (and by inclusion, implicit risk management goals) and fund level strategic mandates- providing evidence that supports the discussions by Blume and Keim (2017).

Several related papers explore 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, Franzoni, Moussawi, and Sedunov (2017) find that stocks with concentrated institutional ownership tend to be accompanied by increased idiosyncratic volatilities. Massa, Schumacher, and

Wang (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. In a similar vein, but from an alternative channel to investor flows, this paper shows that return driven weight changes within portfolios have predictable power over stocks prices and holding preference within the mutual fund sector.

This discussion of flows leads to earlier works exploring the mutual fund flows' effects on demand (Coval and Stafford (2005), Edmans, Goldstein, and Jiang (2012), and Lou (2012)). At the center of this literature is the assumption that investor flows have a scaling effect on the underlying portfolio- outflows reduce the portfolio size by proportion, while inflows scale up in proportion of the same portfolio. I show that even after controlling for portfolio time fixed effects (which accounts for investor flows), there is a significant pattern within the portfolio that counters the dispersion in momentum returns. This apparent rebalancing against passive changes in weights adds to the way the literature predicts flow-based trading.

Previous literature also explores the trading behavior of mutual funds. Related to the current paper, Grinblatt, Titman, and Wermer (1995) document that mutual funds appear to chase stocks that have high historical returns. Cici (2012) explores tax-loss strategies as the counterpoint to the disposition effect (Frazzini (2006)) in explaining the trades of asset managers. Hartzmark (2015) shows rank effect in mutual funds, where fund managers are most sensitive to the best and worst performers within their portfolios. Variables used to capture these effects have no qualitative effect on the findings in this paper.

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, Campbell, and

Sodini (2009), Parker, Schoar, and Sun (2022), and Gabaix, Koijen, Mainardi, Oh, and Yogo (2022)). Camanho, Hau, and Rey (2022) examine rebalancing of currency portfolios. In terms of the aggregate rebalancing demand, Chinco and Fos (2020) argue that rebalancing demand is computationally difficult to aggregate and effectively generates noise. However, as this paper will demonstrate, the rebalancing of the typical large asset within a portfolio is extremely predictable across most mutual funds.

This paper is also related to the large body of literature on investor behavior. Foremost in this literature is the disposition effect of Shefrin and Statman (1985), which posits and tests the behavioral bias that investors sell winners too early and ride losers too long. This effect has been well documented across investors of different types. Empirical works along this line include those of Odean (1998), Frazzini (2006), and Ben-David and Hirshleifer (2012). Recent works in this area include papers by Greenwood and Shleifer (2014) and Barberis, Greenwood, Jin, and Shleifer (2018). Controlling for confounding measurements of these channels—such as unrealized gains and raw returns—has no qualitative effect on this paper's findings. Weights and the passive return-driven changes to weights seem to be the dual drivers of trading by asset managers.

Finally, but importantly, there is also substantial empirical literature on momentum and reversal returns (Jegadeesh and Titman (1993) and Lou (2014)). Recent works find that intermediate lagged past returns, from seven to 12 months ago, tend to forecast future returns (Novy-Marx (2013)). In contrast, recent past returns, from one to six months ago, do not significantly generate such predictability in stock returns. This paper makes additional contributions by showing that quarterly rebalancing by professional investors tends to generate demand in the opposite direction of short-term momentum. Once an econometrician accounts for this missing mechanism in the cross-sectional predictability regressions, recent returns gain additional power to forecast future returns.

II. Mutual Fund Trading and Past Returns

The Thomson-Reuters CDA/Spectrum and the Center for Research in Securities Prices (CRSP) Mutual Fund databases provide the quarterly fund holdings information initialized at the Q1 1990 to Q4 2011 and Q1 2012 to Q2 2021 periods respectively.[3] The CRSP mutual fund files are also used for fund characteristics and returns over the whole sample period. Factor portfolio returns are taken from Ken French's website. Stock returns use the standard CRSP stock files. The universe of equity studied is common stocks from the AMEX, NASDAQ, and NYSE exchanges. Summary statistics for stock-portfolio-quarter observations and the mutual funds that own them are reported in Table 2.

A. Trading Sensitivity to Returns by Position Size

I begin the analysis of this panel of stock-portfolio-time observations by regressing contemporaneous and subsequent trading activity to quarterly returns. The panel consists of all stock positions held by a mutual fund portfolio between the initial quarter-end snapshot and the subsequent two quarter-end snapshots (to account for any possible trades in the two quarters). These regressions are conducted piecewise over different position sizes, generating trade-return sensitivities for separate ranges of initial portfolio weights within each fund portfolio.

[3] The sample periods of the holding data sources were selected to obtain thorough coverage of initial portfolio observations and subsequent changes due to trading. The CRSP's mutual fund holdings data do not have adequate coverage of holdings until after 2011.

Figure 1 shows that portfolios are extremely reactive to the returns of their largest positions. I separate this panel into 10 bins based on a stock's initial portfolio weight in a fund portfolio. Each of Bins 1 to 9 represents a range of 10 basis points. For example, Bin 1 contains positions with greater than 0% up to 0.1% of the portfolio weight, Bin 2 contains stock positions with 0.1% to 0.2% of the portfolio weight, and so on. Any position representing more than 0.90% of a portfolio's total net assets is placed in Bin 10. I then regress trading in the contemporaneous quarter (top panels) and in the following quarter (bottom panels) on returns separated by the bin indicator. Fixed effects are included for time.

The left (right) panels of Figure 1 depict the regression coefficients of quarterly returns on the *Sell* and *Buy* trading variables. *Sell* is 1 if the portfolio decreased its shares in the stock in contemporaneous (top) or subsequent (bottom) quarter and 0 otherwise. Similarly, *Buy* is 1 if the portfolio increased its shares. We observe a visible relationship between the regression coefficients and the range of weights used for both contemporaneous and subsequent trading.

While significantly related to the contemporaneous trades, returns have even greater forecasting power on the future trades. A 1% quarterly return in a stock representing a fund's largest holdings indicates a 0.14% increase in the probability that the stock will be sold in the same quarter and an even higher increase (0.34%) in the probability that it will be sold in the subsequent quarter. Similarly, the probability that mutual funds will buy this stock decreases by 0.09% in the same quarter and 0.03% in the following quarter. In the subsequent sections, this lead-lag effect of portfolio rebalancing on returns will be used to forecast aggregate trading by mutual funds, as well as to document return predictability resulting from the demand driven by these trades.

In summary, mutual funds trade against the returns of their largest positions on average. Their trading reaction to positive returns increase for stocks with higher initial weights; that is, positions with large initial weights are much more likely to be sold and less likely to be bought both during and after realizing high returns. Positions that are initially small have the opposite or no-selling sensitivity after incorporating fund times time-fixed effects. For the smallest bin, high returning stocks are more likely to be bought than sold, which suggests that some performance chasing occurs (Grinblatt, Titman, and Wermer (1995)) for newly initiated and the smallest positions.

B. The *Passive* Measure

The pattern of increasing sensitivity to quarterly returns suggests that mutual funds trade in order to counter the returns accumulated by their largest positions. Table 3 focuses on the rebalancing mechanism by combining stock returns and initial portfolio weights into a parsimonious measure of weight changes- *Passive*. This measure calculates the degree to which stock returns change a stock's relative size in a portfolio each quarter. Specifically, for fund *j*'s holding of stock *i* between quarters *t* and *t-1*, *Passive* is

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

where

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

Here, $\widehat{w}$ is the projected weight of stock *i* in quarter *t* as driven by returns using the previous quarter's observed weights. 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.[4] Therefore, the difference

[4] The measure is calculated using total returns, which assumes that dividend income is reinvested into the same stock. Using simple price returns and assuming that dividend income is reinvested proportionally to the portfolio and gives very similar results.

between $\widehat{w}$ and the initial weight, *Passive*, is the change in the position's weight from the previous quarter as driven by stock returns- 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 project 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 is likely to 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.

Columns 1–6 of Table 3 forecast trading activities on *Passive* after accounting for a gamut of different multivariate specifications.[5] 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 disposition effects and tax-treatment effects (Frazzini (2006) and Cici (2012)). In all the specifications, I find little evidence that returns affect all existing fund positions in the same way.

Instead, the trading activities of a mutual fund are consistently negatively related to *Passive*, indicating a preference for weight management. Under the fully specified model on *Sell* trades in Column 3, a fund manager is 6.938% more likely to sell a stock whose portfolio weight had increased by 1% through *Passive*. This is a 20.43% increase to the 33.96% probability of a net sell each quarter.

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[5] Appendix Table A reports contemporaneous trading.

On the other side of the spectrum of positions with negligible weights, from Column 2, a 10% stock return in a quarter indicates only a 0.20% increase in the likelihood that the position will be sold in the subsequent quarter. Fund managers' buying of stocks follows an opposite pattern. Mutual funds are more reluctant to purchase stocks whose portfolio weights have been driven up by returns. Interpreting the coefficient- 4.844 of *Passive-* in Column 6, the same manager is 14.87% less likely to purchase more stocks for a position that increased its size passively by 1%.

These effects are also independent of portfolio flows. Large inflows from investors are typically met with diversification (Pollet and Wilson (2014)), which automatically shrinks extant positions relative to the portfolio. However, this would not explain the relationship between *Sell* and *Passive*; that is, mechanical diversification due to inflows will not increase the likelihood of an investor actually selling the existing shares. By including Time x Fund–fixed effects, Columns 2, 3, 5, and 6 also explicitly control the possibility that these actions are driven by proportional selling due to redemption (deposit) by investors. Further un-tabulated tests that separate observations to funds experiencing positive and negative flow periods do not qualitatively differ from these results.

Finally, Columns 7–10 examine the trading of actively managed portfolios and index funds separately. While the coefficients are higher in magnitudes for actively managed funds—1% of *Passive,* indicating a 7.86% increase (23.11%, by proportion) in the probability of a sell in the subsequent quarter over 6.23% (18.35%, by proportion), as indicated by Index Funds—the rebalancing effect on *Passive* changes extends to self-proclaimed index funds. The following subsection will explore in detail the channels to explain why such a rebalancing pattern exists and pervades across not only active but also indexing mutual funds.

C. Risk Management and Investment Mandates

Blume and Keim (2017) discuss factors that make institutional investors less likely to hold large-cap stocks. These include a better understanding of diversification and an awareness of small factors related to investing strategies. This section provides evidence supporting these channels by examining the identities of equity funds that have the most intense contrarian rebalancing trades.

The analysis of what drives these rebalancing trades uses a two-stage methodology. In the first stage, for each fund, I regress the panel of its quarterly stock trades against *Passive*, the return-implied changes in portfolio weights. Thereby, per fund observed in the sample, I first construct a measure of its rebalancing intensity. In the second stage of the analysis, I examine what fund characteristics, if any, are related to this measure.

Table 4 shows the index and active funds whose quarterly trades are most negatively related to *Passive*, the return-driven changes in portfolio weights. For each fund, this table regresses the direction of trade (1 for a net sell, –1 for a net buy) from each position and quarter against *Passive* occurring in the subsequent quarter.[6] The table reports the top 10 index (Panel A) and actively managed (Panel B) funds still existing in June 2021, with the highest rebalancing trades—that is, the highest coefficients of trading on *Passive*.

From Panel A, it appears that equal-weighted and style-weighted strategies top the list of index funds with the most predictable contrarian trades (as expressed through quarterly return's effect on portfolio weights). These passive funds, by their investment mandate, have wired-in preferences against holding large granular positions. Equal-weighted holdings schemes automatically drive asset managers to diminish increases in portfolio weights. Style-weighted indices implicitly inverse-weight on market capitalization. For example, S&P Dividend Fund and First Trust Large-Cap Value Funds

[6] See Appendix Table B for a list of funds with the highest contemporaneous rebalancing coefficients.

each numeraire a stock's characteristics (such as dividends paid and book values) by its respective market capitalization. As seen from Columns 9 and 10 of Table 3, the contrarian rebalancing patterns for these specific funds repeat on average for all index funds and extend beyond solely the contemporaneous quarter.

Unlike passive mutual funds, there is a wider characterization of possible active funds that intensely rebalance their holdings. Columns 7 and 8 of Table 3 show that active equity funds trade against *Passive* on average, even while they implement a variety of trading mandates and are allowed certain latitude in their investments. In Panel B of Table 4, we see that the list of funds that rebalance predictably consist of Small-Cap, Mid-Cap, Large-Cap, and Value mandated portfolios. In order to investigate the reason that certain active funds are predictable, I use a second stage of regressions to relate the intensity of each fund's rebalancing patterns to their individual mandates and their fund families' collective practices.

Mutual fund families have self-governance on the risk-taking of their individual funds. Regulatorily, typical mutual funds claiming to be "diversified" in their prospectuses must not let a single issuer exceed 5% of their assets. Individual families are likely to have more stringent mandates in order not to exceed these regulatory limits.[7] Table 5 provides evidence that, consistent with a risk management and diversification channel, the predictable trading by active funds originate, at least partially, at the fund-family level.

In this set of two-stage regressions, Table 5 examines the degree to which the resultant trading behaviors of active funds are explained by Family-Fixed Effects and the characterizations of a fund's

[7] In an interview (https://www.yahoo.com/now/mutual-funds-facebook-amazon-apple-microsoft-google-problem-185739448.html) Vanguard states that "Vanguard closely monitors our funds' underlying portfolio holdings and disclosures, and occasionally pursues modifications to a fund's diversification status to avoid violating the Diversification Rule."

mandate. In particular, in the first stage, I measure the intensity to which a mutual fund rebalances its portfolio. *Rebalancing Intensity* is the regression beta of each fund's stock trading directions (1 for a sell, –1 for a buy) against *Passive* for its panel history of stock-quarter observations.

In the second stage, I regress fund level *Rebalancing Intensity* against family-fixed effects and various fund name–implied mandates. Column 1 of Table 5 shows that unconditionally, family-fixed effects explain about 10.5% (Adjusted R^2) of the variations in the degree to which active mutual funds rebalance. This is similar to marginal increment in the explained variation of 9.8%, documented between Columns 2 and 3, from including the fund-family-fixed effects to a gamut of controls for a fund-level mandate.

Importantly, the regulating role of fund families is absent for Index Funds. As seen in Column 4, Family-Fixed Effects explains -1.7% of the adjusted variation of rebalancing intensity by index funds. This negative marginal adjusted variation from fund families remain after controlling for fund name–implied mandates in Columns 5 and 6. Combined with the prior results on the actively managed mutual funds, this evidence suggests that fund families dictate the varying intensity of weight rebalancing by their active portfolio managers. Certain fund families are more inclined to rebalance than others. I interpret this as evidence of familial practice on rebalancing intensity and risk management.

In sum, fund family level practices explain a large amount of variation in how past returns drive future trading at a quarter-to-quarter horizon for actively managed mutual funds. Additionally, anti-size weighting due to investment strategies explains the rebalancing predictability in passively managed mutual funds.

Given that the whole market is value-weighted and that these rebalancing schemes are aimed at moving asset concentration away from the market-valued weighting schemes, these trades drive demand in the cross-section of large-cap stocks, and certain investors must be taking up the resultant trading demand. I explore the aggregate effects of rebalancing trades on mutual fund holdings and stock returns in the next section.

III. Aggregating Risk Management Trades

This section aggregates the predictable trading attributable to positional rebalancing into the variable *Rebalancing Demand*. I show that this measurement is associated with decreases in the percentage of total shares held by the institutional and 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 Q1 1990 and Q2 2021, a *Passive* change in portfolio weight corresponds to discretionary contrarian trading by individual funds in the following quarter. The total dollar demand attributable to exposure rebalancing by mutual funds, calculated for stock i, can be calculated as

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

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

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

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:

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

That is, *Rebalancing Demand* for each stock over the quarter can be interpreted as the share-weighted passive increase in the average mutual fund portfolio from returns. A 1% increase in *Rebalancing Demand* for a stock indicates that the size of its relative proportion in the mutual fund portfolio that holds it has passively increased by 1% due to returns.

Equation (1) describes the primary measurement of stock demand used in the analysis in this section. Summary statistics on *Rebalancing Demand* are contained in Table 1. Due to its extreme kurtosis, I winsorize the sample at a 2.5% level in each tail. For the return predictability regressions, I use the percentile rank of *Rebalancing Demand*, which simply captures the percentile of each stock's *Rebalancing Demand* within the common stock universe each quarter. The following subsections show that this stock/time panel measurement is robustly predictive of key features associated with stock demand—factors such as changes in the aggregate holdings by institutional portfolios and abnormal excess returns.

A. 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 Q2 2021, *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 equity funds.

Table 6 regresses the net trading of the observed mutual fund portfolios against *Rebalancing Demand*. These panel regressions also include average weights in the observed portfolios and quarterly returns, as well as traditional holdings characteristics, such as book-to-market ratio and log-market capitalization. Fixed effects are included to account for time and stock identity. In the first three columns, the variable on left side is an indicator of net decrease of shares of Equity Mutual Funds. For a single 1% increase in the average equity fund portfolio, the probability that the stock would be sold in net by all equity funds increases by 16.4%. Given that the unconditional probability that Mutual Funds as a sector will increase their holdings of the outstanding share of a stock 52%; a 1% *Rebalancing Demand* decreases this probability by roughly 31.54%.

Columns 4–6 take the percentage of change in the shares held by 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. A 1% *Passive* average increase in the mutual fund portfolios implies a 0.182% total decrease of the stock in the aggregate mutual fund portfolio.

Consistent with trading demand originating from portfolio managers, I find that the predicted *Rebalancing Demand* tends to be strongly 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 to underweight this asset in general. These trades are not netted through the increases in portfolio holdings by other mutual funds, and the counterparty to these demands is substantially composed of retail and noninstitutional investors.

B. 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 nonfundamental 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 for past stock performance. Table 7 Panel A conducts value-weighted Fama-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. 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 -0.508% ($t = -3.915$) returns. This negative return completely reverts subsequently in the rest of the quarter, forecasting a positive return of 0.272% ($t = 2.593$). 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.

Tabulated in Table 7 Panel B, a long-short calendar time portfolio formed by longing the highest quintile portfolio and shorting the lowest quintile portfolio sorted by *Rebalancing Demand* obtains a three-factor adjusted return of -1.044% (*t* = *-2.599*) by the 35th trading day. The same portfolio reverts during the rest of the quarter, with a cumulative holding return of 0.705% (*t* = *2.342*) from the 36th trading date beyond.

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 III.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 univariate 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. Recalling results from Figure 1, mutual funds still tend to chase high-return stocks, especially for positions that were initially small or nonexistent within the portfolio. 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, Yu, and Yuan (2012)), momentum returns are highly related to its short-leg.

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 2, the regression indicates that a single standard deviation in the percentile *Rebalancing Demand* forecasts -0.523% return in the following quarter.

This price effect is temporary. Additionally, I observe longer-term reversals of this price effect. In Columns 3 and 4, 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 0.817% returns over this horizon, which completely subsumes the prior sell-driven price predictability.

An interesting property of *Rebalancing Demand* is that the inclusion of this characteristic 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 shows 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 (Novy-Marx (2012) and Goyal and Wahal (2015))- short-term returns tend to be confounded with the quarter-to-quarter rebalancing by equity mutual funds.

The Fama-Macbeth regression results naturally translate into calendar time trading strategies. Table 9 sorts stocks into portfolios using the *Rebalancing Demand* at the end of each quarter. In these specifications, the portfolio returns are explicitly adjusted using the Carhart Four-Factor Model and a

Five-Factor Model that includes the two- to 12-month momentum and the one-month short run reversal factors.

To exclude potential return-driven events, I also filter out stocks that had extreme poor returns- lower than -20% returns- in the previous quarter. 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 reverts 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 showing 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 -1.157%.

The time series cumulative residuals of the long/short portfolios using the five-factor model are plotted in Figure 2. I observe that the negative returns tend to occur throughout the sample period and that no single period accounts for the significant portion of the excess returns.

C. 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 pricing results.

Figure 3 takes the largest capitalization 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 highest quintile portfolio 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- that is, between Q1 1990 and Q2 2021.

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 -1.61% of returns formed in Table 7s Panel B. Both cumulative negative returns revert over the entirety of the quarter. The Fama-Macbeth regression of cross-sectional stocks based on past returns and the Rebalancing Demand in Table 8 shows that this is no coincidence. Although generally 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. The inclusion of both past returns and Rebalancing Demand in Tables 8 and 9 shows that both economic forces, once an econometrician accounts for both factors, are at play within the financial markets.

The cumulative return figure appears with an ex-post nonfundamental demand pattern; that is, there is a short-term cumulative returns pattern and a subsequent reversal. Such an effect is not solely due to a single quarter (e.g., from the January Effect), and the breakdown of the graph by excluding individual quarters is presented in Appendix Figure C. Additionally, such effects are nonexistent for smaller capitalization portfolios.

Such a trend matches the observed univariate sort on *Rebalancing Demand*, indicating that certain momentum return portfolios and *Rebalancing Demand* coincide due to the mechanical relationship between the stock returns and the institutional response to asset weight management. Accounting for the two mechanisms together offers a novel separation of the channels that momentum returns acts on, and the demand that originates from institutional preferences for granular stocks.

V. Conclusion

The asset management industry's treatment of a large position is consistent with diversification for risk management and strategic investment for certain mandates. This paper shows that after accounting for the rebalancing motives, mutual fund investors display trend-chasing behavior toward an asset's past returns- especially for new and the smallest existing positions.

Furthermore, rebalancing motives drive coordination in investors. Realized returns within a short time frame may drive assets to have outsized exposures across existing investors. These investors, in actively managing their positional exposures, will generate rebalancing demand in the cross-section of equity assets. This paper shows that this demand is statistically significant and economically meaningful.

Ultimately, large granular stocks are an inherent feature of the equity market and investor portfolios. While theory dictates that the market portfolio may be mean efficient, investors reoptimize their portfolios for a variety of diversification, strategic, and regulatory reasons. Yet due to the overlap of common risk management strategies and investment mandates between many equity mutual funds, the rebalancing of their portfolio end up treating largest stocks in the same way. Such trading patterns drives predictable demand originating from sophisticated asset managers. This paper shows this rebalancing pattern against incremental concentration in position weights for risk management and portfolio strategies is a persistent, widespread, and economically meaningful channel of return predictability.

References

Barberis, Nicholas, Robin Greenwood, Lawrence Jin, and Andrei Shleifer. 2018. "Extrapolation and Bubbles" *Journal of Financial Economics* 129(2): 203–227.

Ben-David, Itzhak, and David Hirshleifer. 2012. "Are Investors Really Reluctant to Realize Their Losses? Trading Responses to Past Returns and the Disposition Effect." *The Review of Financial Studies* 25(8): 2485–2532.

Ben-David, Itzhak, Francesco Franzoni, Rabih Moussawi, and John Sedunov. 2021. "The Granular Nature of Large Institutional Investors." *Management Science*, 67(11): 6629–6659.

Blume, Marshall E., and Donald B Keim. 2017. "The Changing Nature of Institutional Stock Investing." *Critical Finance Review*, 6(1): 1–41.

Calvet, Laurent E., John Y. Campbell, and Paolo Sodini. 2009. "Fight or Flight? Portfolio Rebalancing by Individual Investors." *Quarterly Journal of Economics*, 124(1): 301–348.

Camanho, Nelson, Harald Hau, and Hélène Rey. 2022. "Global Portfolio Rebalancing and Exchange Rates." *The Review of Financial Studies*, 35(11): 5228–5274.

Chen, Huaizhi. 2022. "Cash-Induced Demand." *The Journal of Financial and Quantitative Analysis*, forthcoming.

Chinco, Alex, and Vyacheslav Fos. 2021. "The Sound of Many Funds Rebalancing." *The Review of Asset Pricing Studies*, 11(3): 502–511.

Cici, Gjergji. 2012. "The Prevalence of the Disposition Effect in Mutual Funds' Trades." *The Journal of Financial and Quantitative Analysis*, 47(4): 795–820.

Coval, Joshua, and Erik Stafford. 2007. "Asset Fire Sales (and Purchases) in Equity Markets." *The Journal of Financial Economics*, 86(2): 479–512.

Edmans, Alex, Itay Goldstein, and Wei Jiang. 2012. "The Real Effects of Financial Markets: Impact of Prices on Takeovers." *The Journal of Finance* 67(3): 933–971.

Fama, Eugene F., and James D. MacBeth. 1973. "Risk, Return, and Equilibrium: Empirical Tests." *Journal of Political Economy* 81 (3): 607–636.

Frazzini, Andrea. 2006 "The Disposition Effect and Underreaction to News." *The Journal of Finance*, 64(4): 2017–2046.

Gabaix, Xavier. 2011. "The Granular Origins of Aggregate Fluctuations." *Econometrica*, 79(3): 733–722.

Gabaix, Xavier, and Ralph S. J. Koijen. 2021. "In Search of the Origins of Financial Fluctuations: The Inelastic Markets Hypothesis." *NBER Working Paper* No. w28967.

Gabaix, Xaviet, Ralph S. J. Koijen, Federico Mainardi, Sangmin Oh, and Motohiro Yogo. 2022. "Asset Demand of U.S. Households." *Unpublished Working Paper.*

Goyal, Amit, and Sunil Wahal. 2015. "Is Momentum an Echo?" *The Journal of Financial and Quantitative Analysis*, 50(6): 1237–1267.

Greenwood, Robin, and Andrei Shleifer. 2014. "Expectations of Returns and Expected Returns." *The Review of Financial Studies*, 27(3):714–746.

Greenwood, Robin, and David Thesmar. 2011. "Stock Price Fragility." *The Journal of Financial Economics*, 102(3): 471–490.

Grinblatt, Mark, Sheridan Titman, and Russ Wermers. 1995. "Momentum Investment Strategies, Portfolio Performance, and Herding: A Study of Mutual Fund Behavior." *The American Economic Review*, 85(5): 1088–1105.

Hartzmark, Samuel M. 2014. "The Worst, the Best, Ignoring All the Rest: The Rank Effect and Trading Behavior." *The Review of Financial Studies*, 28(4): 1024–1059.

Jegadeesh, Narasimhan, and Sheridan Titman. 1993. "Returns to Buying Winners and Selling Losers." *The Journal of Finance:* 65–91.

Koijen, Ralph S. J., and Motohiro Yogo. 2019. "A Demand System Approach to Asset Pricing." *Journal of Political Economy*, 127(4): 1475–1515.

Lou, Dong. 2012. "A Flow-Based Explanation for Return Predictability." *The Review of Financial Studies*, 25(12): 3457–3489.

Massa, Massimo, David Schumacher, and Yan Wang. 2021. "Who Is Afraid of BlackRock?" *The Review of Financial Studies*, 34(4): 1987–2044.

Novy-Marx, Robert. 2012. "Is Momentum Really Momentum?" *The Journal of Financial Economics*, 103(3): 429–453.

Odean, Terrance. 1998. "Are Investors Reluctant to Realize Their Losses?" *The Journal of Finance*, 53(5): 1775–1798.

Parker, Johnathan A., Antoinette Schoar, and Yang Sun. 2022. "Retail Financial Innovation and Stock Market Dynamics: The Case of Target Date Funds." *Unpublished Working Paper*.

Pavlova, Anna, and Taisiya Sikorskaya. 2022 "Benchmarking Intensity." *The Review of Financial Studies*, forthcoming.

Pollet, Joshua M., and Mungo Wilson. 2008. "How Does Size Affect Mutual Fund Behavior?" *The Journal of Finance*, 63(6): 2941–2969.

Shefrin, Hersh, and Meir Statman. 1985. "The Disposition to Sell Winners Too Early and Ride Losers Too Long: Theory and Evidence." *The Journal of Finance*, 40(3): 777–790.

Shleifer, Andrei. 1986. "Do Demand Curves for Stocks Slope Down?" *The Journal of Finance,* 41(3): 579–590.

Shleifer, Andrei, and Robert W. Vishny. 1992. "Liquidation Values and Debt Capacity: A Market Equilibrium Approach." *The Journal of Finance*, 47(4): 1343–1366.

Shleifer, Andrei, and Robert W. Vishny. 1997. "The Limits of Arbitrage." *The Journal of Finance*, 52(1): 35–55.

Stambaugh, Robert F., Jianfeng Yu, and Yu Yuan. 2012. "The Short of It: Investor Sentiment and Anomalies." *Journal of Financial Economics*, 104(2): 288-302.

Wardlaw, Malcolm. 2020. "Measuring Mutual Fund Flow Pressure as Shock to Stock Returns." *The Journal of Finance*, 75(6): 3221–3243.

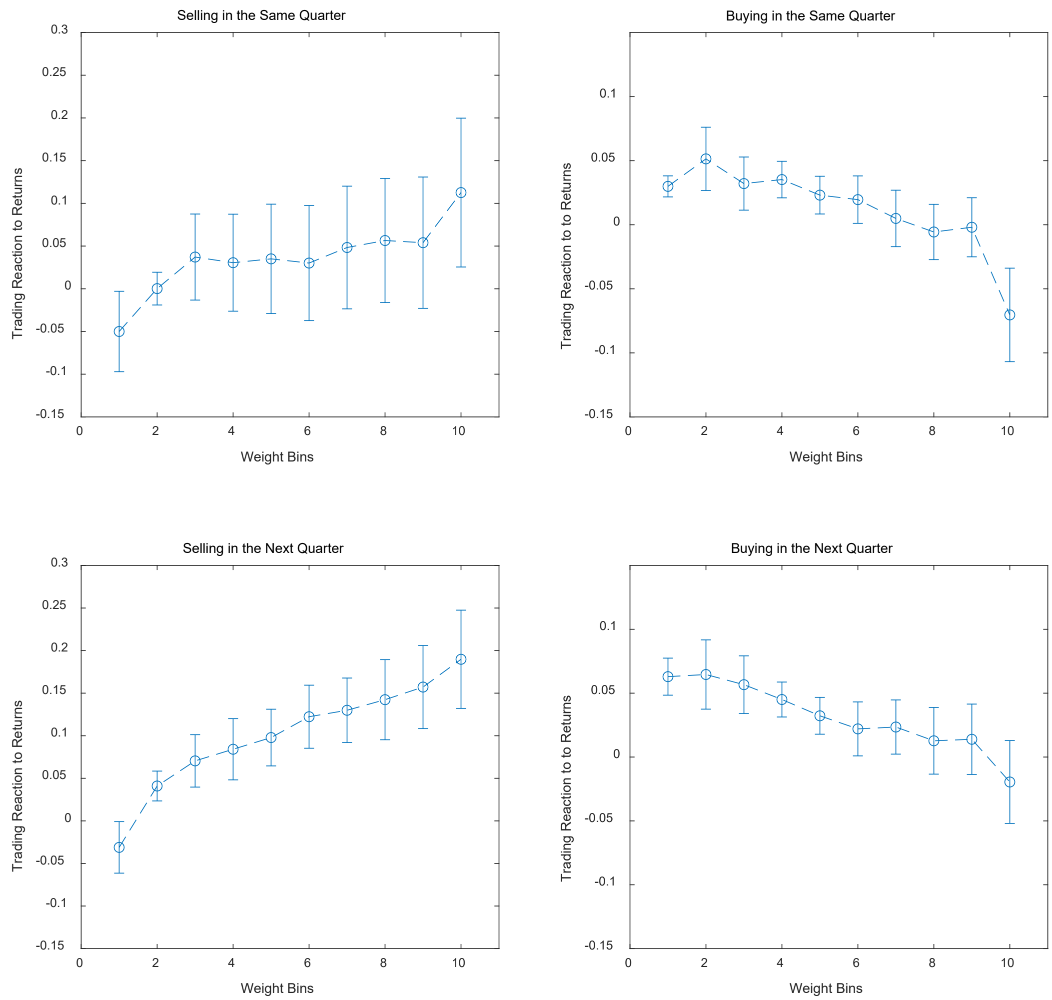

Figure 1. Piecewise regressions of trading on returns using the following specifications:

$$Y_{i,j,t} = \sum_{b} \beta_b \cdot r_{i,t} \cdot (w_{i,j,t-1} \in Bin_b) + FE_t + \epsilon_{t+1,i,j} \qquad \text{(Top)}$$

$$Y_{i,j,t+1} = \sum_{b} \beta_b \cdot r_{i,t} \cdot (w_{i,j,t-1} \in Bin_b) + FE_t + \epsilon_{t+1,i,j} \qquad \text{(Bottom)}$$

for stock *i* in portfolio *j* at time *t*. *Y* is an indictor variable representing the selling or buying of stock *i* by portfolio *j* between *t* and *t+1*. *r* is stock *i*'s return 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 10 basis points. Bin_1 contains positions with weights from 0% to 0.1%, Bin_2 contains positions with weights above 0.1% and below 0.2%, and so forth. Bin_{10} holds positions with weights above 0.9%. The figures plot the estimated beta coefficients of the contemporaneous (top) and subsequent (bottom) period's trading actions on returns for positions of different initial weights. The left panels represent selling, and the right panels represent buying. The 95% confidence interval of the coefficients are reported for each bin. Time-fixed effects are included in each regression.

Figure 2. Cumulative adjusted returns of the 5 minus 1 Calendar Portfolios sorted by *Rebalancing Demand* after factor adjustment. The sample consists of common stocks with price greater than 5 with no more than a 20% loss in the previous quarter's stock returns.

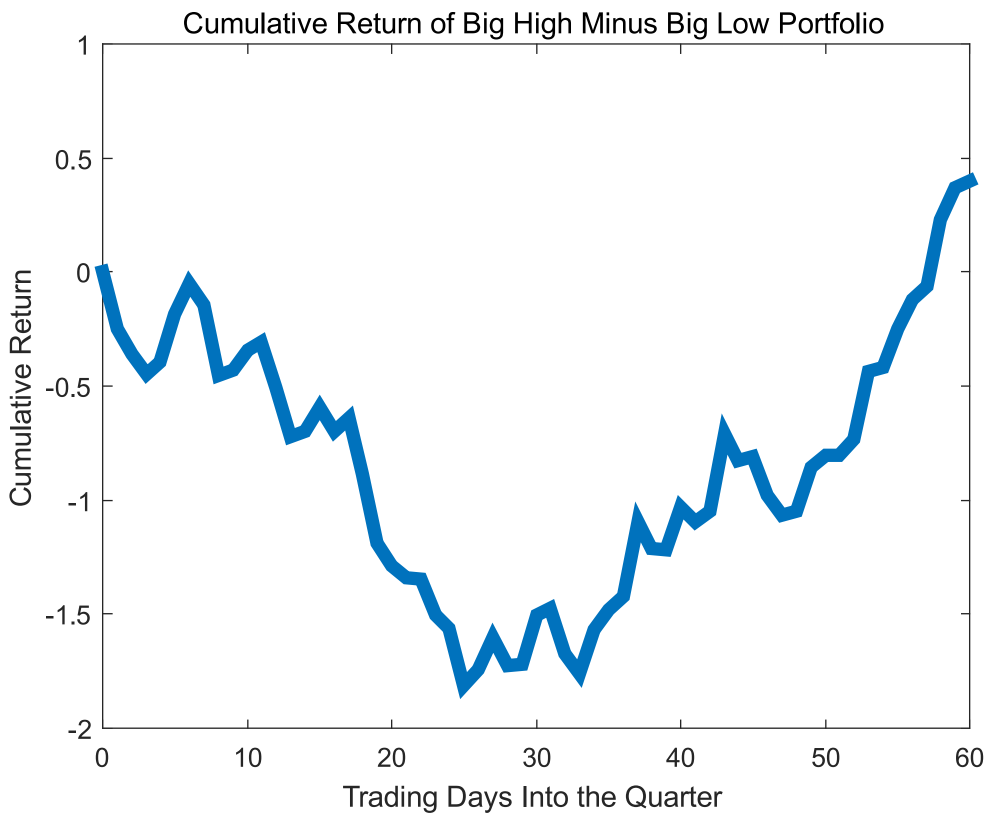

Figure 3. Long-Short Portfolio Returns of the Big High Minus Big Low Portfolio. This portfolio is formed by using the 5 x 5 portfolios sorted by size and the past 2- to 12-month returns between Q1 1990 and Q2 2021 provided by Ken French. Specifically, the strategy longs the Big (stocks in the highest quintile based on size) and High (stocks in the highest quintile of the past 2- to 12-month returns), and shorts the Big (stocks in the highest quintile based on size) and Low (stocks in the lowest quintile of the past 2- to 12-month returns). The pattern is robust to excluding any individual quarter of the year .(See Appendix Figure C.)

Table 1. The Underweighting of the Largest Stocks by Mutual Funds

Size Rank	Name	Size ($ Thousands)	Weight in Market	Weight in MFs	Difference
1	Apple	2,267,638,888	5.05%	4.03%	1.02%
2	Microsoft	2,036,897,054	4.53%	4.25%	0.29%
3	Amazon	1,740,720,916	3.87%	2.92%	0.96%
4	Facebook	830,679,170	1.85%	1.67%	0.18%
5	Alphabet Share C	804,656,564	1.79%	1.27%	0.52%
6	Alphabet Share A	735,076,473	1.64%	1.34%	0.29%
7	Tesla	668,826,851	1.49%	0.98%	0.51%
8	Nvidia	498,462,285	1.11%	1.09%	0.02%
9	JP Morgan Chase	470,870,577	1.05%	0.98%	0.07%
10	Johnson and Johnson	433,825,672	0.97%	0.90%	0.06%
Total		10,487,654,449	23.34%	19.44%	3.91%

This table reports the value and the respective market shares of the 10 largest stocks in the aggregate observable stock market and the observable equity mutual funds in the CRSP universe at the end of Q2 2021.

Table 2. Summary Statistics

Panel A. Individual Holdings of Portfolios

	N	Mean	Std	5th Pctl	25th Pctl	Median	75th Pctl	95th Pctl
Sell	27,041,980	0.4124	0.4923	0	0	0	1	1
Buy	27,041,980	0.3408	0.4740	0	0	0	1	1
Passive	27,041,980	-0.0001%	0.1782%	-0.1698%	-0.0135%	-0.0000%	0.01156%	0.1672%
Weight	27,041,980	0.6026%	1.3894%	0.0033%	0.0389%	0.1747%	0.7225%	2.4919%

Panel B. Individual Mutual Funds

	N	Mean	Std	5th Pctl	25th Pctl	Median	75th Pctl	95th Pctl
Number of Stocks	162,955	166	314	22	44	73	133	559
TNA ($Millions)	162,955	1,390.21	11,954	5.117	44.486	181.885	704.559	4,393.27

Panel C. Stock Characteristics

	N	Mean	Std	5th Pctl	25th Pctl	Median	75th Pctl	95th Pctl
Rebalancing Demand	364,890	-0.0014%	0.1506%	-0.2555%	-0.0512%	-0.0004%	0.0423%	0.2632%
Quarterly Returns	364,890	3.526%	28.731%	-35.208%	-10.101%	1.877%	14.141%	44.860%
Change in Ownership	364,890	-0.444%	1.550%	-2.874%	0.601%	-0.0351%	0.0163%	0.784%
Book-to-Market	364,890	0.7037	3.2368	0.0725	0.3126	0.5593	0.8987	1.8997
Log Size	364,890	19.909	2.012	16.845	18.448	19.789	21.247	23.414

This table summarizes the data used for this study in parts. Panel A summarizes the stock by fund by time observations panel used for analyzing the trading activities of mutual funds on average. *Passive* is the percentage change in quarterly holdings as driven by returns for a position within a mutual fund each quarter. Panel B summarizes the *Number of Stocks* and the *Total Net Assets* of the fund by time observations. Panel C summarizes the stock by time observations used to examine returns and net trading behavior. *Rebalancing Demand* is the average percentage change in quarterly holdings as driven by returns over all portfolios. *Change in Ownership* is the difference in the percent of a stock owned by equity funds between two observed quarters. The sample period of the holdings is from Q1 1990 to Q2 2021.

Table 3. Predictive Regression of *Sell* and *Buy* Actions on *Passive* for the Panel of Fund, Stock, and Quarter Observations

	All Funds						Active Funds		Index Funds	
	Sell			*Buy*			*Sell*	*Buy*	*Sell*	*Buy*
	1	2	3	4	5	6	7	8	9	10
Passive	6.983***	6.848***	6.938***	-1.242***	-3.680***	-4.844***	7.955***	-6.082***	6.230***	-4.498***
	(24.07)	(18.40)	(26.72)	(-4.608)	(-10.54)	(-19.15)	(16.78)	(-13.62)	(21.83)	(-17.41)
Weight		3.938***	3.746***		1.137***	-0.534***	5.044***	-0.609***	3.219***	-0.456***
		(69.58)	(48.58)		(19.99)	(-9.530)	(26.83)	(-8.938)	(20.63)	(-7.745)
Returns		0.0201***			0.0536***					
		(4.790)			(9.295)					
Unrealized Profit		0.000194	-0.00306*		-0.0564***	-0.0105***	-0.00508*	-0.00612*	0.00180	-0.0119***
		(0.0759)	(-1.730)		(-21.69)	(-5.657)	(-1.965)	(-1.796)	(0.933)	(-5.775)
Rank Effect		-0.131	-0.213		-0.127	-0.371	0.382	-1.131***	-0.323**	-0.277
		(-0.813)	(-1.496)		(-0.742)	(-1.238)	(0.593)	(-4.763)	(-2.222)	(-1.047)
Time-Fixed Effects	Yes	No	No	Yes	No	No	No	No	No	No
Time X Fund Fixed Effects	No	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes
Time X Stock Fixed Effects	No	No	Yes	No	No	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.007	0.390	0.418	0.010	0.414	0.453	0.364	0.279	0.438	0.483
N	27,041,980	25,270,399	25,217,811	27,041,980	25,270,399	25,217,811	5,928,038	5,928,038	19,283,372	19,283,372

This table shows the regressions of trading indicators on *Passive*, various controls, and fixed effects due to time/fund and time/stock. *Sell* (*Buy)* is 1 if the fund sold (bought) the stock in net in the subsequent quarter. *Passive* indicates the return driven change in the weight of the stock in the fund from the past quarter. Columns 1–6 regress the sample of all fund-stock-quarter observations. Columns 7 and 8 regress the sample of all actively managed mutual funds. Columns 8 and 9 regress the sample only for index funds. The standard errors are clustered quarterly.

Table 4. Funds Whose Quarterly Trades Are Most Explained by Weight Rebalancing

Panel A. Index Funds

Fund Name	Family Name	Size ($)	Weighting Strat
Multi-Cap Value AlphaDEX Fund	First Trust	144,879,233	Style Weight
Large-Cap US Equity Select ETF	First Trust	26,323,090	Style Weight
FRC Founders Index Fund	First Republic	98,135,907	Equal Weight
Fundamental US Small Company Index Fund	Charles Schwab Investment	1,664,207,116	Style Weight
SPDR S&P Dividend ETF	State Street Global Advisors	17,446,939,672	Dividend Weight
Invesco Equally Weighted S&P 500 Fund	Invesco Counselor Series	6,437,886,527	Equal Weight
Voya Corporate Leaders 100 Fund	Voya Equity Trust	747,846,920	Equal Weight
Invesco S&P 500 Equal Weight ETF	Invesco	25,074,434,119	Equal Weight
First Trust Large-Cap Value AlphaDEX Fund	First Trust	973,288,882	Style Weight
iShares MSCI USA Size Factor ETF	BlackRock	741,068,703	Style Weight

Panel B. Active Funds

Fund Name	Family Name	Size ($)
US Sustainability Targeted Value Portfolio	DFA Group	198,359,758
Small-Cap II Fund	SEI Institutional Investments	433,344,081
All America Portfolio	Mutual of America Financial	14,964,551
Small-Cap Fund	SEI Institutional Managed	631,626,989
Systematic US Large-Cap Value Fund	SunAmerica Series	479,228,331
Multi-Manager Small-Cap Strategies	Columbia Funds Series	1,170,460,246
Mid-Cap Value Fund	AIG	774,501,154
Small-Cap Value Fund	American Beacon Funds	5,345,919,250
Mid-Cap Value Fund I	Principal Funds	2,390,156,185
Small-Cap Diversified Value Fund	Hotchkis & Wiley	386,961,699

This table reports the 10 Active and Index Funds whose quarterly trades are most explained by the rebalancing of their previous quarter's return-driven changes in portfolio weight. *Size* is the total observed portfolio size at the end of Q2 2022. *Weighting Strat* is each fund's self-described weighting strategy.

Table 5. Fund Attributes and Rebalancing Patterns

	Rebalancing Intensity					
	Active Funds			Index Funds		
	1	2	3	4	5	6
Small Cap		10.83***	10.36***		31.96***	31.85***
		(7.431)	(6.435)		(4.229)	(3.773)
Mid Cap		9.844***	7.378***		10.65	17.29*
		(5.762)	(3.978)		(1.279)	(1.877)
Large Cap		-1.768	-2.299		6.642	13.67
		(-0.938)	(-1.087)		(0.726)	(1.207)
Value Style		13.09***	12.27***		29.11***	32.81***
		(8.550)	(6.828)		(3.434)	(3.332)
Blend Style		-10.45	-14.37		-57.54	-58.79
		(-1.302)	(-1.334)		(-0.954)	(-0.627)
Growth Style		-3.664***	-6.258***		-50.70***	-54.20***
		(-2.626)	(-3.908)		(-5.457)	(-5.122)
Diversified		-0.499	-5.592		38.77	-4.809
		(-0.0621)	(-0.643)		(1.021)	(-0.104)
Fund-Family-Fixed Effects	Yes	No	Yes	Yes	No	Yes
Adj. R^2	0.105	0.095	0.193	-0.017	0.048	0.040
N	2,199	2,217	2,199	1,189	1,195	1,189

This table regresses the average portfolio rebalancing intensity against self-reported styles and fund-family-fixed effects. *Rebalancing Intensity* is measured as the panel regression beta of each fund's trading direction (1 for a sell, –1 for a buy) against *Passive*, the return-driven change in a portfolio weight. *Small Cap*, *Mid Cap*, *Large Cap*, *Value Style*, *Blend Style*, *Growth Style*, and *Diversified* are indicator variables that show whether these investment mandates are implied by a fund's name. Active and Index Funds are regressed separately to characterize the differences in the variation (Adjusted R^2) explained by the mutual fund-family-fixed effects.

Table 6. Change in Net Mutual Fund Ownership on Rebalancing Demand

This table reports the regression coefficients of changes to Mutual Fund ownership on *Rebalancing Demand* and stock characteristics. *Net Decrease in Mutual Fund Ownership* is 1 if the stock was sold in net by the equity funds in our sample, and 0 otherwise. *Change in Equity Fund Ownership* is the percentage of shares owned by equity funds in the current quarter minus that of the previous quarter. *Rebalancing Demand* is the share weighted average *Passive* from the previous quarter. The standard errors are clustered quarterly.

	Net Decrease by Equity Funds			Change in Equity Fund Ownership		
	1	2	3	4	5	6
Rebalancing Demand	17.65***	14.96***	16.40***	-0.168***	-0.146***	-0.182***
	(11.13)	(10.78)	(13.31)	(-4.579)	(-4.091)	(-5.877)
Returns	-0.0677***	-0.0508***	-0.0630***	0.00124***	0.00111***	0.00132***
	(-6.257)	(-4.677)	(-6.841)	(4.702)	(4.066)	(5.374)
Average Weight	14.21***	5.728***	5.824***	-0.195***	-0.127***	-0.123***
	(26.35)	(15.14)	(16.04)	(-13.63)	(-12.32)	(-11.41)
Book-to-Market Ratio		-0.000395	-8.99e-05		3.57e-05**	1.12e-05
		(-1.368)	(-0.662)		(2.555)	(1.096)
Log-Market Value		0.0559***	0.0448***		-0.000444***	-0.000737***
		(17.80)	(10.17)		(-7.980)	(-6.261)
Time-Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Stock-Fixed Effect	No	No	Yes	No	No	Yes
Adj. R^2	0.118	0.149	0.190	0.077	0.079	0.118
N	340,923	340,923	340,487	340,923	340,923	340,487

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* and controls. *Rebalancing Demand Rank* is the cross-sectional percentile rank of the average change in portfolio concentration of a stock. The first-stage cross-sectional regressions are weighted by stock market cap, averaged, and then reported in the table.

	Cumulative Returns Over the Quarter			
	1st to 35th Trading Date		36th to End of Quarter	
	1	2	3	4
Rebalancing Demand Rank	*-0.4889%*	*-0.5075%*	0.2574%	0.2717%
	(-2.908)	(-3.915)	(2.539)	(2.593)
Book-to-Market Ratio		-0.2751%		-0.0921%
		(-0.986)		(-0.383)
Log Market Value		0.0394%		-0.1948%
		(0.4181)		(-2.959)
Avg. Adj. R^2	0.0238	0.0576	0.0172	0.0506
Avg. N	3114.6	3114.6	3114.6	3114.6

Panel B. This panel reports calendar time value-weighted excess returns of quintile portfolios sorted by *Rebalancing Demand.* Stocks are sorted by 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.

	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	2.350%	0.586%	0.601%	0.540%	-0.251%	-0.115%
	(3.582)	(2.665)	(2.685)	(1.086)	(-1.344)	(-0.626)
2	2.028%	0.478%	0.403%	1.103%	0.389%	0.367%
	(3.437)	(2.052)	(1.816)	(2.438)	(2.200)	(2.855)
3	2.280%	0.863%	1.010%	1.119%	0.468%	0.417%
	(3.990)	(2.985)	(3.725)	(2.568)	(2.169)	(1.892)
4	1.533%	0.186%	0.095%	0.938%	0.236%	0.125%
	(3.019)	(0.988)	(0.537)	(2.168)	(1.691)	(1.026)
5	1.183%	-0.362%	-0.443%	1.332%	0.572%	0.591%
	(2.057)	(-1.887)	(-2.295)	(2.860)	(4.019)	(4.117)
LS	-1.170%	-0.949%	-1.044%	0.792%	0.823%	0.705%
	(-2.997)	(-2.395)	(-2.599)	(2.657)	(2.724)	(2.342)

Table 8. Value-Weighted Fama-Macbeth Regressions of *Rebalancing Demand*, Characteristics, and Stock Returns

The first-stage cross-sectional regressions are weighted by stock market cap and then averaged and reported in the table. *Rebalancing Demand Rank* is the cross-sectional percentile rank of the average change in a stock's concentration within portfolios as driven by returns. It is standardized by its unconditional standard deivation 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.

	Next Quarter's Returns		Next 4 Quarter's Returns	
	1	2	3	4
Rebalancing Demand Rank	-0.523%	-0.468%	0.563%	0.817%
	(-3.580)	(-3.741)	(1.984)	(3.344)
Ret3m	4.302%	2.755%	-1.449%	-3.006%
	(2.448)	(1.757)	(-0.398)	(-0.905)
Ret4_6m		0.414%		2.950%
		(0.310)		(1.204)
Ret7_12m		1.361%		-1.499%
		(1.409)		(-0.997)
Book-to-Market Ratio		-0.086%		-1.321%
		(-0.294)		(-1.786)
Log Market Value		-0.136%		-0.333%
		(-1.263)		(-1.123)
Avg. Adj. R^2	0.0316	0.1030	0.0281	0.0938
Avg. N	3114.6	3114.6	3114.6	3114.6

Table 9. Calendar Time Sorted Portfolios Over Quarters

This table reports the adjusted excess returns of calendar time portfolios sorted on *Rebalancing Demand*. Common stocks with lag prices greater than 5 dollars 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.

Rank	Excess Return	CAPM Adjusted	3-Factor Adjusted	4-Factor Adjusted	5-Factor Adjusted
1	2.806%	0.668%	0.609%	0.776%	0.742%
	(3.946)	(2.908)	(2.704)	(3.357)	(3.234)
2	2.825%	0.641%	0.543%	0.769%	0.707%
	(3.766)	(2.102)	(2.019)	(2.803)	(2.650)
3	3.128%	1.159%	1.036%	0.994%	0.962%
	(4.446)	(3.395)	(3.384)	(3.094)	(2.993)
4	2.102%	0.052%	-0.094%	-0.097%	-0.082%
	(3.040)	(0.207)	(-0.440)	(-0.432)	(-0.363)
5	2.287%	-0.120%	-0.106%	-0.476%	-0.414%
	(2.836)	(-0.432)	(-0.389)	(-1.822)	(-1.637)
LS	-0.518%	-0.788%	-0.715%	-1.252%	-1.157%
	(-1.150)	(-1.708)	(-1.585)	(-2.819)	(-2.669)

Appendix

Table A. Contemporaneous Regression of *Sell* and *Buy* Actions on *Passive* for the Panel of Fund, Stock, and Quarter Observations

	All Funds						Active Funds		Index Funds	
	Sell			*Buy*			*Sell*	*Buy*	*Sell*	*Buy*
	1	2	3	4	5	6	7	8	9	10
Passive	2.747***	2.660***	5.190***	-3.403***	-4.285***	-5.794***	8.248***	-7.127***	4.873***	-5.541***
	(6.742)	(5.788)	(10.03)	(-10.10)	(-10.42)	(-13.46)	(6.237)	(-7.710)	(9.821)	(-12.72)
Weight		2.051***	2.290***		-0.0696	-1.727***	3.332***	-1.932***	1.915***	-1.599***
		(26.29)	(37.52)		(-1.202)	(-25.41)	(25.48)	(-16.87)	(21.38)	(-24.08)
Returns		-0.00586			0.0244***					
		(-1.378)			(5.827)					
Unrealized Profit		0.0889***	0.0492***		-0.0385***	-0.0123***	0.0425***	-0.0126***	0.0426***	-0.0109***
		(26.71)	(23.68)		(-17.91)	(-7.420)	(9.891)	(-3.687)	(19.70)	(-6.020)
Rank Effect		0.330	0.472		-0.347	-0.610	0.521	-1.582***	0.437	-0.496
		(1.116)	(1.193)		(-1.122)	(-1.344)	(0.745)	(-3.363)	(1.088)	(-1.164)
Time-Fixed Effects	Yes	No	No	Yes	No	No	No	No	No	No
Time X Fund-Fixed Effects	No	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes
Time X Stock-Fixed Effects	No	No	Yes	No	No	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.007	0.406	0.432	0.005	0.415	0.449	0.343	0.271	0.463	0.489
N	27,041,980	25,270,399	25,217,811	27,041,980	25,270,399	25,217,811	5,928,038	5,928,038	19,283,372	19,283,372

This table reports the regression coefficients of trading indicators on *Passive*, various controls, and fixed effects due to time/fund and time/stock. *Sell (Buy)* is 1 if the fund sold (bought) the stock in net in the same quarter. *Passive* indicates the return-driven change in the weight of the stock in the fund. Columns 1–6 regress the sample of all fund-stock-quarter observations. Columns 7 and 8 regress the sample of all actively managed mutual funds. Columns 9 and 8 regress the sample only for index funds. The standard errors are clustered quarterly.

Table B. Funds Whose Quarterly Trades Are Most Explained by Contemporaneous Weight Rebalancing

This table reports the 10 Active Funds and Index Funds whose quarterly trades are most explained by the rebalancing of their current quarter's return-driven changes in portfolio weight. *Size* is the total observed portfolio size at the end of Q2 2022. For index funds, *Weighting Strat* lists each fund's self-described weighting strategy.

Panel A. Index Funds

Fund Name	Family Name	Size ($)	Weighting Strat
Equally Weighted S&P 500 Fund	AIM/Invesco	6,437,886,527	Equal Weight
Invesco VI Equally Weighted S&P 500 Fund	AIM/Invesco	330,581,606	Equal Weight
Invesco S&P 500 Equal Weight ETF	Invesco	25,074,434,119	Equal Weight
Invesco Russell 1000 Equal Weight ETF	Invesco	570,222,911	Equal Weight
Invesco S&P Mid-Cap 400 Equal Weight ETF	Invesco	116,459,962	Equal Weight
S&P Small-Cap 600 Equal Weight ETF	Invesco	55,618,904	Equal Weight
First Trust Value Line Dividend Index Fund	First Trust	9,044,539,211	Equal Weight
iShares MSCI USA Equal Weighted ETF	BlackRock	389,979,256	Equal Weight
Equal Weight US Large-Cap Equity ETF	Goldman Sachs	699,927,024	Equal Weight
QMA Strategic Alpha Small-Cap Value ETF	PGIM Investments	11,157,903	Style/Inverse Weight

Panel B. Active Funds

Fund Name	Family Name	Size ($)
Small-Cap Diversified Value Fund	Hotchkis & Wiley	386,961,699
Parametric Dividend Income Fund	Eaton Vance Mutual Funds	33,314,245
All America Portfolio	Mutual of America Financial	14,964,551
Diversified Mid-Cap Growth Fund	T. Rowe Price	2,216,635,868
Price Structured Mid-Cap Growth Fund	Lincoln Variable Insurance	1,215,580,306
Mid-Cap Growth Fund	Commerce Funds	295,134,096
Diversified Mid-Cap Growth Portfolio	Voya Partners	1,350,498,488
Small/Mid-Cap Value VP	Transamerica Series	533,216,720
Health Care Fund	Guggenheim	16,416,822
Royce Small-Cap Portfolio	Royce Capital	355,959,439

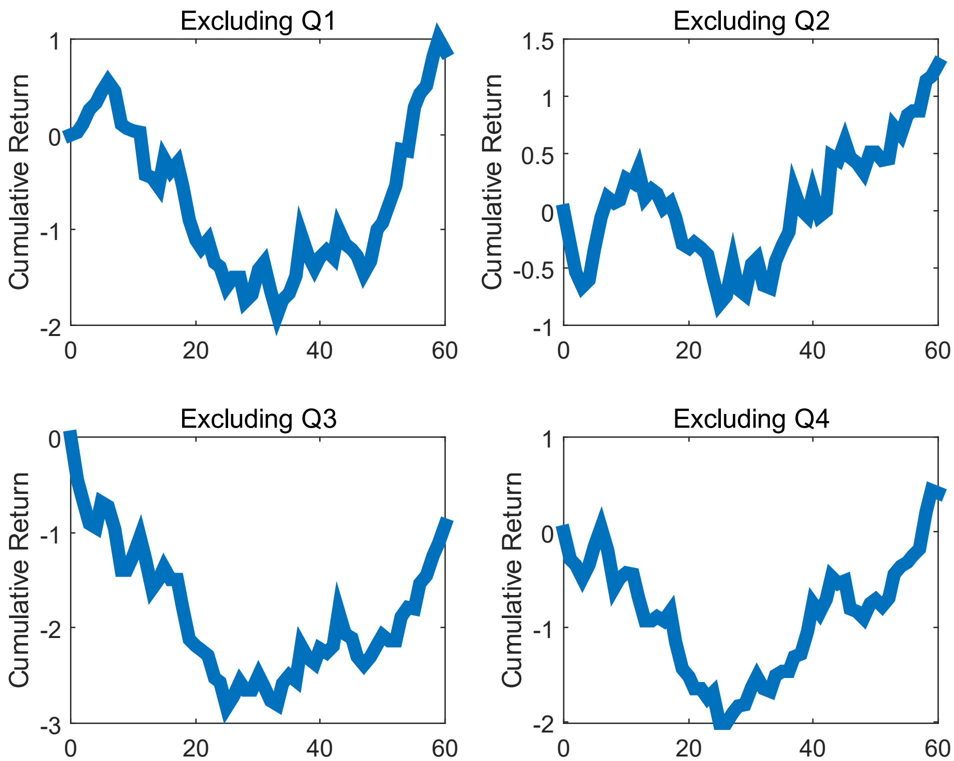

Figure C. Long-Short Portfolio Returns of the Big High Minus Big Low Portfolio.

These portfolio returns are formed by using the 5 x 5 portfolios sorted by size and the past 2- to 12-month returns between Q1 1990 and Q2 2021 provided by Ken French, excluding specific quarters. Specifically, the strategy longs the Big (stocks in the highest quintile based on size) and High (stocks in the highest quintile of the past 2- to 12-month returns), and shorts the Big (stocks in the highest quintile based on size) and Low (stocks in the lowest quintile of the past 2- to 12-month returns).