Factor Rebalancing[*]

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Abstract

When a mutual fund has persistent demand for a priced factor, the fund needs to rebalance its portfolio's exposure to that factor as stock characteristics change over time. We establish this behavior of "factor rebalancing" and examine its implications for return predictability. We show that factor rebalancing is prevalent in mutual funds' holding changes, and this behavior poses a source of predictable price pressure that operates independently from the passive trading induced by retail flows. Consistent with factor rebalancing, stocks whose characteristics are misaligned with underlying funds' factor demand subsequently have lower returns, while well-aligned stocks subsequently have higher returns. We rule out alternative explanations based on private information, skills, and herding. (*JEL* G12, G23, G40)

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1 Introduction

In the simplest model of asset pricing, an asset's price is determined by discounting its future cash flows to the present value. Such a framework does not leave much space for demand shocks to directly affect asset prices. However, mounting evidence has increasingly challenged this view, showing that variations in asset demand can have a significant impact on equilibrium prices, even when these variations contain little information or impose no obvious risks (see Gabaix and Koijen 2022 for a recent review on the existing evidence). In particular, two popular sources of demand changes have been proposed. The first source relies on retail investors moving money into and out of mutual funds. Even though funds are merely serving as intermediaries overseeing the pass-through of money flows, their passive trading can have a direct impact on asset prices (Coval and Stafford, 2007; Lou, 2012). The second source stems from mutual fund indexing. As the constituents of an index change, funds adjust their portfolios to the index, generating shifts in asset demand (Harris and Gurel, 1986; Shleifer, 1986; Wurgler and Zhuravskaya, 2002; Chang, Hong, and Liskovich, 2015; Pavlova and Sikorskaya, 2020).

In this paper, we start with the following observation: mutual fund demand shifts extend beyond passive adjustments to portfolios in response to retail flows or index constituent changes. Instead, mutual funds are much more active, often targeting priced factors and rebalancing their portfolios to align with these factors. Such proactive portfolio management, we posit, can significantly influence asset prices, primarily through its effect on asset demand.

Motivated by this observation, we propose a source of institutional demand that operates regularly and predictably at the factor level. Central to our thesis is the tendency of mutual funds to target a select few well-known factors, such as value and momentum, and have persistent demand for these factors. This persistence in factor demand, when coupled with changing stock characteristics, induces a regular rebalancing motive aimed at maintaining a stable factor exposure, a behavior we term "factor rebalancing." When a significant number of mutual funds simultaneously undertake such rebalancing, it creates a predictable pattern of price pressure on the involved stocks, leading to return predictability in the cross section. Under this framework, a stock's expected return is now determined not solely by its inherent characteristics but also by the interplay between these characteristics and the factor demand of the underlying funds. This alternative approach offers a more comprehensive understanding of the drivers of stock returns, underscoring the influential role of mutual fund asset demand.

To fix the idea, consider two value stocks, A and B. Both stocks currently have the same book-to-market (BM) ratio. However, their histories diverge: stock A has long been a value stock, while stock B used to be a growth stock but recently became a value stock due to a drop in its share price. As a result, stock A is currently held mostly by value-oriented funds while stock B is by growth-oriented funds. All else equal, if the expected return is entirely determined by the BM ratio, as traditional asset pricing models suggest, one should expect both stocks to have similar returns in subsequent periods. However, through the lens of factor rebalancing, a different picture emerges: stock B is likely to experience lower returns due to the higher propensity of its growth-oriented holders to sell, which would depress the stock price, at least in the short run.

To test this mechanism, we start by estimating mutual funds' factor demand and verifying its persistence over time. Each month, we regress a fund's monthly raw returns over the last 60 months on the monthly returns of several well-known priced factors over the same period. The loading on each factor reveals the fund's exposure to that factor over the past five years. Although factor loadings, by construction, are positively autocorrelated due to overlapping estimation windows, we demonstrate strong persistence even for non-overlapping loadings estimated five years apart. We obtain similar levels of persistence using a holding-based measure, calculated as the average characteristic of all stocks in a fund's portfolio. We continue to use this holding-based measure for robustness in the paper's other analyses.

After confirming the persistence of factor demand, we examine its implications for trading behavior. Given the prevalence of value and momentum strategies, our analysis focuses on value and momentum as the two factors targeted by mutual funds; here, we focus on value to simplify exposition. We first show that both value and growth funds trade according to their factor demand through portfolio rebalancing, by replacing stocks that no longer align with their factor demand with stocks that do. Examining mutual fund trades at the stock level, we find that factor demand interacts with stock characteristics to predict subsequent trading patterns. In particular, when there is a "misalignment" between a stock's characteristic and the underlying funds' factor demand, this stock will face more selling pressure in the subsequent quarter.

In principle, for growth stocks held by value funds, the selling pressure from value funds could be counteracted by the buying pressure from growth funds. However, in reality, such counteraction is very limited. This is because each fund has a limited investment universe and is sluggish in trading stocks outside its current portfolio (Koijen and Yogo, 2019). We find that, for a median-sized mutual fund, 85 percent of stocks that are currently held were also held in the previous quarter. In addition, when acquiring stocks, funds are 2.5 times more likely to increase their existing holdings than to initiate new positions in previously unowned stocks. Therefore, selling pressure due to misalignment is likely to dominate.

We next examine the return predictability implications of factor rebalancing. We first aggregate *fund*-level factor loadings to the *stock* level: for each stock in each quarter, we calculate the holdings-weighted average factor loadings of its underlying funds. The resulting measures, termed *factor demand*, represent the average factor loadings of a stock's underlying funds. We then form 25 (5×5) portfolios by independently sorting stocks based on their own characteristics and their factor demand. Out of the 25 value-based portfolios, the two that are most "misaligned"—that is, the one with the highest BM ratio but held by funds with the lowest value demand, and the one with the lowest BM ratio but held by funds with the highest value demand—earn the lowest annualized value-weighted returns of 8.5% and 6.6%, respectively. In comparison, the two most "well-aligned" portfolios earn annualized value-weighted returns of 17.0% and 14.0%.

The analysis so far assumes that funds rebalance based on the *level* of stock characteristics, but funds may also rebalance as a response to *changes* in stock characteristics. For robustness, we double-sort stocks based on changes in stock characteristics and factor demand. Interestingly, while results are similar to before, they are quantitatively smaller for value but larger for momentum. This suggests that factor rebalancing may be more based on levels for value and more based on changes for momentum.

We identify two additional return patterns from the 25 value-based portfolios. First, holding the BM ratio constant, we compare portfolios different in their value demand. Value stocks with the highest value demand outperform those with the lowest value demand by 5.5% in an annualized return. Conversely, growth stocks with low value demand earn higher returns than those with high value demand by 10.4% per year on average. Second, we evaluate the performance of the high-minus-low (HML) value strategy as a function of value demand. Among stocks held by the most value-oriented funds, the HML strategy delivers an annualized return of 7.4%. In contrast, among stocks held by the most growth-oriented funds, the HML strategy delivers an annualized return of -8.5%, resulting in a "growth premium." The existence of a sizable growth premium over the last four decades may shed light on the puzzling phenomenon that growth funds are popular despite the unconditional underperformance of growth stocks (Lettau et al. 2018). For momentum, we apply the same procedure and sort all stocks into 25 portfolios based on their past one-year returns (skipping the most recent month) and the underlying funds' momentum demand. The return results are also in line with portfolio rebalancing, but with a smaller magnitude.

We test the robustness of our portfolio sorting results to various alternative specifications. First, we measure portfolio performance using equal-weighted portfolio returns and alphas from different factor models (CAPM and three-factor). Second, to mitigate concerns that some portfolios may contain too few stocks, we reduce the number of portfolios from 25 to 9 (3×3). Third, we replace the loading-based measure of factor demand with an alternative holding-based measure. In all these alternative specifications, we find similar return patterns in support of factor rebalancing.

In subsample analysis, we test the robustness of our portfolio-sorting results in both the first and second half of the sample, among stocks either high or low in mutual fund ownership, and among both small-cap and large-cap stocks. Overall, the return patterns are more pronounced in the latter sample, among stocks with higher mutual fund ownership, and among large-cap stocks. For momentum, the return patterns are stronger among stocks with higher mutual fund ownership and when we sort stocks based on changes in past returns, but weaker in the latter sample and among large-cap stocks. Overall, consistent with the literature on the relationship between momentum and value, the empirical regularities of the two strategies appear to be complementary to each other (Asness, Moskowitz, and Pedersen, 2013).

To quantify the price impact of factor rebalancing, we estimate price elasticities for different HML and WML (winner-minus-loser) portfolios. To do so, we make additional assumptions about which kind of demand is inelastic. For example, we assume value funds' demand for value stocks is inelastic from quarter to quarter. Our estimated factor-level elasticities fall between -0.04 and -0.35, with an average estimate of -0.23. Overall, these numbers are larger than the estimates at the stock level (Chang, Hong, and Liskovich, 2015), but on par with those estimated at the factor and market levels (Gabaix and Koijen, 2022; Ben-David et al., 2021; Haddad et al., 2021).

Last, we consider a few alternative explanations and argue that none of these alternatives can fully account for our results. First, flow-induced trading cannot explain our findings, because it is either orthogonal to or goes in the opposite direction of our observed return patterns. Second, we show that mutual fund herding behavior is unlikely to explain our findings, as it would imply different return patterns across size groups than what we observe. For example, contrary to the herding literature, our return evidence for value is stronger in large-cap stocks. Third, we find no systematic relation between our return patterns and subsequent firm fundamentals, implying that the return predictability we uncover does not reflect superior information of some funds about future stock fundamentals. Fourth, we examine the possibility that our findings are driven by fund specialization in certain factors. This would imply that factor-targeting funds, such as value and momentum funds, have superior stock-picking skills and better performance than unspecialized funds. As shown above, this skill-based explanation is not supported by subsequent stock fundamentals. Moreover, we find no evidence of outperformance for these funds based on their four-factor alphas: on average, value and momentum funds exhibit annualized four-factor alphas of only 28 basis points (bps) and −8 bps, respectively.

A vast literature has linked movements in stock prices to various mutual fund behaviors.[1] We share the similar prior that trading without information content can induce price pressure and affect equilibrium price. However, the trading motive we propose is different: rebalancing induced by persistent factor demand. We also contribute to the discussion on the relationship between institutional demand and asset prices.[2] We propose a different source of institutional demand and link it to cross-sectional return predictability. In this regard, we build on the earlier work by Ben-David et al. (2021) and Li (2021) and show that, independent from retail flows, mutual funds actively maintain persistent exposure to factors such as value and momentum, leading to frequent, systematic rebalancing and predictable returns in characteristics-managed portfolios.

By showing that factor demand helps forecast future stock returns, we expand the existing set

[1]For example, flow-induced trading (Coval and Stafford 2007; Lou 2012; Akbas et al. 2015; Edelen et al. 2016; Huang et al. 2019), herding (Lakonishok et al. 1992; Nofsinger and Sias 1999; Wermers 1999; Sias 2004; Dasgupta et al. 2011), positive-feedback trading (Lakonishok et al. 1992; Nofsinger and Sias 1999; Cohen et al. 2002), and behavioral patterns such as the disposition effect and the V-shaped selling schedule (Grinblatt and Han 2005; Frazzini 2006; An and Argyle 2020).

[2]Earlier papers such as Harris and Gurel (1986) and Shleifer (1986) have shown that the demand curve is downward-sloping at the stock level. The literature on the index inclusion effect further quantifies the price impact of institutional demand (Wurgler and Zhuravskaya 2002; Chang et al. 2015; Pavlova and Sikorskaya 2020). Recent literature, such as Gabaix and Koijen (2022), examines the relationship between aggregate demand and aggregate stock returns.

of cross-sectional stock return predictors. The literature has primarily focused on stocks' own characteristics as return predictors. We argue that the characteristics of the underlying investors also matter, as they interact with stock characteristics to affect stock returns. In this regard, our paper is also related to the strand of literature that compares stock-picking ability across funds with different styles. For example, earlier studies have shown that stocks held by growth funds and positive-feedback funds tend to earn higher returns (Grinblatt and Titman 1989; Grinblatt et al. 1995; Cohen et al. 2002). These studies do not account for the interaction between stock and fund characteristics and typically find a relatively small difference in returns. We show that an important source of return predictability is the interaction between stock characteristics and fund factor demand. Therefore, our results also have implications for value and momentum by showing that conditioning on fund characteristics substantially improves the performance of both value and momentum strategies.

The rest of the paper proceeds as follows. Section 2 explains how we measure factor demand and shows the properties of these measures. Section 3 provides evidence for mutual funds' factor rebalancing behavior and its associated return predictability. Section 4 provides additional evidence on trading and price elasticity. Section 5 explores a few alternative explanations. Section 6 concludes.

2 Factor demand

In this section, we begin by describing the data. We then explain our measures of factor demand, examine their properties, and illustrate their aggregate patterns over time.

2.1 Data

Our data cover all US equity mutual funds from 1980 to 2019. Quarterly fund holdings data are from the Thomson/Refinitiv Mutual Fund Holdings (S12) database. Fund-level characteristics such as total net assets (TNA), monthly returns, and expense ratios are from the CRSP Survivor-Bias-Free US mutual fund database.[3] The two datasets are then merged using the MFLinks files

[3]As in Lou (2012), monthly fund returns are calculated as net returns plus 1/12 of annual fees and expenses; TNA is summed across all share classes; net returns and expense ratios are computed as the TNA-weighted averages across

provided by the Wharton Research Data Services (WRDS).

We follow a procedure that is standard in the literature to arrive at the final sample (e.g., Lou, 2012; Jiang and Verardo, 2018). First, because we focus on the US equity market, we include only domestic equities held by US equity funds; thus, for example, we drop funds that specialize in bonds and international equities. Second, we require the reporting date, the date for which holdings information is recorded, and the filing date, the date on which a holdings report is filed, to be no more than six months apart. Third, because some mutual funds misreport their investment objective codes, we follow Jiang and Verardo (2018) and require the ratio of equity holdings to TNA to be between 0.80 and 1.05, thereby focusing on funds that primarily invest in equities. Fourth, we require a minimum fund size of $1 million. Finally, we require that the TNAs reported in the Thomson Reuters database and in the CRSP database do not differ by more than a factor of two.

Panel A of Table 1 reports, for each year, the number of funds and the average (median) fund size in our sample. From 1980 to 2019, both the number of funds and fund size increase by almost twenty times. To compare with sample characteristics in earlier studies, Panel B reports the summary statistics in Lou (2012)'s sample. The two samples are similar in sample size and firm size. One difference is that our sample has slightly fewer funds in the earlier years, but more in later years.

Other data sources are standard: stock prices, stock returns, and accounting variables are from the CRSP/COMPUSTAT merged database; factor returns are from Kenneth R. French's website. Additionally, stock-level characteristics, such as book-to-market ratio and past one-year returns, are constructed following the standard procedures in their respective original studies.

2.2 Measuring factor demand

For each fund j in month t, we use observations from month $t-59$ to month t, a total of 60 months, and run the following rolling time-series regression:

$$\begin{aligned} rret_{j,t+1-k} = \alpha_{j,t} + \phi_{j,t}^{MKT} MKT_{t+1-k} + \phi_{j,t}^{HML} HML_{t+1-k} + \phi_{j,t}^{SMB} SMB_{t+1-k} + \phi_{j,t}^{MOM} MOM_{j,t+1-k} \\ + \phi_{j,t}^{CMA} CMA_{t+1-k} + \phi_{j,t}^{RMW} RMW_{t+1-k} + \phi_{j,t}^{flow} flow_{j,t+1-k} + \varepsilon_{j,t,t+1-k} \end{aligned} \quad (1)$$

all share classes. For other fund characteristics, values from the share class with the largest TNA are used to represent the entire fund.

where $k = 1, 2, \ldots, 60$. On the left-hand side, $rret$ represents raw fund returns. On the right-hand side, MKT represents excess market returns, and HML, SMB, MOM, CMA, and RMW represent the returns for value, size, momentum, investment, and profitability strategies, respectively. We require a fund to have at least 60 months of returns data and each rolling-window estimation to have at least 24 monthly observations.[4] We also control for the sensitivity of fund returns to retail flows by including $flow$, where $flow_{j,t} = \frac{TNA_{j,t}}{TNA_{j,t-1}} - \left(1 + ret_{j,t}\right)$ and ret represents net fund returns. Therefore, for fund j in month t, we obtain seven beta coefficients: $\phi_{j,t}^{MKT}$ to $\phi_{j,t}^{flow}$. We will from now on refer to these coefficients as fund-level factor loading or factor demand interchangeably.[5]

In Equation (1), each $\phi_{j,t}$ measures the loading of fund j's return on a given factor over the last 60 months. Therefore, $\phi_{j,t}$ should be interpreted as a measure of *average* demand over the last five years rather than *current* demand as of month t. This procedure induces a high autocorrelation in $\phi_{j,t}$, an issue we will return to in Section 2.3 when discussing the persistence of factor demand. Compared to mutual fund classifications or investment objectives from industry data providers such as Lipper or Wiesenberger, which often rely on funds' self-reported investment objectives and can be misreported or missing, our loading-based measures are available for all funds with at least five years of return data and are less subject to reporting errors.

We have included seven factors on the right-hand side of Equation (1), but our main analysis will be devoted to value and momentum; one can therefore regard the other five factors as control variables. The reasons are as follows. First, value and momentum are among the most robust asset pricing factors in both the US and global markets (Asness, Moskowitz, and Pedersen, 2013). Second, and more related to our mechanism of factor rebalancing, it is reasonable to expect that mutual funds target profitable factors such as value and momentum, which are well-known and have long been practiced in the investing world (for example, value investing was pioneered by Benjamin Graham and David Dodd in the 1930s.) In comparison, although investment and profitability are robust factors in predicting returns, they were discovered more recently and are therefore less likely to be targeted by mutual funds. This is further evidenced in reported investment objectives

[4]While our main sample starts in 1980, the mutual fund return data extend to earlier periods and we go back to as early as possible in estimating Equation (1). Therefore, factor betas are available from the beginning of our main sample.

[5]We include retail flow in the main specification to control for the direct impact of contemporaneous flows on fund returns (Dou, Kogan, and Wu, 2020). Estimated factor loadings are quantitatively similar if we exclude retail flow from the specification.

of mutual funds, which often mention "value" or "growth," occasionally "momentum," but rarely "profitability" or "investment." Third, while many mutual funds do specialize in stocks of a given size bracket, it is unlikely that there is much rebalancing induced by changes in firm size. This is because firm size is extremely persistent: it takes years or even decades for a small firm to grow into a medium-sized one. In comparison, as we will show in Section 3.1, for value and momentum, both the BM ratio and past one-year return change frequently at the stock level. Consequently, funds targeting these strategies need to rebalance regularly.

Another popular way to measure mutual funds' factor exposure is by aggregating stock characteristics based on fund holdings.[6] Both approaches can capture aspects of the factor demand, with slightly different emphases: our loading-based measures, with a focus on the correlation between fund and factor returns, capture trading activities between two reporting dates; by contrast, holding-based measures provide an up-to-date snapshot of the current exposure (Kacperczyk, Sialm, and Zheng, 2008). To entertain the second possibility, later we will repeat our main analyses using holding-based measures of fund demand to demonstrate robustness.

Table 2 reports the summary statistics of fund-level factor demand. Panel A shows that an average (median) mutual fund has a market beta of one. It has a sizable and positive size beta, which is consistent with the results reported in Lettau, Ludvigson, and Manoel (2018), and a small and negative investment beta. For value, momentum, profitability, and flow, its betas are near zero.

Panel B of Table 2 cross-validates our measures of factor demand by reporting average factor betas by fund style, where fund style is based on Lipper investment objective classification. Column (1) shows that the average SMB beta increases from −0.08 for large-cap funds to 0.73 for small-cap funds. Column (2) shows that the average HML beta is −0.19 for growth funds and 0.23 for value funds. Growth funds load positively on momentum, which can be explained by the negative correlation between the BM ratio and past one-year return, and negatively on investment and profitability, which can be explained by growth firms investing more and profiting less. Panel C of Table 2 reports the average factor betas for index and non-index funds. Overall, as expected,

[6] Lettau, Ludvigson, and Manoel (2018) examine mutual fund characteristics by examining quarter-end stock holdings. They argue that the estimation of factor loadings may be biased due to different volatilities at the long and short legs of a given factor. As a result, they find that factor loadings are not symmetric around zero, making loadings hard to interpret without a benchmark scale. For our analysis, however, we rely on cross-fund variation in factor loadings at a given time—not on the absolute magnitude of factor loadings—and we define fund strategies based on their relative position in the cross section. A systematic bias in the scale of factor loadings therefore does not affect our analysis.

an average index fund has little exposure to any of the seven factors. In comparison, with an SMB beta of 0.25, an average non-index fund is much more likely to invest in smaller stocks.

2.3 Persistence of factor demand

A fund's demand for a given factor can be persistent over time for at least three reasons. First, mutual funds face rigid mandates.[7] Many of them have a specific investment objective, such as growth, and by mandate they need to keep a relatively stable exposure to this factor. Therefore, as the set of stocks considered "growth" changes, they will need to rebalance their portfolios. Relatedly, some funds have mandates to beat or stick to a benchmark, often represented by a popular index with stable exposure to certain factors. The incentive to minimize the tracking error (or to maximize the "information ratio") prompts funds to keep a persistent exposure to the underlying factors. Second, even for mutual funds that have no specific investment objective and are thus more flexible in their choice of investment, they may choose to target one or several trading strategies to construct their portfolios, either to take advantage of well-known pricing factors or to simplify the complex process of investment decision-making. Third, some funds may keep a persistent exposure to a given factor out of habit. Here, we use the term "habit" loosely, without specifying its underlying causes. Economically, a number of factors may contribute to habit, such as persistent beliefs in the profitability of a trading strategy, a stable investment philosophy, and persistent use of the same analytical methods.

As discussed above, fund-level factor loadings are estimated using overlapping windows and are therefore positively autocorrelated. To demonstrate persistence beyond this mechanical high autocorrelation, we adopt the following approach. First, we convert fund j's loadings on factor X to the quarterly level by keeping the last observation of each quarter, denoted as $\hat{\phi}^X_{j,q}$. We do so because our analysis in subsequent sections relies on holdings data, which are only reliably observed at the quarterly frequency. Next, for factor X, we run the following panel regression:

$$\hat{\phi}^X_{j,q} = \alpha_q + b \times \hat{\phi}^X_{j,q-20} + \epsilon_{j,q}, \tag{2}$$

[7]See, for example, Baker, Bradley, and Wurgler (2011) for mandates to beat fixed benchmark and Gabaix and Koijen (2022) for mandates on fixed allocation to certain assets.

where X represents market, value, size, and momentum (the Carhart four factors).[8] Regression (2) lags factor loadings by 20 quarters (60 months) to ensure that the estimation windows for the two sides are non-overlapping.[9] We additionally include quarter fixed effects and double-cluster standard errors at the fund and year-quarter levels.

In Table 3, columns (1) through (4) each represent a different factor loading. Factor loadings are rather persistent in the time series, suggesting that factor exposure is indeed relatively persistent at the fund level. For example, in columns (3) and (4), loadings on value and momentum indicate quarterly autocorrelations of 0.95 (= $0.369^{0.05}$) and 0.94 (= $0.293^{0.05}$). Of the four factors, size beta is the most persistent over time, primarily because size as a strategy requires only infrequent rebalancing.

Columns (5) and (6) present additional regressions to explore the underlying sources of this persistence. Column (5) re-runs column (1) by adding a dummy variable for size funds and its interaction with the size loading. The dummy variable indicates whether a fund specializes in a size bracket (e.g., small-cap, medium-cap, and large-cap) and is therefore more subject to mandates in its factor demand. The interaction term captures the incremental persistence in size beta induced by mandates. In column (5), both size beta and the interaction term are positive and significant, suggesting that both mandates and other forces drive the persistence of size demand. Column (6) runs a similar regression for value loadings and finds a similar pattern.[10]

2.4 Aggregate trends in factor demand

While a thorough examination of the determinants of factor demand is beyond the scope of this paper, we present some stylized facts about their aggregate trends. Figure 2 plots the evolution of aggregate factor loadings. In each subfigure, the blue dashed line represents the TNA-weighted loading, the green dashed line represents the equal-weighted loading, and the red solid line represents the five-year cumulative return of the corresponding factor. Overall, the aggregate

[8] Results for the other three factors are similar and omitted for simplicity.

[9] We can lag by one more quarter to further ensure that the estimation windows are non-overlapping. Results are essentially unchanged.

[10] In the Online Appendix, Table A.2 runs additional regressions to show that persistent factor demand exists among both index funds and non-index funds. In particular, factor demand is more persistent among non-index funds. Table A.2 runs additional regressions to show that factor demand is persistent after controlling for active shares (Cremers and Petajisto 2009).

factor loadings for size, value, and momentum all increase from 1980 up to the Great Recession, after which they decline. These patterns align with those reported by Lettau, Ludvigson, and Manoel (2018).[11]

3 Factor rebalancing

In this section, we present direct evidence of mutual funds' factor rebalancing behavior; that is, as stocks characteristics such as the BM ratio and past one-year return change, funds rebalance their portfolios to maintain a persistent exposure to value or momentum factors. We then examine the asset-pricing predictions of factor rebalancing.

3.1 Transition probability

For factor rebalancing to have an impact on the return predictability in the cross section, three conditions are needed. First, the stock characteristic entailed by the factor must vary sufficiently quickly over time; otherwise, there is no need for funds to rebalance to begin with. The latter, for example, is the case with rebalancing based on size: because firm size is rather stable over time, trading on size does not involve frequent rebalancing. Second, for a given fund, its factor demand should be sufficiently persistent—and more persistent than the stock characteristic associated with that factor. If factor demand is not persistent, it would mean that funds are not really targeting that factor, which in turn reduces the need for factor rebalancing. Third, due to institutional frictions and other constraints, funds rebalance with a delay. This means, for example, that even the most value-oriented funds would hold some "legacy" growth stocks in their portfolios from past trades. In this section, we empirically confirm the first two conditions; we leave the third condition to Section 3.4.

To establish the first condition, Panel A of Table 4 shows the one-year transition probabilities of a stock moving between quintiles sorted on the BM ratio.[12] We primarily focus on the diagonal

[11]An interesting observation is that there appears to be a lead-lag relationship between factor returns and factor demand. For example, in subfigure 2a, HML returns peak ahead of HML loadings. This finding suggests that mutual funds may tilt their portfolios towards the factors that have performed well in the past, effectively trying to time the factors. We do not go into the details in this paper and leave this exploration for future work.

[12]Tables A.4 and A.5 in the Online Appendix show more details about transition probabilities at other frequencies.

terms, which represent the probabilities of a stock remaining in the same quintile. The diagonal terms range from 0.45 to 0.72, suggesting that a stock switches to a different quintile with an average probability between 28% to 55%. Panel C shows the transition probability matrix for quintiles sorted on the past one-year return (skipping the most recent month). Overall, the diagonal terms in Panel C have lower values than those in Panel A, suggesting a greater need to rebalance the momentum strategy. Intuitively, this is because the past one-year return is more volatile than the BM ratio.

To establish the second condition, Panel B of Table 4 shows the one-year transition probabilities of a fund moving between different quintiles sorted on value loadings. The diagonal terms are greater than those in Panel A, suggesting that fund demand for value is more persistent than the BM ratio. Panel D shows the transition probabilities between fund quintiles sorted on fund momentum loadings, where the diagonal terms, again, are greater than those in Panel C. Therefore, we confirm that, for value and momentum, fund factor demand is indeed more persistent than stock characteristics.

3.2 Fund-level evidence of factor rebalancing

We next investigate how mutual funds rebalance portfolios based on stock characteristics. Mutual funds need to periodically rebalance their portfolios to maintain a persistent exposure to factors such as value and momentum. They may rebalance in response to *changes* in stock characteristics—the need to get rid of stocks that become misaligned with their investment strategy—as well as *levels* of stock characteristics—the need to acquire more stocks that align with their investment strategy. Since characteristics such as the BM ratio and past one-year return change relatively fast, the level and changes of these characteristics are highly correlated. In our analysis, we examine the effects of both.

We start by examining the relationship between changes in stock characteristics and mutual fund trading in the next quarter using the following trade-level regression:

$$trade_{i,j,q+1} = \alpha + \gamma_1 \Delta BM_{i,q} + \gamma_2 \Delta r_{i,q-4,q-\frac{1}{3}} + \gamma_3 \Delta ME_{i,q} + \gamma_4 \Delta \beta_{i,q} \tag{3}$$

$$+ \gamma_5 \Delta OP_{i,q} + \gamma_6 \Delta INV_{i,q} + \varepsilon_{i,j,q+1}, \tag{4}$$

where the dependent variable, $trade_{i,j,q+1} \equiv \Delta Shares_{i,j,q+1}/Shrout_{i,q}$, measures percentage trading in stock i by fund j in quarter $q+1$.[13] We adjust the trade measure for flow-induced trading (FIT) to separate mutual funds' active portfolio rebalancing trades from those driven by retail flows. Results are quantitatively similar without these adjustments.[14] The independent variables are four-quarter changes in stock i's characteristics, including book-to-market ratio, $\Delta BM_{i,q}$; past one-year return (skipping the most recent month), $\Delta r_{i,q-4,q-1/3}$; market beta, $\Delta\beta_{i,q}$; market capitalization (in billions), $\Delta ME_{i,q}$; operating profitability, $\Delta OP_{i,q}$; and investment, $\Delta INV_{i,q}$. To differentiate funds with different trading styles, we run the above regression for subsamples of funds with high or low factor betas. These subsamples include value, growth, momentum, and contrarian funds.

Panel A of Table 5 reports the regression results for Equation (4). Columns (1) and (2) focus on growth and value funds, defined as funds in the bottom and top quintile of $\phi_{j,q}^{HML}$. In column (1), growth funds' trades load negatively on changes in the BM ratio. In comparison, in column (2), value funds' trades load positively on changes in the BM ratio. These patterns are consistent with value and grow funds rebalancing stocks based on their BM ratios. Columns (3) and (4) focus on momentum and contrarian funds, defined as funds in the bottom and top quintile of $\phi_{j,q}^{MOM}$. As before, momentum funds' trades load positively on changes in past one-year return while contrarian funds trade the opposite way. All of these coefficients are statistically significant at the 1% level with standard errors clustered at the fund and quarter levels, even after controlling for additional characteristics such as market beta, size, investment and profitability.

Translating the coefficients into economic magnitudes, a one-standard-deviation increase in the 4-quarter change in BM ratio results in growth funds selling 3.45% of the total outstanding shares, while value funds purchase 2.30% of the total outstanding shares. For momentum and contrarian funds, a one-standard-deviation increase in the 4-quarter change in past returns results in contrarian funds selling 3.42% of the total outstanding shares and momentum funds purchasing 2.91% of the

[13]Throughout the paper, we use i to refer to stocks and j to refer to funds.

[14]More specifically, we follow Lou (2012) and define FIT for stock j in quarter q as

$$FIT_{j,q} = \frac{\sum_i Shares_{i,j,q-1} \times flow_{j,q} \times PSF}{\sum_i Shares_{i,j,q-1}},$$

where $flow_{j,q}$ is the dollar flow to fund j in quarter q scaled by the fund's lagged TNA, and $Shares_{i,j,q-1}$ is the number of shares held by fund j at the beginning of quarter q. PSF is the partial scaling factor that accounts for the proportional purchases and sales for inflows and outflows, respectively. We take the values of PSF from Lou (2012): a dollar inflow corresponds to 62 cents additional purchase of the fund's current portfolio; a dollar outflow corresponds to a one-dollar sale of the existing portfolio.

total outstanding shares.[15]

We next investigate predictable trading based on *levels* of stock characteristics as follows:

$$trade_{i,j,q+1} = \alpha + \gamma_1 BM_{i,q} + \gamma_2 r_{i,q-4,q-\frac{1}{3}} + \gamma_3 ME_{i,q} + \gamma_4 \beta_{i,q} \tag{5}$$

$$+ \gamma_5 OP_{i,q} + \gamma_6 INV_{i,q} + \varepsilon_{i,j,q+1}. \tag{6}$$

Panel B of Table 5 reports the regression results. Value funds' trades positively load on the level of BM, while growth funds' trades load negatively. We also find similar results for momentum and contrarian funds when examining how they respond to past one-year returns. Results are statistically significant except those of contrarian funds. Overall, evidence from Table 5 confirms that mutual funds rebalance their portfolios to maintain their factor exposure and further suggests that the factor rebalancing relies on both changes and levels of stock characteristics.

3.3 Investment universe

After showing evidence of mutual funds engaging in factor rebalancing, we further posit that such rebalancing behavior generates predictable trading and return at the stock portfolio level. To see the intuition, take value rebalancing as an example. Consider two value stocks, A and B, with the same BM ratio. Stock A has long been a value stock, while stock B used to be a growth stock but recently became a value stock due to a drop in share price. As a result, stock A is currently held primarily by value funds, while stock B is currently held primarily by growth funds. However, the underlying growth funds have the incentive to sell stock B to maintain their exposure to growth stocks. This means that, compared to stock A, stock B faces more selling pressure from its current investors and will experience lower returns in subsequent periods.

In the above example, the selling pressure on stock B from growth funds may be offset if some value funds have an equally strong demand to buy it. However, the selling pressure is likely to outweigh the buying pressure, due to the following reasons. First, most funds have a relatively small investment universe. As a result, it takes time for the "new" value stocks to enter the choice sets of value funds. Figure 3 confirms this intuition. In the current quarter, the median fund retains

[15] In Panel A of Table 5, the standard deviations of the first independent variables are 0.2094, 0.2771, 0.5705, and 0.6470 for each column, respectively.

90% of the positions held in the previous quarter. In fact, more than 15% of the funds do not change their portfolio composition at all in a given quarter.[16] Therefore, while the sellers have a strong incentive to offload "misaligned" stocks like stock B, potential buyers, facing a large array of value stocks, may not even consider stock B as an option.

Second, reinforcing the notion of a small investment universes, we find that funds, on average, tend to trade stocks that are already in their portfolios rather than initiate new positions. In the mutual fund holdings data, we categorize all quarterly portfolio adjustments into five different types: (1) new buy (initiating a new position from zero); (2) additional buy (increasing holding for an existing position); (3) partial sell (reducing holding for, but not liquidating, an existing position); (4) liquidation; and (5) no change. Overall, more than 60% of quarterly changes are additional buys and partial sells, whereas new buys and liquidations only take up around 10% of the quarterly changes.

The above small investment universe could arise, for example, if mutual funds have limited attention (Barber and Odean, 2008; Hartzmark, 2015). It is neither realistic nor efficient for mutual funds to be monitoring all stocks at all times. Instead, they choose to focus on a small set of stocks in a boundedly rational way. As a result, funds are naturally more attentive to stocks already in their portfolios or investment universe. Therefore, in the case of stock B above, value funds not currently holding it may remain oblivious to its recent shift to a value stock. Taken together, we contend that the selling pressure from existing funds is unlikely to be fully offset by trading from the other funds.

3.4 Portfolio returns: main results

We test these predictions from factor rebalancing through portfolio sorting. To see the intuition, suppose that we double-sort stocks into 25 (5×5) portfolios based on the BM ratio and the underlying funds' value demand, as shown in Figure 1 below. The top-right corner and the bottom-left corner (both in red) represent two "misaligned" portfolios: growth stocks in the hands of value funds and value stocks in the hands of growth funds. Both are expected to face more selling pressure from the

[16] Koijen and Yogo (2019) show that, for a median-sized mutual fund, 85 percent of stocks currently held by that fund were also held by the same fund in the previous quarter, implying that the investment universe is highly persistent over time at the fund level.

underlying funds in subsequent periods. In comparison, the top-left corner and the bottom-right corner (both in blue) represent two portfolios "well-aligned" in stocks' BM ratio and underlying funds' demand for value. As a result, they do not face the same selling pressure, and may even experience some additional buying pressure, given that they are well within the investment universe of their underlying investors.

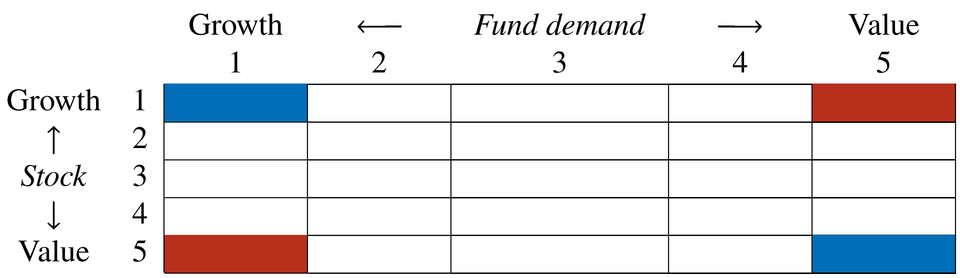

Figure 1: Stock portfolios well-aligned and misaligned between own characteristics and underlying funds' demand for value

In Panel A of Table 6, at the end of each quarter, all stocks are independently sorted into 25 portfolios based on their BM ratios, $BM_{i,q}$, and their underlying funds' demand for value, $\Phi_{i,q}^{HML}$, where $\Phi_{i,q}^{HML}$ is calculated as the shares-weighted average $\phi_{j,q}^{HML}$ of funds holding stock i in the previous quarter:

$$\Phi_{i,q}^{HML} = \frac{\sum_{\text{fund } j} Shares_{i,j,q-1} \cdot \phi_{j,q}^{HML}}{\sum_{\text{fund } j} Shares_{i,j,q-1}}; \tag{7}$$

$\Phi_{i,q}^{MOM}$ is calculated similarly by replacing $\phi_{j,q}^{HML}$ with $\phi_{j,q}^{MOM}$.

To address potential microstructure issues and focus on mutual fund behavior, we exclude stocks with a price below five dollars, a total mutual fund ownership below 1%, or a market capitalization in the bottom decile. One concern, related to the third condition of factor rebalancing discussed in Section 3.1, is whether the two "misaligned" portfolios contain enough stocks. This is a common issue associated with the independent sorting procedure.[17] Panel A immediately addresses this concern: both portfolios contain, on average, more than 25 stocks. Therefore, even the most value-oriented funds hold some growth stocks and the most growth-oriented funds hold some value stocks, establishing the third condition of factor rebalancing. Similarly, in Panel C, the two

[17] We prefer independent sorting to conditional sorting because a stock (and fund) is classified as value stock (fund) based on its ranking among all stocks (funds), not conditionally within a subgroup.

"misaligned" portfolios each contain more than 60 stocks.[18] Panels A and B also indicate that independent sorting on two correlated variables may lead to uneven distribution of stocks across sorted portfolios, an issue we will return to later.

In Panel B, which concerns the 25 portfolios sorted on the BM ratio and funds' value demand, each cell represents the annualized value-weighted return of that portfolio in the following quarter. We interpret the table in three ways. First, we examine the four corner portfolios. Consistent with the evidence of mutual fund rebalancing, the top-right and the bottom-left corners—the two "misaligned" portfolios—substantially underperform the other two corners—the two "well-matched" portfolios. The "misaligned" portfolios earn average annualized returns of 6.6% and 8.5% while the "well-matched" portfolios earn 14.0% and 17.0%.

Second, we compare returns for stocks that have similar BM ratios but different value demands from the underlying funds. By moving horizontally across each row, one can get a sense of how stock returns depend on the value demand of their underlying investors. The last column (column "5 – 1") takes the differences in returns between two extreme portfolios in Φ^{HML}. Among growth stocks (in the bottom BM-quintile), those held by growth funds *outperform* those held by value funds by an annualized return of 10.4%. In contrast, among value stocks (in the top BM-quintile), those held by growth funds *underperform* by 5.5%. Therefore, a stock's future return depends not only on its own BM ratio, but also on the underlying funds' demand for value.

Third, the last row (in line "HML") examines the profitability of the HML strategy across funds with different value demands. For stocks in the bottom Φ^{HML}-quintile—that is, stocks primarily held by growth funds—there is a striking growth *premium*: growth stocks outperform value stocks by 8.5% every year. This growth premium is statistically significant and is at odds with the vast literature documenting a value premium based on an unconditional sort on the BM ratio. Once we move away from the bottom Φ^{HML}-quintile, the usual value premium reappears and reaches 7.4% in the top Φ^{HML}-quintile. This evidence implies, from the perspective of portfolio management, that a value strategy conditional on value funds enhances the unconditional value strategy. Moreover, the growth premium we document can justify the persistent popularity of growth funds despite the

[18] Table A.8 in the Online Appendix reports the pre-formation sorting characteristics of the 25 portfolios. As expected, for both value and momentum, the two sorting variables are monotonically distributed across the portfolios and exhibit substantial cross-quantile dispersions in both directions, eliminating concerns that stocks' investor base may be homogeneous.

unconditional value premium.

Panel D concerns the 25 portfolios sorted on past one-year return and funds' momentum demand. The results, by and large, are consistent with those in Panel C. The performance of the momentum strategy depends on the corresponding momentum demand from underlying funds. Specifically, from the bottom quintile (contrarian funds) to the top quintile (momentum funds), the annualized winner-minus-loser (WML) return increases from 1.0% (t = 0.28) to 7.2% (t = 2.03), though the difference is borderline significant. This sizable spread in returns to momentum strategy indicates that loser stocks perform as well as winner stocks when the underlying funds have contrarian demands and that winner stocks significantly outperform loser stocks when the underlying funds have a strong demand for momentum. The latter also shows a slight improvement in momentum returns over an average momentum return of 4.0% in our sample.

Table 7 considers several alternative metrics for portfolio returns. Panels A1 and A2 demonstrate that the identified patterns are evidenced with equal-weighted returns, indicating that our findings are not exclusively attributable to large-cap stocks. Notably, the momentum effect appears more distinctly in small-cap stocks. Panels B1 and B2 consider CAPM alpha and confirm the previous patterns in raw returns. Moving further, Panels C1 and C2 introduce alphas derived from three-factor models. For value, we use market, size, and momentum while purposely omitting the value factor to avoid the confounding effect from the factor itself; for momentum, we use market, size, and value. While the patterns in three-factor alphas for value stocks mirror those in CAPM alphas, the patterns for momentum stocks exhibit some attenuation.

There are a few possible reasons why the price effect of factor rebalancing is weaker in momentum than in value. Most notably, after the momentum crash documented by Daniel and Moskowitz (2017), mutual funds significantly reduced their exposure to momentum. For example, an average mutual fund has a ϕ^{MOM} of 0.03 before 2009 but only −0.05 after 2009. At the same time, mutual funds' demand for momentum also gets slightly less persistent. These two effects lead to a weaker momentum-related rebalancing post-2009, dampening the overall results for momentum in our sample. Another counterbalancing force is the disposition effect. As documented by Frazzini (2006), mutual funds exhibit a tendency to ride losses and realize gains, which may neutralize the potential price impact from momentum rebalancing. Lastly, as we demonstrate below, it could be that momentum rebalancing operates more through changes in stock characteristics rather than levels. In Section 3.7.2, we conduct a subsample analysis to shed additional light on the underlying factors influencing the performance in momentum.

3.5 Portfolio returns: changes in stock characteristics

We next test whether rebalancing based on changes in stock characteristics also leads to predictable returns. For example, if value funds rebalance based on changes in the BM ratio, then a stock's future return will be determined by both the underlying funds' factor demand and recent changes in the BM ratio.

To test this alternative mechanism, we repeat the previous portfolio sorting exercise by replacing the current BM ratio (past one-year return) with the change in the BM ratio (past one-year return) over the last four quarters. Panel A of Table 8 reports the results. Our findings are similar but with different magnitudes: results are weaker for value but stronger for momentum. Therefore, we conclude that factor rebalancing can also stem from trading responses to changes in stock characteristics. Furthermore, a comparison of the two sets of results suggests that value rebalancing may be based more on the level while momentum rebalancing may be based more on changes.[19]

3.6 Portfolio returns: holding-based measures

As discussed in Section 2, an alternative way to measure a fund's factor demand is by aggregating stock characteristics based on its holdings. We now construct this alternative measure of factor demand. Specifically, we measure fund j's holding-based demand for value and momentum in quarter q as

$$BM_{j,q}^{fund} = \frac{\sum_{\text{stock } i} Dollar_{i,j,q} \cdot BM_{i,q}}{\sum_{\text{stock } i} Dollar_{i,j,q}}, \tag{8}$$

and

[19] A stronger test of this dynamic argument would control for current stock characteristics such as the BM ratio. This, for example, can be done through a triple-sorting exercise. We do not do it in Panel A of Table 8, because the correlation between the level and the change is too high that it leaves a rather limited scope for triple-sorting. Indeed, the correlation between the BM ratio and its one-year change is 0.36, and the correlation between the past one-year return and its one-year change is 0.72. More detailed results are included in Table A.10 of the Online Appendix.

$$RET_{j,q}^{fund} = \frac{\sum_{\text{stock } i} Dollar_{i,q} \cdot RET_{i,q}}{\sum_{\text{stock } i} Dollar_{i,j,q}}, \tag{9}$$

where $Dollar_{i,j,q}$ is the dollar amount of stock i held by fund j at the end of quarter q, and $BM_{i,q}$ and $RET_{i,q}$ are stock i's BM ratio and past one-year return by the end of quarter q. In the Online Appendix, we confirm that these alternative measures are also highly persistent: regressing a fund's BM^{fund} and RET^{fund} on their corresponding one-quarter lagged values yields autocorrelation coefficients of 0.79 and 0.64, both of which are highly significant.

Next, we aggregate fund-level factor demand to the stock-level in each quarter as

$$\overline{BM}_{i,q} = \frac{\sum_{\text{stock } i} Shares_{i,j,q} \cdot BM_{j,q}^{fund}}{\sum_{\text{stock } i} Shares_{i,j,q}}, \tag{10}$$

and

$$\overline{RET}_{i,q} = \frac{\sum_{\text{stock } i} Shares_{i,j,q} \cdot RET_{j,q}^{fund}}{\sum_{\text{stock } i} Shares_{i,j,q}}. \tag{11}$$

With these two holding-based stock-level factor demand measures, we repeat the portfolio analysis as in Section 3.4. Panel B of Table 8 provides a summary of returns from these alternative portfolio sorts. To highlight the impact of factor rebalancing on well-aligned and misaligned stocks, we focus on the high-minus-low portfolios, HML and WML, across the stock-level factor demand. The results are largely consistent with those in Table 6. Specifically, the value-weighted HML return is 8.5% per annum in stocks with the highest $\overline{BM}$ and only 0.3% in stocks with the lowest $\overline{BM}$, indicating a difference of 8.2% (t = 1.6).

3.7 Robustness checks

3.7.1 Flow-induced trading

A competing mechanism that also generates price pressure is flow-induced trading (FIT), as studied by Lou (2012). Conceptually, the two forces represent rather different sources of price pressure: factor rebalancing captures the active selection of stocks into and out of the portfolio while FIT reflects the passive purchases or sales in response to retail flows. Empirically, however, there is a concern that our factor rebalancing and corresponding asset pricing evidence may be due to a flow effect instead. We showed the robustness of our portfolio rebalancing results to the impact of FIT in Section 3.2. To rule out the confounding effects from FIT on asset prices, we calculate post-formation FIT for the 25 sorted portfolios and report the results in Table 10. For value, the FIT for the HML portfolios (in line "HML") decreases from −0.23% for the low-Φ^{HML} stocks to −0.56% for the high-Φ^{HML} stocks, a direction opposite to that of our factor-rebalancing results in Table 6. For momentum, all WML portfolios (in line "WML") have a positive FIT but with a similar level, which clearly does not line up well with the dispersion in WML returns we document in Table 10. Therefore, FIT cannot account for the documented return predictability from factor rebalancing.

3.7.2 Subsample analysis

We perform a series of subsample analyses and report the results in Tables A.6 and A.7 in the Online Appendix. For simplicity, we only report the HML return for different Φ^{HML}-quintiles; that is, instead of reporting the portfolio returns for the 25 portfolios, we only report the last row in each panel in Table 6.

In Table A.6, Panels A and B study two subperiods: 1980 to 1999 and 2000 to 2018. In both subperiods, the HML strategy, measured either by raw returns or portfolio alphas, performs substantially better conditional on stocks held by value funds. Overall, the difference doubles in the second half of the sample. Panels C and D sort stocks based on their mutual fund ownership. More specifically, in each quarter, before beginning to sort stocks into 25 portfolios, we first sort them into high or low mutual fund ownership using the median mutual fund ownership as the cutoff. Overall, return patterns are robust in both subsamples, although, perhaps as expected, the results are stronger in the subsample of high mutual fund ownership. Panels E and F sort stocks based on size. In each quarter, stocks are first sorted—as in Panels C and D—into large or small based on their firm size before being sorted into 25 portfolios. Results are robust in both subsamples, but more pronounced for larger stocks.

Table A.7 repeats the same set of exercises for the momentum strategy. Overall, the return patterns are less robust in subsamples. For instance, the return difference in WML strategy across different Φ^{MOM}-quintiles virtually disappears after 1999. This coincides with the disappearance of momentum profitability over the last two decades and is partially driven by the momentum crash after the Great Recession. Panel A also sheds light on the insignificant alpha in Table 7: three-factor alpha is large and positive in earlier samples and its disappearance is primarily driven by the second half of the sample. Panels C and D show that, consistent with Table A.6, the return patterns are most robust among stocks with high mutual fund ownership. Panels E and F show that, unlike the value strategy, in which large stocks are more profitable than small ones, the momentum strategy works better for small stocks.

3.7.3 3×3 sort

We next address the concern about the small number of firms in some corner portfolios due to independent sorts, which pertains primarily to value. Instead of sorting all stocks into 25 (5×5) portfolios, we independently sort them into 9 (3×3) portfolios and report the corresponding results in Table 9. Panel D shows that even the portfolio with the fewest stocks now has more than 100 stocks on average. Because there is less variation across portfolios, the differences in returns are not as pronounced as before. However, the patterns of misaligned and well-aligned portfolios and HML returns remain the same and are robust to alternative asset-pricing models.

4 Additional evidence

In this section, we first provide further stock-level evidence in support of the price impact induced by factor rebalancing. We achieve this by analyzing how trading from a subset of mutual funds, such as value funds, aggregates to the sorted portfolios. Next, we quantify the magnitude of this price impact by estimating the corresponding demand elasticities at the factor level. We end this section by briefly discussing long-term mutual fund ownership and return patterns.

4.1 Whose trading matters?

In the previous section, we focused on the 5×5 double-sorted portfolios and demonstrated how portfolio returns depend on the underlying funds' factor demand. To strengthen the connection between factor rebalancing and stock returns, for the double-sorted portfolios, we further examine the trading patterns among subsets of funds, in the spirit of fund-level regressions in Section 3.2. According to our mechanism, the selling of the bottom-left corner portfolio in Figure 1 is primarily driven by growth funds, whereas the selling of the top-right corner portfolio is driven by value funds.

For the value strategy, we classify funds with HML beta, ϕ^{HML}, above the median as value funds and the rest as growth funds; a similar classification is used for separating between momentum and contrarian funds. In Panel A of Table 11, we decompose stock-level mutual fund ownership changes into those from value funds and growth funds. The left segment of the panel shows the ownership change for growth funds, highlighting a pronounced trading activity in low-Φ^{HML} stocks (column 1). In aggregate, growth funds increase their ownership of the low-BM (growth) stocks by 0.35% and decrease their ownership of the high-BM (value) stocks by 0.14%. The right segment of Panel A is concerned with value funds, which increase their high-BM stock holdings by 0.05 % more than their low-BM stock holdings (column 5).

Panel B of Table 11 delves into the momentum strategy. Here, the trading activities of momentum funds appear to be more pronounced: momentum funds increase their ownership of the winner stocks by 0.63% more than the loser stocks (column 5 on the right). In sum, this portfolio-level breakdown substantiates that funds with different investment strategies actively trade to uphold stable factor exposures, as predicted by factor rebalancing, significantly impacting mutual fund ownership dynamics across portfolios.

4.2 Implied price elasticity

An underlying premise of the price impact induced by factor rebalancing is that the demand curve is downward sloping. Therefore, it is helpful to quantify the implied price elasticity associated with factor rebalancing and place our findings in the context of studies that examine inelastic demand-induced price pressure. Since we do not model the demand system or have an exogenous variation in demand, we need to make additional assumptions about what part of the demand is inelastic. Because of these specific assumptions, our estimated price elasticities should be interpreted with caution.

Take value as an example. We further assume that value funds—defined as having an HML beta above the median of all funds—have inelastic, positive demand for value stocks and inelastic, negative demand for growth stocks in their investment universe. For stocks demanded mostly by value funds, $\Delta Demand$ of the HML portfolio is defined as the difference between the long and short legs in quarterly value-fund ownership changes.[20] To get the price elasticity associated with these demand changes, we divide $\Delta Demand$ by quarterly returns of this HML portfolio ($\Delta Return$):[21]

$$Elasticity = -\frac{\Delta Demand}{\Delta Return}. \tag{12}$$

With a flat or perfectly elastic demand curve, the price elasticity approaches $-\infty$, while with downward-sloping or inelastic demand, the estimate approaches zero. We make similar assumptions about inelastic demand for all four types of funds—value, growth, contrarian, and momentum—and calculate the implied price elasticities for various HML and WML portfolios. $\Delta Demand$ from these four types of funds are taken from columns 1 and 5 in Table 11.

The price elasticity estimates are reported in Table 12. Overall, our estimated elasticities range from -0.04 to -0.35, with an average of -0.21. It is worth noting that our estimation of price elasticity is at the factor level, which is different from prior studies that focus on the micro (stock) level or macro (market) level. Compared to the existing literature, our results indicate that the price elasticity at the factor level is significantly lower (i.e., more inelastic) than those found in studies of micro elasticity (Harris and Gurel 1986; Shleifer 1986; Chang et al. 2015), but it is similar to the estimates obtained at the factor and market levels (Gabaix and Koijen 2022; Ben-David et al. 2021; Haddad et al. 2021). One potential reason for such a low price elasticity is the lack of a close substitute for well-known and robust factors such as value, size, and momentum. In fact, among these factors, value and momentum tend to complement, rather than substitute, each other. In contrast, it is arguably easier to find a close substitute for a particular stock like Apple or Google among all stocks.

4.3 Long-term patterns

So far, our focus has primarily been on analyzing mutual funds' quarterly rebalancing and its associated impact on stock prices. However, what happens when we examine the same sorted port-

[20] To get the percentage changes in holding, we scale the number of shares by the total shares outstanding.

[21] In order to isolate the part of HML return that is attributed to factor rebalancing rather than other factors that drive the average HML return, we define $\Delta Return$ as the difference between the HML return and the average HML return across all five high-minus-low portfolios.

folios over a longer term? If mutual funds rebalance sufficiently quickly while stock characteristics continue to evolve, we would expect the predictable trading documented in Section 3 to gradually decline in subsequent quarters, leading to a narrowing gap in returns between the "well-aligned" and "misaligned" portfolios.

Figure 4 confirms this intuition. The left panel plots long-term gaps in mutual fund ownership and cumulative returns between two HML portfolios (corresponding to 5-1 HML portfolio in Table 6). The right panel plots the same difference for momentum (corresponding to 5-1 WML portfolio in Table 6). The figures start at quarter 0 when the portfolios are formed. For both value and momentum, over the next eight quarters, the ownership gap between the two high-minus-low portfolios gradually diminishes, and the cumulative return difference rapidly drops to zero within 8 quarters, becoming indistinguishable from zero. This pattern of longer-term return reversal is consistent with the findings of many other studies on price impact, such as Lou (2012). Therefore, mutual funds appear to rebalance their factor exposures rather quickly, and most of the pricing impact is concentrated in the immediate quarter.

5 Alternative explanations

In this section, we address a few alternative explanations that may account for the stock-level evidence documented in the previous sections. Section 3.7 has already ruled out flow-induced trading as a potential explanation for our results. We now turn to explanations based on stocks' subsequent fundamentals, fund manager skills, and mutual fund herding behavior.

5.1 Subsequent stock fundamentals

In the real world, mutual funds can trade for various reasons beyond simple factor rebalancing. One such motive is that fund managers may have access to private information about firm fundamentals. This means that stocks purchased by fund managers with this informational advantage are more likely to perform well in the future. Under this view, the return dispersion shown in Table 6 may instead indicate fund managers' superior ability to forecast firm fundamentals.

We assess this possibility by examining stocks' post-formation standardized earnings surprises (SUE) and cumulative abnormal returns (CAR) around earnings announcement dates, where SUE is calculated as the difference between actual earnings and analysts' forecasts, normalized by the current stock price, and CAR represents the size and value-adjusted abnormal returns in a three-day window surrounding the earnings announcement. The results for 25 portfolios sorted based on stock characteristics and fund betas are presented in Table 13. If the fund manager's ability to forecast fundamentals is the main driver of the documented return predictability, we should expect SUEs and CARs to line up with our return patterns.

Panels A and B report the results for value. In Panel A, across the five HML portfolios, their SUEs are all negative and similar in magnitude. In Panel B, the CARs for the five HML portfolios roughly align with our return evidence, but the magnitude is much smaller and can account for only a tiny fraction of the return dispersion. Panels C and D show the results for momentum, where the pattern of SUEs for the five WML portfolios contradicts our return evidence for momentum. Specifically, the low-Φ^{MOM} WML portfolio has a higher SUE than high-Φ^{MOM}. The monotonicity of CAR for the WML portfolios is similar to our return evidence, though again with a smaller magnitude. Therefore, we do not find evidence that the return patterns documented in Table 6 can be explained by subsequent firm fundamentals.

5.2 Other skill-based explanations

The ability to forecast future fundamentals is only one aspect of mutual fund skill. It is possible that value funds specialize in value stocks and growth funds specialize in growth stocks, and that their specializations explain higher returns in the stocks they trade. We argue that this explanation also cannot fully reconcile some of our documented patterns in stock returns. Common proxies for mutual fund skill, such as return gap, active shares, and sensitivity to public information, typically result in a less than 3% difference in annualized stock returns (Kacperczyk and Seru 2007; Kacperczyk, Sialm, and Zheng 2008; Cremers and Petajisto 2009; Jiang and Verardo 2018; Jiang and Zheng 2018). Yet, growth stocks traded by growth funds outperform similar stocks traded by value funds by more than 10%, a discrepancy that cannot be easily explained by previous research on mutual fund performance.

Moreover, since the funds we consider are deliberately pursuing their respective strategies, they are unlikely to hold stocks that are not aligned with their investment philosophies. If their specializations explain the return predictability, it should also be reflected in the magnitude of *fund* performance. That is, growth funds and value funds should outperform compared to other unspecialized funds. However, this claim is not supported by the data. Despite targeting profitable factors, value and momentum funds exhibit annualized four-factor alphas of only 28bps and -8bps, respectively. Growth and contrarian funds, on the other hand, do not exhibit statistically significant alphas (see Table A.9 in the Online Appendix). This evidence is at odds with the notion that fund skills are responsible for the results we document.

Our analysis focuses on mutual fund rebalancing at a quarterly frequency; however, admittedly, some fund managers' skills may be more pronounced at a higher frequency. Binsbergen et al. (2022) show that high-turnover funds profit from holdings shorter than two weeks. It is therefore possible that some skilled high-turnover funds contribute to return dispersions we document at the quarterly level. We leave this question for future research to explore at a higher frequency.

5.3 Herding

It is possible that our results are influenced by mutual fund herding. According to Wermers (1999), stocks with a substantial increase in mutual fund ownership in the previous quarter tend to outperform later on. Meanwhile, Dasgupta, Prat, and Verardo (2011) demonstrate that stocks with persistent growth in mutual fund ownership tend to underperform subsequently. It is worth noting that factor rebalancing and herding are not mutually exclusive. Wermers (1999) proposes that positive feedback trading can contribute to herding, where traders follow a common signal (e.g., past stock returns) to buy past winners and sell past losers. Similar to this mechanism, taking the BM ratio as a common signal can lead to herding in either value or growth stocks. However, our subsample analysis suggests that our results are unlikely to be driven by the herding behavior documented in previous research. The most obvious contradiction is that our return patterns in value are much more pronounced among large-cap stocks. In comparison, both Wermers (1999) and Dasgupta, Prat, and Verardo (2011) find that herding has a greater impact on small-cap stocks.

6 Conclusion

In this paper, we propose a new source of price pressure in the form of factor rebalancing. We argue and document that a mutual fund's demand for a certain pricing factor, measured by the loading of the fund's returns on factor returns, is persistent over time. Because stock characteristics are time-varying and change frequently, this creates an incentive for funds to rebalance their portfolios so that they can keep the same exposure to the factor. This rebalancing motive consequently leads to predictable trading from mutual funds collectively and contributes to cross-sectional return predictability. We empirically confirm that mutual fund trading is predictable based on stock characteristics and fund factor demand. We show that combining these two variables significantly enhances the return predictability of well-known trading strategies such as value and momentum.

Our results have implications for several strands of the literature. First, to the best of our knowledge, this factor rebalancing is novel to the literature. The economic significance of our results is sufficiently large that our mechanism warrants more attention. Second, we enlarge the set of predictors for stock returns by showing that fund characteristics such as factor loadings can be used to forecast conditional factor returns. Third, we contribute to the literature that links asset demand to price dynamics. Most previous research has examined price impacts at either the stock or the market level. Our analysis focuses on the factor level.

While we have demonstrated consistent results on trading behavior and return predictability, a few questions remain open. First, to the extent that our asset-pricing results represent profitable trading opportunities to be exploited, it remains unclear why they have been sustained for almost 40 years and why some arbitrageurs have not exploited them. Second, it is also interesting to explore if factor rebalancing applies to other pricing factors and has similar implications for return predictability. In the Online Appendix, Table A.12 presents some preliminary evidence on using factor demand for predicting future factor returns. We leave these questions for future research.

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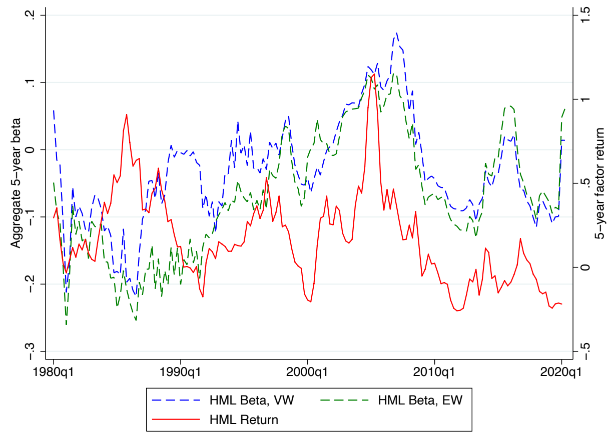
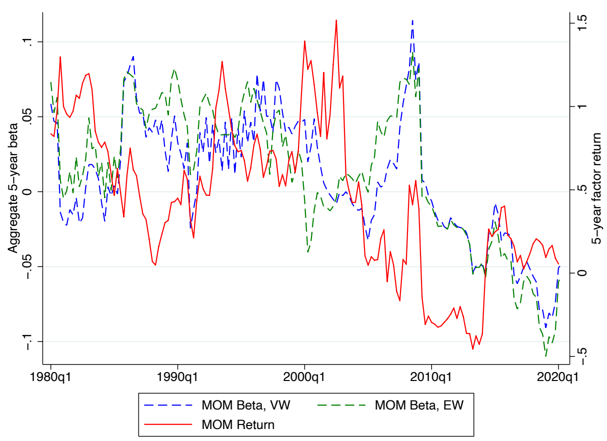
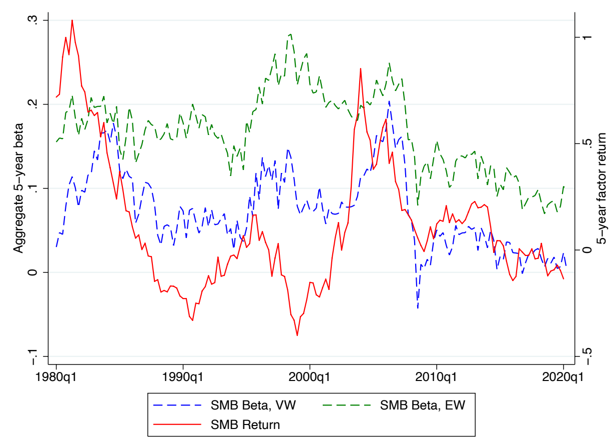


(a) Value



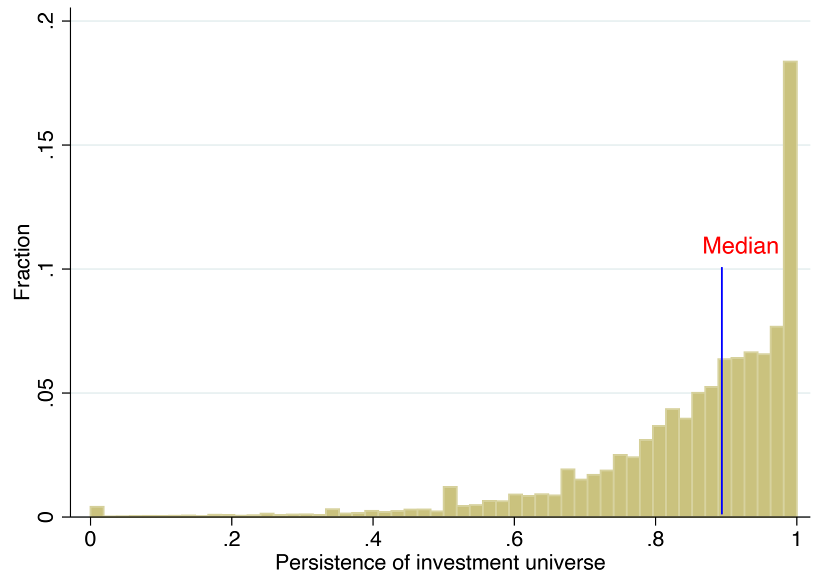
(b) Momentum



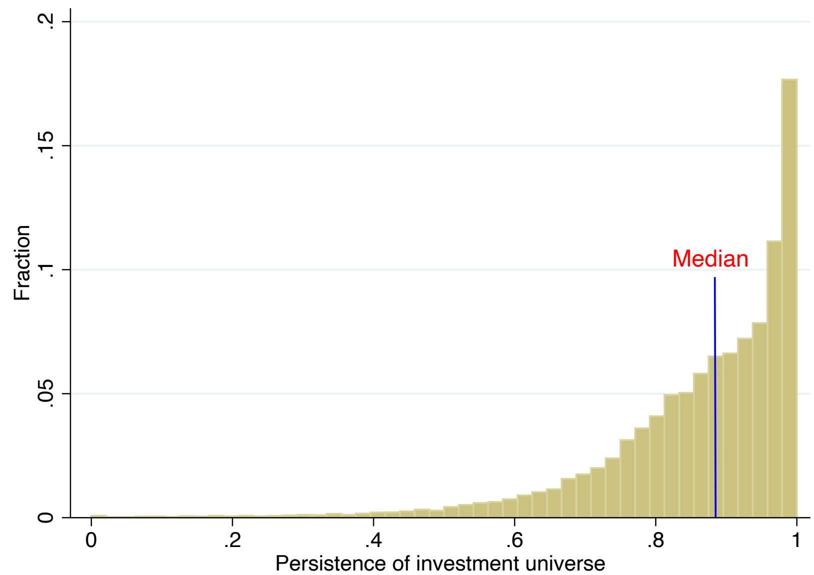
(c) Size

Figure 2: Aggregate patterns for factor betas

Note: This figure plots the time series dynamics of factor betas of the aggregate mutual fund industry from 1980 to 2019. The three subfigures represent value, momentum and size, respectively. In each subfigure, the blue dashed line represents the TNA-weighted beta, the green dashed line represents the equal-weighted beta, and the red solid line represents the past five-year return of the corresponding factor.



(a) All funds



(b) Funds holding at least 100 positions

Figure 3: Persistence of investment universe
Note: This figure examines the persistence of mutual fund holdings. In each quarter, persistence is calculated as the fraction of positions that were also held in the previous quarter. Panel A plots the distribution for all funds. Panel B focuses on funds that hold at least 100 positions.

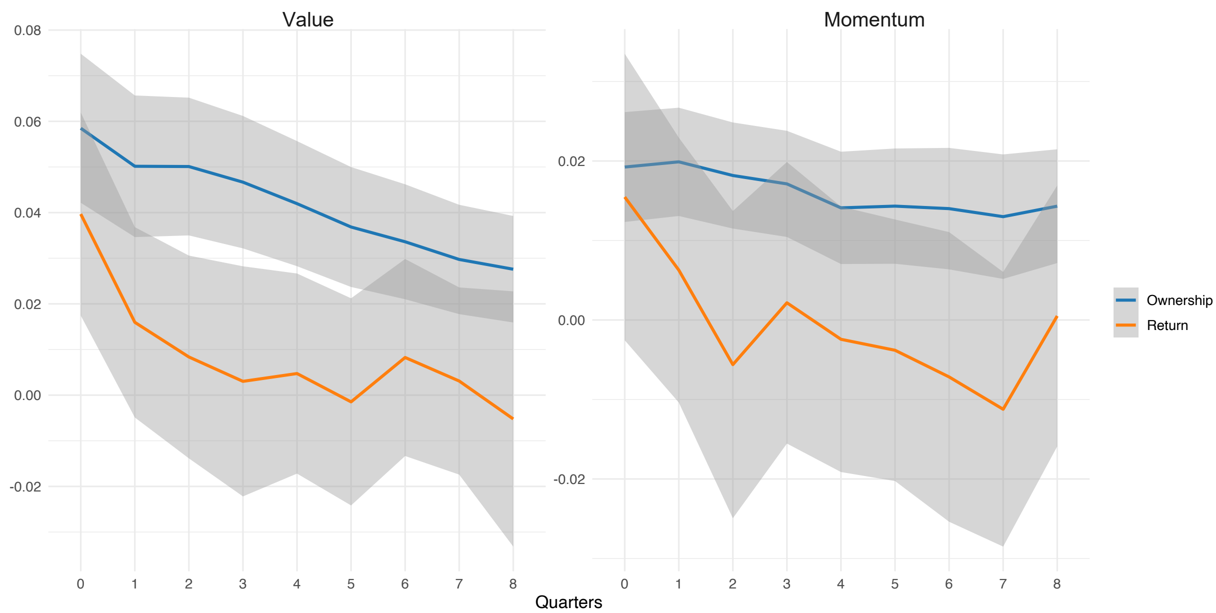


Figure 4: Long-term long-short portfolio returns and mutual fund ownership
Note: This figure plots long-term gaps in mutual fund ownership and cumulative returns between two long-short portfolios for value and momentum. The left and right panels correspond to value (HML) and momentum (WML), respectively. At the beginning of quarter 0, we form 5×5 portfolios by sorting stocks based on BM (past one-year return) and underlying funds' loading on the value (momentum) factor. The same portfolios are held for the next 8 quarters. We compute and plot the gaps in cumulative returns and mutual fund ownership between HML (WML) portfolios with the highest and lowest underlying factor demand. The shaded areas represent 95% confidence intervals.

Table 1: Summary statistics for the mutual fund sample

Note: This table presents summary statistics of our sample of US domestic equity mutual funds, for each year in the period from 1980 to 2019. We exclude international, fixed income, and precious metal funds, and restrict the sample to funds with equity holdings to TNA ratio between 0.80 and 1.05, and with a minimum fund size of $1 million. We obtain fund size, monthly returns, and capital flows data from the CRSP survivorship-bias-free mutual fund database, and fund holdings data from the Thomson Reuters Mutual Fund Holdings database. The two databases are merged using the MFLinks file provided by WRDS. The number of mutual funds at the end of each year is reported as *# of funds*, and total net assets under management are reported as *TNA* in millions of US dollars. Panels A and B show summary statistics for our main sample and the sample used by Lou (2012), respectively.

	Panel A: Our sample					Panel B: Lou (2012)'s sample		
		TNA ($ million)		Gross return			TNA ($ million)	
Year	# of funds	Mean	Median	Mean	Median	# of funds	Mean	Median
1980	196	187	67	0.09	0.10	228	147	53
1981	149	194	82	0.08	0.08	226	138	54
1982	186	206	76	0.21	0.23	232	171	54
1983	232	271	115	-0.01	-0.01	255	222	97
1984	223	270	109	0.01	0.01	270	221	86
1985	223	323	149	0.17	0.16	297	276	114
1986	231	368	176	0.04	0.04	341	298	106
1987	234	413	188	-0.22	-0.21	376	286	87
1988	261	430	175	0.02	0.02	405	285	82
1989	275	502	185	0.00	0.01	440	340	95
1990	321	413	131	0.09	0.08	480	306	84
1991	347	562	178	0.09	0.09	579	379	100
1992	839	323	86	0.07	0.08	685	426	115
1993	1,033	449	105	0.03	0.04	925	442	106
1994	1,355	453	97	-0.01	-0.02	1,044	450	105
1995	1,519	568	126	0.04	0.03	1,168	611	134
1996	1,695	769	151	0.06	0.05	1,314	750	146
1997	2,119	875	136	-0.02	-0.03	1,480	934	163
1998	2,058	1,118	170	0.20	0.20	1,570	1,071	167
1999	2,059	1,487	222	0.18	0.21	1,686	1,307	188
2000	1,972	1,489	246	-0.06	-0.07	1,890	1,284	186
2001	1,890	1,332	235	0.13	0.14	1,915	1,019	155
2002	2,135	958	158	0.07	0.07	1,970	771	112
2003	3,228	966	156	0.13	0.13	2,001	976	146
2004	3,245	1,154	189	0.12	0.12	1,961	1,129	166
2005	3,469	1,260	214	0.03	0.03	1,918	1,252	197
2006	3,907	1,385	219	0.08	0.08	1,789	1,400	222
2007	4,239	1,471	210	-0.02	0.00			
2008	4,350	821	119	-0.23	-0.24			
2009	4,066	1,174	189	0.05	0.05			
2010	3,588	1,380	232	0.11	0.12			
2011	3,397	1,372	226	0.11	0.10			
2012	3,321	1,646	272	0.02	0.02			
2013	3,387	2,192	351	0.09	0.09			
2014	3,573	2,247	329	0.04	0.03			
2015	3,814	2,141	270	0.04	0.04			
2016	3,887	2,268	262	0.02	0.03			
2017	3,959	2,829	314	0.06	0.05			
2018	3,729	2,710	302	-0.14	-0.14			
2019	3,592	3,514	402	0.08	0.08			

Table 2: Summary statistics of factor betas

Note: This table summarizes the distribution of factor betas for mutual funds. For each fund j in month t, we estimate factor betas by using observations from month $t-59$ to month t and running the following rolling time-series regression:

$$rret_{j,t+1-k} = \alpha_{j,t} + \phi_{j,t}^{MKT} MKT_{t+1-k} + \phi_{j,t}^{HML} HML_{t+1-k} + \phi_{j,t}^{SMB} SMB_{t+1-k} + \phi_{j,t}^{MOM} MOM_{j,t+1-k}$$
$$+ \phi_{j,t}^{CMA} CMA_{t+1-k} + \phi_{j,t}^{RMW} RMW_{t+1-k} + \phi_{j,t}^{flow} flow_{j,t+1-k} + \varepsilon_{j,t,t+1-k},$$

where $k = 1, 2, \ldots, 60$; $rret$ is raw fund returns; MKT is excess market returns; and HML, SMB, MOM, CMA, and RMW are returns for value, size, momentum, investment, and profitability strategies, respectively. We also control for retail flows with $flow$, where $flow_{j,t} = \frac{TNA_{j,t}}{TNA_{j,t-1}} - \left(1 + ret_{j,t}\right)$ and ret represents net fund returns. We require that a fund should have at least 60 months of returns data and that each rolling window contain at least 24 monthly observations. Panel A reports the mean, standard deviation and percentiles of factor betas across all funds. Panel B reports the mean factor betas by Lipper mutual fund classifications. Panel C reports the mean factor betas by index fund status provided by CRSP.

	ϕ^{MKT}	ϕ^{SMB}	ϕ^{HML}	ϕ^{MOM}	ϕ^{CMA}	ϕ^{RMW}	ϕ^{flow}
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Panel A: Summary statistics						
Mean	0.98	0.16	-0.02	0.00	-0.08	-0.04	0.01
Std. dev.	0.22	0.36	0.34	0.18	0.41	0.33	0.18
P5	0.64	-0.31	-0.52	-0.27	-0.68	-0.55	-0.17
P25	0.90	-0.10	-0.20	-0.08	-0.26	-0.17	-0.03
P50	0.99	0.07	-0.01	0.00	-0.06	-0.01	0.00
P75	1.07	0.38	0.16	0.07	0.11	0.13	0.04
P95	1.28	0.83	0.47	0.28	0.46	0.38	0.23
	Panel B: Summary statistics by fund style						
All	0.98	0.16	-0.02	0.00	-0.08	-0.04	0.01
Growth	1.04	0.29	-0.19	0.09	-0.23	-0.16	0.00
Value	1.00	0.20	0.23	-0.07	0.06	0.10	-0.01
Large cap	0.98	-0.08	-0.02	0.01	-0.07	0.00	-0.01
Medium cap	1.03	0.38	-0.03	0.03	-0.10	-0.05	0.00
Small cap	1.02	0.73	0.07	0.03	-0.10	0.00	0.00
	Panel C: Index funds vs. non-index funds						
All index funds	1.02	0.09	-0.02	-0.06	-0.08	0.01	0.00
Enhanced	1.36	0.08	-0.04	-0.01	-0.04	0.03	-0.01
Base	0.93	0.07	0.01	-0.04	-0.05	0.05	-0.04
Pure	1.01	0.09	-0.02	-0.06	-0.09	0.00	0.01
All non-index funds	1.00	0.25	-0.01	0.02	-0.09	-0.03	0.00

Table 3: Persistence of factor demand

Note: This table examines the persistence of factor demand. $\phi_{j,q}$ and $\phi_{j,q-20}$ are the loadings on a given factor for fund j in quarter q and quarter $q-20$, respectively, and therefore are estimated using non-overlapping five-year windows. For funds classified as small cap, medium cap, and large cap according to the Lipper mutual fund classifications, d_{Size} equals 1, indicating it is a size-specialized fund; otherwise, it equals 0. For funds classified as value or growth funds according to the Lipper mutual fund classifications, d_{BM} equals 1, indicating a fund focusing on the BM ratio; otherwise, it equals 0. Standard errors double-clustered by fund and quarter are reported in parentheses. *, **, *** indicate statistical significance at 10%, 5% and 1% levels, respectively.

	$\phi^{MKT}_{j,q}$	$\phi^{SMB}_{j,q}$	$\phi^{HML}_{j,q}$	$\phi^{MOM}_{j,q}$	$\phi^{SMB}_{j,q}$	$\phi^{HML}_{j,q}$
	(1)	(2)	(3)	(4)	(5)	(6)
$\phi^{MKT}_{j,q-20}$	0.348***					
	(0.019)					
$\phi^{SMB}_{j,q-20}$		0.747***			0.424***	
		(0.012)			(0.021)	
$\phi^{HML}_{j,q-20}$			0.369***			0.297***
			(0.015)			(0.021)
$\phi^{MOM}_{j,q-20}$				0.293***		
				(0.019)		
d_{Size}					0.031***	
					(0.009)	
$d_{\text{Size}} \times \phi^{SMB}_{j,q-20}$					0.469***	
					(0.024)	
d_{BM}						-0.039***
						(0.012)
$d_{\text{BM}} \times \phi^{HML}_{j,q-20}$						0.234***
						(0.027)
Quarter FE	✓	✓	✓	✓	✓	✓
Observations	153,331	153,331	153,331	153,331	153,331	153,331
R^2	0.235	0.568	0.236	0.184	0.639	0.255

Table 4: One-year transition probability of stocks characteristics and mutual fund factor loadings

Note: This table reports the one-year transition probabilities of stocks and funds across characteristic quintiles. Panels A and B are for value, and Panels C and D are for momentum. Stocks are sorted by book-to-market ratios (BM) in Panel A and by past-year returns ($r_{q-4,q-1/3}$, skipping the most recent month) in Panel C. Funds are sorted by HML loadings (ϕ^{HML}) in Panel B and by MOM loadings (ϕ^{MOM}) in Panel D. One-year transition probability is the probability of moving from one quintile in the current quarter to another quintile four quarters later.

Panel A: Stock $BM_{i,q}$

	1	2	3	4	5
1	**0.68**	0.23	0.06	0.03	0.01
2	0.16	**0.50**	0.24	0.07	0.02
3	0.03	0.21	**0.45**	0.25	0.07
4	0.01	0.05	0.22	**0.48**	0.23
5	0.01	0.01	0.05	0.22	**0.72**

Panel B: Fund $\phi^{HML}_{j,q}$

	1	2	3	4	5
1	**0.74**	0.20	0.04	0.02	0.01
2	0.19	**0.53**	0.21	0.06	0.02
3	0.04	0.21	**0.51**	0.20	0.04
4	0.01	0.06	0.20	**0.56**	0.17
5	0.01	0.02	0.04	0.18	**0.75**

Panel C: Stock $r_{i,q-4,q-1/3}$

	1	2	3	4	5
1	**0.25**	0.20	0.18	0.18	0.19
2	0.19	**0.22**	0.23	0.22	0.14
3	0.17	0.23	**0.25**	0.22	0.14
4	0.18	0.22	0.23	**0.21**	0.15
5	0.26	0.19	0.17	0.18	**0.20**

Panel D: Fund $\phi^{MOM}_{j,q}$

	1	2	3	4	5
1	**0.75**	0.18	0.04	0.02	0.01
2	0.15	**0.56**	0.21	0.06	0.02
3	0.04	0.20	**0.51**	0.22	0.04
4	0.02	0.06	0.21	**0.54**	0.17
5	0.01	0.02	0.04	0.18	**0.74**

Table 5: Regressing FIT-adjusted trades in shares on levels or changes of stock characteristics

Note: This table reports how mutual funds rebalance their portfolios based on stock characteristics. The dependent variable, $\Delta Shares_{i,j,q+1}/Shrout_{i,q}$, is FIT-adjusted trading of stock i in shares by fund j in quarter $q+1$, normalized by stock i's total shares outstanding as of quarter q. Stock characteristics include the book-to-market ratio (cross-sectionally demeaned), $BM_{i,q}$; past one-year return (skipping the most recent month), $r_{i,q-4,q-1/3}$; market beta, $\beta_{i,q}$; market capitalization (in billions), $ME_{i,q}$; operating profitability, $OP_{i,q}$; and investment, $INV_{i,q}$. The independent variables in Panel A are 4-quarter changes in stock characteristics between quarter $q-4$ and q, and in Panel B are current levels of stock characteristics in quarter q. Columns 1 and 2 use growth and value funds in the bottom and top quintile of $\phi^{HML}_{j,q}$, respectively. Columns 3 and 4 use contrarian and momentum funds in the top quintile of $\phi^{MOM}_{j,q}$, respectively. The data sample is from 1980Q1 to 2018Q4. Standard errors clustered at the quarter and fund levels are reported in parentheses. *, **, *** indicate statistical significance at 10%, 5% and 1% levels, respectively. Intercepts are omitted.

	$\Delta Shares_{i,j,q+1}/Shrout_{i,q}$			
Fund type	Low-$\phi^{HML}_{j,q}$ (growth)	High-$\phi^{HML}_{j,q}$ (value)	Low-$\phi^{MOM}_{j,q}$ (contrarian)	High-$\phi^{MOM}_{j,q}$ (momentum)
	(1)	(2)	(3)	(4)
Panel A: 4Q-changes of characteristics				
$\Delta BM_{i,q}$	-0.165***	0.083***		
	(0.028)	(0.022)		
$\Delta r_{i,q-4,q-1/3}$			-0.060***	0.045***
			(0.011)	(0.012)
$\Delta\beta_{i,q}$	0.060***	0.026**	0.029*	0.033**
	(0.014)	(0.011)	(0.015)	(0.014)
$\Delta ME_{i,q}$	-4.435***	-2.501***	-2.094***	-4.591***
	(0.633)	(0.507)	(0.663)	(0.528)
$\Delta OP_{i,q}$	-0.008*	-0.006**	-0.010**	0.000
	(0.005)	(0.003)	(0.005)	(0.004)
$\Delta INV_{i,q}$	-0.026***	-0.018***	-0.019***	-0.021***
	(0.005)	(0.005)	(0.005)	(0.004)
Observations	3,232,590	5,390,468	2,349,658	4,995,286
R^2	0.002	0.001	0.002	0.002
Panel B: Level of characteristics				
$BM_{i,q}$	-0.019*	0.018**		
	(0.011)	(0.008)		
$r_{i,q-4,q-1/3}$			-0.014	0.098***
			(0.013)	(0.015)
$\beta_{i,q}$	0.015	-0.024**	-0.008	-0.020*
	(0.012)	(0.011)	(0.013)	(0.011)
$ME_{i,q}$	-1.443***	-0.963***	-1.524***	-1.252***
	(0.151)	(0.106)	(0.130)	(0.134)
$OP_{i,q}$	-0.045***	-0.007*	-0.028***	-0.022***
	(0.006)	(0.003)	(0.005)	(0.005)
$INV_{i,q}$	0.158***	0.119***	0.164***	0.154***
	(0.015)	(0.014)	(0.015)	(0.016)
Observations	3,400,955	5,531,588	2,416,300	5,240,059
R^2	0.011	0.005	0.007	0.013

Table 6: Characteristics of portfolios sorted on stock characteristics and funds factor demand

Note: This table reports the average number of stocks (Panels A and C) and subsequent annualized value-weighted portfolio returns (Panels B and D) for each of the 25 double-sorted portfolios. In each quarter, stocks are independently sorted into 25 portfolios based on their BM ratios or past one-year returns (skipping the most recent month) and on their stock-level factor demand Φ^{HML} or Φ^{MOM}, which are the shares-weighted average HML and MOM loadings of a stock's underlying funds. t-statistics are reported in the brackets. Data are from 1980Q2 to 2018Q4.

Value

Panel A: Average number of stocks

		Low-Φ^{HML}	⟵	*Fund*	⟶	High-Φ^{HML}
		1	2	3	4	5
Low-BM	1	220	132	71	41	27
↑	2	124	142	110	72	45
Stock	3	61	103	122	115	92
↓	4	35	67	106	134	150
High-BM	5	26	50	92	139	184

Panel B: Annualized portfolio return (%)

		Low-Φ^{HML}	⟵	*Fund*	⟶	High-Φ^{HML}		
		1	2	3	4	5	**5−1**	
Low-BM	1	17.0	11.9	8.8	10.0	6.6	**-10.4**	[-2.47]
↑	2	14.5	14.3	10.6	11.2	10.1	**-4.4**	[-1.34]
Stock	3	17.3	14.1	12.5	10.7	11.7	**-5.5**	[-1.77]
↓	4	11.2	15.2	13.9	11.9	13.2	**2.0**	[0.65]
High-BM	5	8.5	16.4	15.2	12.8	14.0	**5.5**	[1.51]
HML		**-8.5**	**4.5**	**6.4**	**2.8**	**7.4**	**15.9**	
		[-2.02]	[1.46]	[2.43]	[0.95]	[2.72]	[3.52]	

Momentum

Panel C: Average number of stocks

		Low-Φ^{MOM}	⟵	*Fund*	⟶	High-Φ^{MOM}
		1	2	3	4	5
Low-RET	1	131	107	98	87	70
↑	2	124	117	104	87	63
Stock	3	106	116	110	95	69
↓	4	87	102	108	108	90
High-RET	5	60	68	85	115	165

Panel D: Annualized portfolio return (%)

		Low-Φ^{MOM}	⟵	*Fund*	⟶	High-Φ^{MOM}		
		1	2	3	4	5	**5−1**	
Low-RET	1	7.5	7.5	9.9	8.3	12.4	**4.9**	[1.46]
↑	2	10.2	10.9	12.1	11.5	14.0	**3.8**	[1.19]
Stock	3	10.0	11.4	13.5	12.9	17.2	**7.3**	[2.82]
↓	4	10.5	11.6	11.5	14.4	16.2	**5.6**	[2.44]
High-RET	5	8.4	8.5	12.7	16.2	19.5	**11.1**	[3.36]
WML		**1.0**	**1.0**	**2.8**	**7.9**	**7.2**	**6.2**	
		[0.28]	[0.29]	[0.91]	[2.32]	[2.03]	[1.70]	

Table 7: Alternative measures for portfolio returns when portfolios are sorted on stock characteristics and funds factor demand

Note: This table reports alternative performance measures for each of the 25 double-sorted portfolios. For brevity, we only report the top and bottom portfolios sorted on stock characteristics. In each quarter, stocks are independently sorted into 25 portfolios based on their BM ratios and stock-level factor demand Φ^{HML} (Panels A1, B1, and C1), or on their past one-year returns (skipping the most recent month) and stock-level factor demand Φ^{MOM} (Panels A2, B2, and C2). Φ^{HML} or Φ^{MOM} are the shares-weighted average HML and MOM loadings of a stock's underlying funds. Panels A1 and A2 report equal-weighted annualized returns. Panels B1 and B2 report portfolio alphas based on CAPM. Panel C1 reports alphas from a three-factor model of market, size, and momentum; Panel C2 reports alphas from a three-factor model of market, size, and value. t-statistics are reported in the brackets (t-statistics for alphas are Newey-West adjusted with 4 lags). Data are from 1980Q2 to 2018Q4.

Value

Panel A1: EW portfolio returns (annualized, %)

		Low-Φ^{HML}	$\longleftarrow$	*Fund*	$\longrightarrow$	High-Φ^{HML}		
		1	2	3	4	5	5−1	
Low-BM	1	15.7	12.1	9.1	9.9	6.4	-9.3	[-2.64]
High-BM	5	11.8	16.7	16.2	15.0	13.9	2.1	[0.66]
HML		-3.9	4.6	7.1	5.1	7.5	11.4	
t-stats		[-1.04]	[1.72]	[3.06]	[2.24]	[3.42]	[2.99]	

Panel B1: CAPM alpha (annualized, %)

		Low-Φ^{HML}	$\longleftarrow$	*Fund*	$\longrightarrow$	High-Φ^{HML}		
		1	2	3	4	5	5−1	
Low-BM	1	5.0	3.0	1.0	2.8	-2.3	-7.3	[-8.94]
High-BM	5	-2.1	7.2	7.8	5.3	6.3	8.4	[11.50]
HML		-7.1	4.2	6.8	2.5	8.6	15.8	
t-stats		[-5.64]	[5.20]	[8.01]	[3.58]	[11.80]	[12.12]	

Panel C1: MKT+SMB+MOM 3-factor alpha (annualized, %)

		Low-Φ^{HML}	$\longleftarrow$	*Fund*	$\longrightarrow$	High-Φ^{HML}		
		1	2	3	4	5	5−1	
Low-BM	1	1.1	0.8	-1.2	1.5	-2.7	-3.8	[-5.07]
High-BM	5	2.6	10.1	10.4	7.8	9.2	6.6	[10.76]
HML		1.5	9.3	11.7	6.2	11.9	10.4	
t-stats		[1.51]	[12.80]	[13.54]	[10.68]	[17.67]	[9.26]	

Momentum

Panel A2: EW portfolio returns (annualized, %)

		Low-Φ^{HML}	$\longleftarrow$	*Fund*	$\longrightarrow$	High-Φ^{HML}		
		1	2	3	4	5	5−1	
Low-RET	1	7.8	8.3	8.0	8.3	10.2	2.4	[0.93]
High-RET	5	12.5	13.4	14.5	18.8	22.7	10.2	[4.30]
WML		4.7	5.2	6.5	10.5	12.5	7.8	
t-stats		[1.53]	[1.90]	[2.41]	[3.56]	[4.27]	[3.33]	

Panel B2: CAPM alpha (annualized, %)

		Low-Φ^{HML}	$\longleftarrow$	*Fund*	$\longrightarrow$	High-Φ^{HML}		
		1	2	3	4	5	5−1	
Low-RET	1	-2.6	-2.8	1.0	-1.5	0.7	3.3	[4.28]
High-RET	5	0.4	0.0	4.0	6.6	7.8	7.4	[10.66]
WML		3.0	2.9	3.0	8.1	7.1	4.2	
t-stats		[2.93]	[2.84]	[3.59]	[10.02]	[7.79]	[3.44]	

Panel C2: MKT+SMB+HML 3-factor alpha (annualized, %)

		Low-Φ^{HML}	$\longleftarrow$	*Fund*	$\longrightarrow$	High-Φ^{HML}		
		1	2	3	4	5	5−1	
Low-RET	1	-5.9	-5.5	0.3	-0.5	3.6	9.5	[17.53]
High-RET	5	0.1	0.1	4.3	8.7	11.4	11.3	[15.16]
WML		6.0	5.6	4.0	9.2	7.8	1.8	
t-stats		[7.68]	[6.81]	[5.15]	[10.82]	[7.59]	[1.79]	

Table 8: Returns for portfolios sorted on changes in stock characteristics and funds factor demand

Note: This table reports the performance of portfolios sorted on changes in stock characteristics and funds factor demand. In Panel A, each quarter, we independently sort all stocks into 5×5 portfolios based on their changes in BM ratios over the last four quarters, denoted by $\Delta_4 BM$, and their stock-level factor demand Φ^{HML}, where $\Phi^{HML}$is calculated as the shares-weighted average ϕ^{HML} of a stock's underlying funds. Each cell reports the subsequent return for each of the five long-short portfolios that long the portfolio high in $\Delta_4 BM$ and short the portfolio low in $\Delta_4 BM$. In Panel B, each quarter, we independently sort all stocks into 5×5 portfolios based on their changes in past one-year returns (skipping the most recent month) over the last four quarters, denoted by $\Delta_4 RET$, and their stock-level factor demand Φ^{MOM}, where $\Phi^{MOM}$is calculated as the shares-weighted average ϕ^{MOM} of a stock's underlying funds. Each cell reports the subsequent return for each of the five long-short portfolios that long the portfolio high in $\Delta_4 RET$ and short the portfolio low in $\Delta_4 RET$. In both panels, we report annualized value- and equal-weighted returns, CAPM alphas, and 3-factor alphas. t-statistics are reported in the brackets. Data are from 1980Q1 to 2018Q4.

Panel A: Portfolios sorted on changes in stock characteristics and funds factor demand

Value	Low-Φ^{HML}	$\longleftarrow$	Fund	$\longrightarrow$	High-Φ^{HML}	**5−1**
VW return	-7.5	-5.1	-3.3	-0.6	-0.1	**7.4**
	[-1.77]	[-1.48]	[-1.04]	[-0.18]	[-0.02]	**[1.78]**
EW return	-6.0	-8.5	-6.3	-2.8	-2.8	**3.3**
	[-1.74]	[-2.79]	[-2.29]	[-1.18]	[-1.06]	**[1.10]**
CAPM alpha	-8.2	-7.4	-5.4	-2.6	-2.9	**5.3**
	[-7.54]	[-8.57]	[-6.73]	[-3.17]	[-3.43]	**[5.01]**
3-factor alpha	1.8	0.1	1.4	3.5	4.4	**2.7**
	[2.21]	[0.22]	[2.28]	[5.52]	[6.76]	**[2.52]**
Momentum	Low-Φ^{MOM}	$\longleftarrow$	Fund	$\longrightarrow$	High-Φ^{MOM}	**5−1**
VW return	0.0	0.3	2.4	7.8	8.5	**8.6**
	[-0.02]	[0.09]	[0.88]	[2.46]	[3.09]	**[2.68]**
EW return	4.3	4.2	6.1	7.4	10.6	**6.2**
	[1.75]	[2.10]	[2.98]	[3.16]	[4.29]	**[2.70]**
CAPM alpha	2.1	2.2	2.8	7.1	8.4	**6.2**
	[2.88]	[2.87]	[4.03]	[8.71]	[11.76]	**[7.81]**
3-factor alpha	2.5	2.9	2.4	7.5	8.6	**6.1**
	[3.28]	[3.71]	[3.41]	[8.84]	[11.64]	**[7.35]**

Panel B: Portfolios sorted on stock characteristics and holdings-based factor demand

Value	Low-$\overline{BM}$	$\longleftarrow$	Fund	$\longrightarrow$	High-$\overline{BM}$	**5−1**
VW return	0.3	2.7	5.2	8.6	8.5	**8.2**
	[0.05]	[1.01]	[2.17]	[3.07]	[2.56]	**[1.59]**
EW return	0.5	3.7	7.2	10.0	7.1	**6.5**
	[0.12]	[1.48]	[2.95]	[3.57]	[2.54]	**[1.36]**
CAPM alpha	-0.4	1.9	5.3	10.7	11.8	**12.2**
	[-0.32]	[2.77]	[8.68]	[15.22]	[14.63]	**[9.49]**
3-factor alpha	6.5	5.1	8.0	12.7	13.6	**7.2**
	[5.52]	[8.26]	[13.27]	[17.63]	[16.46]	**[5.64]**
Momentum	Low-$\overline{RET}$	$\longleftarrow$	Fund	$\longrightarrow$	High-$\overline{RET}$	**5−1**
VW return	2.8	-0.4	-1.8	4.1	7.6	**4.8**
	[0.88]	[-0.12]	[-0.54]	[1.26]	[2.04]	**[1.15]**
EW return	5.9	2.6	3.2	5.4	11.8	**6.0**
	[2.10]	[0.97]	[1.22]	[2.11]	[3.91]	**[1.95]**
CAPM alpha	4.0	2.1	0.3	6.6	7.9	**3.9**
	[4.82]	[2.63]	[0.30]	[8.10]	[8.21]	**[3.67]**
3-factor alpha	5.2	3.0	0.5	7.7	11.2	**6.0**
	[6.12]	[3.70]	[0.56]	[9.61]	[12.11]	**[5.72]**

Table 9: Returns and characteristics for 3×3 stock portfolios double-sorted on the BM ratio demand for value

Note: This table reports returns, alphas, and number of stocks for 3×3 stock portfolios double-sorted on the BM ratio and stock-level value demand (Φ^{HML}), where $\Phi^{HML}$is the shares-weighted average ϕ^{HML} of the underlying funds. Panels A, B, and C report the value-weighted returns, equal-weight returns and alphas based on a 3-factor model of market, size and momentum for each of the 9 portfolios and the corresponding HML portfolios, respectively. Panel D reports the average number of stocks for each portfolio. t-statistics are reported in the bracket (t-statistics for alphas are Newey-West adjusted with 4 lags). Data are from 1980Q2 to 2018Q4.

Panel A: VW portfolio returns (annualized, %)

		Low-Φ^{HML}	←*Fund*→	High-Φ^{HML}		
		1	2	3	3−1	
Low-BM	1	14.12	10.31	8.90	-5.2	[-1.97]
Stock↨	2	14.26	12.09	11.17	-3.1	[-1.31]
High-BM	3	12.70	13.47	13.08	0.4	[0.04]
HML		-1.41	3.17	4.18	5.59	
		[-0.55]	[1.85]	[2.25]	[2.27]	

Panel B: EW portfolio returns (annualized, %)

		Low-Φ^{HML}	←*Fund*→	High-Φ^{HML}		
		1	2	3	3−1	
Low-BM	1	14.59	11.02	8.94	-5.65	[-2.64]
Stock↨	2	15.44	13.81	12.64	-2.80	[-1.40]
High-BM	3	15.20	15.51	13.76	-1.44	[-0.61]
HML		0.61	4.49	4.81	4.20	
		[0.25]	[2.73]	[2.65]	[2.11]	

Panel C: MKT+SMB+MOM 3-factor alpha (annualized, %)

		Low-Φ^{HML}	←*Fund*→	High-Φ^{HML}		
		1	2	3	3−1	
Low-BM	1	1.74	1.86	0.90	-0.84	[-2.45]
Stock↨	2	5.84	4.39	4.49	-1.36	[-10.67]
High-BM	3	6.43	7.43	8.24	1.81	[-1.72]
HML		4.69	5.58	7.34	2.65	
		[7.77]	[13.00]	[17.34]	[4.30]	

Panel D: Number of stocks

		Low-Φ^{HML}	←*Fund*→	High-Φ^{HML}
		1	2	3
Low-BM	1	477	238	103
Stock↨	2	214	327	278
High-BM	3	102	266	450

Table 10: Evidence for flow-induced trading

Note: This table reports quarterly average flow-induced trading (FIT) for each of the 25 double-sorted portfolios. In each quarter, stocks are independently sorted into 25 portfolios based on their BM ratios or past one-year returns (skipping the most recent month) and on their stock-level factor demand Φ^{HML} or Φ^{MOM}, where Φ^{HML} and Φ^{MOM} are calculated as the shares-weighted average ϕ^{HML} and ϕ^{MOM} of a stock's underlying funds, respectively. We follow Lou (2012) and define FIT for stock j in quarter q as $FIT_{j,q} = \frac{\sum_i Shares_{i,j,q-1} \times flow_{j,q} \times PSF}{\sum_i Shares_{i,j,q-1}}$, where $flow_{j,q}$ is the dollar flow to fund j in quarter q scaled by the fund's lagged TNA and $Shares_{i,j,q-1}$ is the number of shares held by fund j at the beginning of quarter q. PSF is the partial scaling factor to account for the proportional purchases and sales for inflows and outflows, respectively. We take the values of PSF from Lou (2012): a dollar inflow corresponds to 62 cents additional purchase of the fund's current portfolio; a dollar outflow corresponds to one dollar sale of the existing portfolio. The panels report quarterly average FIT for value and momentum-related portfolios, respectively.

Panel A: Flow-induced trading (FIT, %) - value

		Low-Φ^{HML}	⟵	*Fund*	⟶	High-Φ^{HML}
		1	2	3	4	5
Low-BM	1	-0.02	-0.07	0.10	0.11	0.42
↑	2	-0.40	-0.31	-0.29	-0.05	0.17
Stock	3	-0.35	-0.29	-0.17	-0.04	0.18
↓	4	-0.24	-0.27	-0.16	-0.19	0.03
High-BM	5	-0.25	-0.21	-0.13	-0.29	-0.14
HML		**-0.23**	**-0.14**	**-0.23**	**-0.39**	**-0.56**

Panel B: Flow-induced trading (FIT, %) - momentum

		Low-Φ^{MOM}	⟵	*Fund*	⟶	High-Φ^{MOM}
		1	2	3	4	5
Low-RET	1	-0.40	-0.42	-0.46	-0.49	-0.25
↑	2	-0.23	-0.38	-0.35	-0.31	-0.27
Stock	3	-0.14	-0.33	-0.31	-0.22	-0.19
↓	4	-0.07	-0.18	-0.14	-0.08	0.04
High-RET	5	0.20	-0.10	0.06	0.10	0.42
WML		**0.60**	**0.32**	**0.52**	**0.59**	**0.67**

Table 11: Decomposition of total mutual fund ownership changes

Note: This table reports average ownership changes from funds with low and high factor betas for 25 sorted portfolios of stocks. In each quarter, stocks are independently sorted into 25 portfolios based on their BM ratios or past one-year returns (skipping the most recent month) and on their Φ^{HML} or Φ^{MOM}, calculated as the shares-weighted average ϕ^{HML} and ϕ^{MOM} of the underlying funds, respectively. In each quarter, value (momentum) funds are defined as funds with HML (MOM) beta higher than the cross-sectional median and growth (contrarian) funds are defined as those lower than the cross-sectional median. We calculate ownership changes from these funds in the subsequent quarter for each portfolio and report their time-series averages. Panels A and B report ownership changes for value and momentum, respectively.

Panel A: Decomposition of mutual fund ownership change (%) for value

		Growth funds						Value funds				
		Low-Φ^{HML}	⟵	*Fund*	⟶	High-Φ^{HML}		Low-Φ^{HML}	⟵	*Fund*	⟶	High-Φ^{HML}
		1	2	3	4	5		1	2	3	4	5
Low-BM	1	**0.34**	0.14	0.10	0.06	0.00	1	0.13	0.11	0.15	0.11	**0.18**
↑	2	**0.18**	0.08	0.06	0.07	-0.01	2	0.13	0.12	0.16	0.18	**0.21**
Stock	3	**0.20**	0.10	0.06	0.03	-0.05	3	0.15	0.16	0.13	0.17	**0.17**
↓	4	**0.09**	0.07	0.06	0.02	0.00	4	0.08	0.20	0.14	0.20	**0.26**
High-BM	5	**-0.14**	0.02	0.01	0.00	0.01	5	0.13	0.19	0.18	0.23	**0.23**
HML		**-0.48**	-0.12	-0.09	-0.06	0.01		0.00	0.08	0.03	0.12	**0.05**

Panel B: Decomposition of mutual fund ownership change (%) for momentum

		Contrarian funds						Momentum funds				
		Low-Φ^{MOM}	⟵	*Fund*	⟶	High-Φ^{MOM}		Low-Φ^{MOM}	⟵	*Fund*	⟶	High-Φ^{MOM}
		1	2	3	4	5		1	2	3	4	5
Low-RET	1	**0.21**	0.23	0.23	0.26	0.17	1	-0.02	0.01	-0.03	0.01	**-0.10**
↑	2	**0.16**	0.15	0.17	0.20	0.21	2	0.03	0.07	0.04	0.09	**0.14**
Stock	3	**0.03**	0.07	0.10	0.11	0.12	3	0.06	0.11	0.10	0.11	**0.31**
↓	4	**0.01**	0.00	0.04	0.10	0.11	4	0.07	0.17	0.18	0.17	**0.36**
High-RET	5	**0.02**	-0.05	0.06	0.04	0.09	5	0.16	0.24	0.24	0.40	**0.53**
WML		**-0.19**	-0.29	-0.17	-0.22	-0.08		0.18	0.23	0.26	0.39	**0.63**

Table 12: Estimates of price elasticity of demand

Note: This table reports the price elasticity associated with factor-rebalancing demand shifts

$$Elasticity = -\frac{\Delta Demand}{\Delta Return},$$

where $\Delta Demand$ is the average quarterly change in the number of shares held by funds with inelastic demand, scaled by the total number of shares outstanding. Funds with inelastic demand are defined as value (momentum) funds with HML (MOM) beta higher than the cross-sectional median and growth (contrarian) funds with HML (MOM) beta lower than the cross-sectional median. $\Delta Return$ is the difference between each long-short portfolio return and the average long-short portfolio return.

	HML portfolio		
	Growth funds	Value funds	Diff.
	(1)	(2)	(3)
$\Delta Demand$	-0.48%	0.05%	0.53%
$\Delta Return$	-2.76%	1.21%	3.97%
$-\Delta Demand/\Delta Return$	-0.17	-0.04	-0.13
	WML portfolio		
	Contrarian funds	Momentum funds	Diff.
	(4)	(5)	(6)
$\Delta Demand$	-0.19%	0.63%	0.82%
$\Delta Return$	-0.75%	1.79%	2.54%
$-\Delta Demand/\Delta Return$	-0.25	-0.35	-0.32

Table 13: Subsequent fundamentals for 5×5 stock portfolios double-sorted on stock characteristics and fund betas

Note: This table reports the subsequent fundamentals for the 25 portfolios sorted on BM ratios (past one-year return) and stock-level value (momentum) demand. Fundamentals are measured by standardized earnings surprise (SUE) and cumulative abnormal returns (CAR) and aggregated to the portfolio level by value-weighting stock-level quantities. SUE is defined as earnings surprise relative to analysts' forecasts, normalized by the current stock price. CAR is defined as the size and value-adjusted abnormal returns in a three-day window around the earnings announcements. Panels A and B report results for value. Panels C and D report results for momentum.

Value

		Panel A: SUE (%)							Panel B: CAR (%)					
		Low-Φ^{HML}	$\longleftarrow$	*Fund*	$\longrightarrow$	High-Φ^{HML}			Low-Φ^{HML}	$\longleftarrow$	*Fund*	$\longrightarrow$	High-Φ^{HML}	
		1	2	3	4	5	5−1		1	2	3	4	5	5−1
Low-BM	1	0.16	0.24	0.24	0.33	0.36	0.20	1	0.39	0.12	-0.38	-0.31	-0.14	-0.53
↑	2	0.12	0.17	0.15	0.15	0.20	0.08	2	0.37	0.15	-0.07	-0.13	-0.18	-0.55
Stock	3	-0.04	0.18	0.16	0.20	0.12	0.15	3	0.23	0.26	-0.03	-0.17	0.19	-0.05
↓	4	-0.15	-0.02	-0.06	0.04	0.07	0.22	4	-0.14	0.30	-0.08	0.12	0.03	0.17
High-BM	5	-0.86	-0.63	-0.45	-0.45	-0.49	0.36	5	-0.03	0.05	0.08	0.19	0.03	0.06
HML		-1.02	-0.87	-0.69	-0.78	-0.86	0.16		-0.42	-0.06	0.46	0.50	0.17	0.59

Momentum

		Panel C: SUE (%)							Panel D: CAR (%)					
		Low-Φ^{MOM}	$\longleftarrow$	*Fund*	$\longrightarrow$	High-Φ^{MOM}			Low-Φ^{MOM}	$\longleftarrow$	*Fund*	$\longrightarrow$	High-Φ^{MOM}	
		1	2	3	4	5	5−1		1	2	3	4	5	5−1
Low-RET	1	-1.12	-0.90	-0.64	-0.51	-0.44	0.68	1	0.05	-0.19	-0.06	0.26	0.20	0.15
↑	2	-0.21	-0.16	-0.07	-0.04	-0.08	0.13	2	-0.01	0.06	0.20	0.14	-0.03	-0.02
Stock	3	0.04	0.10	0.09	0.14	0.14	0.10	3	-0.09	0.01	-0.03	0.19	0.23	0.32
↓	4	0.26	0.23	0.30	0.21	0.20	-0.06	4	-0.04	-0.03	-0.09	0.13	0.47	0.51
High-RET	5	0.68	0.60	0.53	0.46	0.47	-0.21	5	-0.49	-0.05	0.16	0.11	0.38	0.87
WML		1.79	1.49	1.17	0.98	0.90	-0.89		-0.53	0.14	0.23	-0.15	0.18	0.72

Online Appendix for

"Factor Demand and Factor Returns"

Table A.1: Persistence of Investment Universe by Fund Type

Note: In each quarter, persistence is calculated as the fraction of positions that were also held in the previous quarter. In each quarter, value (momentum) funds are defined as funds with HML (MOM) beta higher than the cross-sectional median and growth (contrarian) funds are defined as those lower than the cross-sectional median.

Fund type	Persistence	
	Mean	Median
Value	0.87	0.91
Growth	0.83	0.87
Momentum	0.80	0.84
Contrarian	0.88	0.92

Table A.2: Persistence of factor demand for value and momentum

Note: This table examines the persistence of factor demand. $\phi_{j,q}$ represents the loading to a given factor estimated using the five-year window in which q is the last quarter; $\phi_{j,q-20}$ represents the loading to a given factor estimated when $q-20$ is the last quarter of the five-year window. Therefore, $\phi_{j,q}$ and $\phi_{j,q-20}$ do not overlap in their estimation periods. *PureIndex* is an indicator for passive index funds. *AllIndex* is an indicator for all index funds. Standard errors clustered at fund and date levels are reported in parentheses. *, **, *** indicate statistical significance at 10%, 5% and 1% levels, respectively.

	$\phi_{j,q}^{HML}$		$\phi_{j,q}^{MOM}$	
	(1)	(2)	(3)	(4)
$\phi_{j,q-20}^{HML}$	0.478***	0.475***		
	(0.014)	(0.014)		
$\phi_{j,q-20}^{MOM}$			0.421***	0.418***
			(0.017)	(0.017)
AllIndex	0.021*		-0.037***	
	(0.012)		(0.005)	
AllIndex$\times\phi_{j,q-20}^{HML}$	-0.143***			
	(0.039)			
PureIndex		0.020		-0.039***
		(0.012)		(0.005)
PureIndex$\times\phi_{j,q-20}^{HML}$		-0.141***		
		(0.041)		
AllIndex$\times\phi_{j,q-20}^{MOM}$			-0.189***	
			(0.048)	
PureIndex$\times\phi_{j,q-20}^{MOM}$				-0.187***
				(0.050)
Quarter FE	✓	✓	✓	✓
Observations	95,876	95,876	95,876	95,876
R^2	0.310	0.309	0.271	0.271

Table A.3: Persistence of factor demand for value and momentum, controlling for active shares

Note: This table examines the persistence of factor demand. $\phi_{j,q}$ represents the loading to a given factor estimated using the five-year window in which q is the last quarter; $\phi_{j,q-20}$ represents the loading to a given factor estimated when $q-20$ is the last quarter of the five-year window. Therefore, $\phi_{j,q}$ and $\phi_{j,q-20}$ do not overlap in their estimation periods. ActiveShare and ActiveShare (SD) are a fund's minimum active share across all U.S.-equity benchmarks and active share against self-declared benchmarks, respectively, from Cremers and Petajisto (2009). Standard errors clustered at fund and date levels are reported in parentheses. *, **, *** indicate statistical significance at 10%, 5% and 1% levels, respectively.

	$\phi^{HML}_{j,q}$		$\phi^{MOM}_{j,q}$	
	(1)	(2)	(3)	(4)
$\phi^{HML}_{j,q-20}$	0.886***	1.013***		
	(0.054)	(0.066)		
$\phi^{MOM}_{j,q-20}$			0.535***	0.596***
			(0.064)	(0.062)
ActiveShare	-0.007		-0.030***	
	(0.024)		(0.010)	
ActiveShare (SD)		-0.013		-0.023***
		(0.024)		(0.007)
ActiveShare $\times\phi^{HML}_{j,q-20}$	-0.546***			
	(0.066)			
ActiveShare (SD) $\times\phi^{HML}_{j,q-20}$		-0.620***		
		(0.084)		
ActiveShare $\times\phi^{MOM}_{j,q-20}$			-0.252***	
			(0.080)	
ActiveShare (SD) $\times\phi^{MOM}_{j,q-20}$				-0.263***
				(0.077)
Quarter FE	✓	✓	✓	✓
Observations	125,512	87,000	125,512	87,000
R^2	0.307	0.364	0.184	0.228

Table A.4: Transition probability of stocks

Note: This table reports the probability of a stock moving from one characteristic quintile to another quintile over time. In Panels A and B, stocks are sorted into different quintiles in each quarter based on their book-to-market ratios (BM). In Panels C and D, stocks are sorted into different quintiles in each quarter based on their returns over the last year ($r_{t-4,t-1/3}$, skipping the most recent month). One-quarter transition probability represents the probability of moving from one quintile to another quintile between the current quarter and the next quarter. One-year transition probability represents the probability of moving from one quintile to another quintile between the current quarter and four quarters later.

Panel A: One-quarter transition, BM

	1	2	3	4	5
1	**0.86**	0.12	0.01	0.00	0.00
2	0.10	**0.72**	0.16	0.02	0.00
3	0.00	0.14	**0.67**	0.17	0.01
4	0.00	0.01	0.16	**0.69**	0.14
5	0.00	0.00	0.01	0.14	**0.85**

Panel B: One-year transition, BM

	1	2	3	4	5
1	**0.68**	0.23	0.06	0.03	0.01
2	0.16	**0.50**	0.24	0.07	0.02
3	0.03	0.21	**0.45**	0.25	0.07
4	0.01	0.05	0.22	**0.48**	0.23
5	0.01	0.01	0.05	0.22	**0.72**

Panel C: One-quarter transition, $r_{t-4,t-1/3}$

	1	2	3	4	5
1	**0.61**	0.23	0.09	0.05	0.02
2	0.23	**0.36**	0.25	0.12	0.04
3	0.10	0.25	**0.33**	0.24	0.08
4	0.05	0.12	0.25	**0.36**	0.21
5	0.03	0.05	0.10	0.23	**0.60**

Panel D: One-year transition, $r_{t-4,t-1/3}$

	1	2	3	4	5
1	**0.25**	0.20	0.18	0.18	0.19
2	0.19	**0.22**	0.23	0.22	0.14
3	0.17	0.23	**0.25**	0.22	0.14
4	0.18	0.22	0.23	**0.21**	0.15
5	0.26	0.19	0.17	0.18	**0.20**

Table A.5: Transition probability of funds

Note: This table reports the probability of a fund moving from one factor beta quintile to another quintile over time. Funds are sorted into different quintiles in each quarter based on their factor betas, which are estimated by regressing fund returns on factor returns in a five-year rolling window. Panels A and B report transition probabilities based on ϕ^{HML} and Panels C and D report transition probabilities based on ϕ^{MOM}. The one-quarter transition probability is the probability of moving from one quintile to another between the current quarter and the next quarter. One-year transition probability is the probability of moving from one quintile to another between the current quarter and four quarters later.

Panel A: One-quarter transition, ϕ^{HML}

	1	2	3	4	5
1	**0.88**	0.11	0.01	0.00	0.00
2	0.11	**0.75**	0.13	0.01	0.00
3	0.01	0.13	**0.73**	0.12	0.01
4	0.00	0.01	0.12	**0.76**	0.10
5	0.00	0.00	0.01	0.10	**0.89**

Panel B: One-year transition, ϕ^{HML}

	1	2	3	4	5
1	**0.74**	0.20	0.04	0.02	0.01
2	0.19	**0.53**	0.21	0.06	0.02
3	0.04	0.21	**0.51**	0.20	0.04
4	0.01	0.06	0.20	**0.56**	0.17
5	0.01	0.02	0.04	0.18	**0.75**

Panel C: One-quarter transition, ϕ^{MOM}

	1	2	3	4	5
1	**0.89**	0.10	0.01	0.00	0.00
2	0.09	**0.77**	0.13	0.01	0.00
3	0.01	0.12	**0.73**	0.13	0.01
4	0.00	0.01	0.13	**0.76**	0.10
5	0.00	0.00	0.01	0.10	**0.89**

Panel D: One-year transition, ϕ^{MOM}

	1	2	3	4	5
1	**0.75**	0.18	0.04	0.02	0.01
2	0.15	**0.56**	0.21	0.06	0.02
3	0.04	0.20	**0.51**	0.22	0.04
4	0.02	0.06	0.21	**0.54**	0.17
5	0.01	0.02	0.04	0.18	**0.74**

Table A.6: Returns for 5 × 5 stock portfolios double-sorted on BM ratios and stock-level value demand, subsample analysis

Note: This table reports returns and alphas for 25 portfolios double-sorted on BM ratios and stock-level value demand, Φ^{HML}, where Φ^{HML} is calculated as the shares-weighted average ϕ^{HML} of the underlying funds. Panel A uses data from 1980Q1 to 1999Q4. Panel B uses data from 2000Q1 to 2018Q4. Panel C uses stocks above the median mutual fund ownership in each quarter. Panel D uses stocks below the median mutual fund ownership in each quarter. Panel E uses stocks above the median firm size in each quarter. Panel F uses stocks below the median firm size in each quarter. The alphas are calculated using a 3-factor model of market, size, and momentum. t-statistics are reported in the bracket (t-statistics for alphas are Newey-West adjusted with 4 lags). Data are from 1980Q2 to 2018Q4.

Panel A: Pre-1999 (annualized, %)

	Low-Φ^{HML} 1	High-Φ^{HML} 5	**5–1**
HML VW ret	-2.71	7.57	**10.29**
	[-0.51]	[2.08]	**[2.05]**
HML EW ret	0.10	4.41	**4.31**
	[0.02]	[1.53]	**[1.02]**
CAPM alpha	1.78	12.87	**11.09**
	[1.07]	[14.15]	**[6.75]**
3-factor alpha	9.13	15.06	**5.93**
	[6.28]	[12.56]	**[3.52]**

Panel B: Post-1999 (annualized, %)

	Low-Φ^{HML} 1	High-Φ^{HML} 5	**5–1**
HML VW ret	-13.94	7.17	**21.11**
	[-2.17]	[1.79]	**[2.88]**
HML EW ret	-7.65	10.44	**18.09**
	[-1.32]	[3.19]	**[2.93]**
CAPM alpha	-14.00	6.48	**20.48**
	[-7.69]	[6.69]	**[10.06]**
3-factor alpha	-9.31	8.89	**18.20**
	[-7.03]	[10.88]	**[12.42]**

Panel C: High MF ownership (annualized, %)

	Low-Φ^{HML} 1	High-Φ^{HML} 5	**5–1**
HML VW ret	-10.26	2.75	**13.01**
	[-2.13]	[0.88]	**[2.51]**
HML EW ret	-5.61	1.91	**7.51**
	[-1.19]	[0.68]	**[1.54]**
CAPM alpha	-8.35	3.02	**11.37**
	[-6.64]	[3.26]	**[7.59]**
3-factor alpha	-0.55	5.28	**5.83**
	[-0.54]	[5.62]	**[4.19]**

Panel D: Low MF ownership (annualized, %)

	Low-Φ^{HML} 1	High-Φ^{HML} 5	**5–1**
HML VW ret	-1.78	7.96	**9.74**
	[-0.44]	[2.21]	**[2.14]**
HML EW ret	3.03	8.44	**5.41**
	[0.85]	[2.92]	**[1.33]**
CAPM alpha	0.11	9.65	**9.54**
	[0.10]	[10.11]	**[8.06]**
3-factor alpha	5.79	14.01	**8.22**
	[6.01]	[15.37]	**[7.66]**

Panel E: Large stocks (annualized, %)

	Low-Φ^{HML} 1	High-Φ^{HML} 5	**5–1**
HML VW ret	-7.37	6.22	**13.59**
	[-1.61]	[2.21]	**[2.63]**
HML EW ret	-4.29	6.40	**10.69**
	[-0.99]	[2.34]	**[2.34]**
CAPM alpha	-5.77	6.99	**12.76**
	[-4.57]	[9.53]	**[8.96]**
3-factor alpha	1.52	9.22	**7.70**
	[1.33]	[13.15]	**[5.91]**

Panel F: Small stocks (annualized, %)

	Low-Φ^{HML} 1	High-Φ^{HML} 5	**5–1**
HML VW ret	-2.52	4.68	**7.20**
	[-0.59]	[1.51]	**[1.46]**
HML EW ret	-1.40	2.72	**4.11**
	[-0.35]	[0.97]	**[0.93]**
CAPM alpha	0.08	5.71	**5.63**
	[0.06]	[6.93]	**[4.38]**
3-factor alpha	7.34	8.70	**1.37**
	[6.13]	[11.12]	**[1.13]**

Table A.7: Returns for 5×5 stock portfolios double-sorted on past one-year returns and stock-level momentum demand, subsample analysis

Note: This table reports returns and alphas for 25 portfolios double-sorted on past one-year returns (skipping the most recent month) and stock-level momentum demand, Φ^{MOM}, where Φ^{MOM} is calculated as the shares-weighted average ϕ^{MOM} of the underlying funds. Panel A uses data from 1980Q1 to 1999Q4. Panel B uses data from 2000Q1 to 2018Q4. Panel C uses stocks above the median mutual fund ownership in each quarter. Panel D uses stocks below the median mutual fund ownership in each quarter. Panel E uses stocks above the median firm size in each quarter. Panel F uses stocks below the median firm size in each quarter. The alphas are calculated using a 3-factor model of market, size, and value. t-statistics are reported in the bracket (t-statistics for alphas are Newey-West adjusted with 4 lags). Data are from 1980Q2 to 2018Q4.

Panel A: Pre-1999 (annualized, %)

	Low-Φ^{MOM}	High-Φ^{MOM}	
	1	5	**5−1**
WML VW ret	2.72	15.58	**12.87**
	[0.66]	[3.78]	**[2.69]**
WML EW ret	10.38	20.39	**10.01**
	[3.54]	[6.46]	**[3.71]**
CAPM alpha	1.89	12.71	**10.82**
	[1.79]	[13.20]	**[11.70]**
3-factor alpha	4.32	15.37	**11.05**
	[4.07]	[17.10]	**[8.57]**

Panel B: Post-1999 (annualized, %)

	Low-Φ^{MOM}	High-Φ^{MOM}	
	1	5	**5−1**
WML VW ret	-0.66	-0.73	**-0.07**
	[-0.12]	[-0.13]	**[-0.01]**
WML EW ret	-0.57	5.13	**5.70**
	[-0.11]	[1.09]	**[1.51]**
CAPM alpha	2.34	0.73	**-1.60**
	[1.43]	[0.52]	**[-0.89]**
3-factor alpha	4.15	3.13	**-1.02**
	[3.58]	[2.04]	**[-0.76]**

Panel C: High MF ownership (annualized, %)

	Low-Φ^{MOM}	High-Φ^{MOM}	
	1	5	**5−1**
WML VW ret	0.65	9.77	**9.12**
	[0.18]	[2.53]	**[2.27]**
WML EW ret	3.78	11.30	**7.51**
	[1.20]	[3.33]	**[2.62]**
CAPM alpha	1.02	10.54	**9.52**
	[0.97]	[9.82]	**[7.65]**
3-factor alpha	4.35	12.49	**8.14**
	[5.28]	[10.44]	**[6.75]**

Panel D: Low MF ownership (annualized, %)

	Low-Φ^{MOM}	High-Φ^{MOM}	
	1	5	**5−1**
WML VW ret	2.79	5.33	**2.55**
	[0.77]	[1.45]	**[0.66]**
WML EW ret	5.70	12.12	**6.41**
	[1.83]	[3.95]	**[2.25]**
CAPM alpha	4.81	5.08	**0.27**
	[4.63]	[5.86]	**[0.26]**
3-factor alpha	6.73	5.29	**-1.43**
	[7.25]	[6.38]	**[-1.68]**

Panel E: Large stocks (annualized, %)

	Low-Φ^{MOM}	High-Φ^{MOM}	
	1	5	**5−1**
WML VW ret	1.06	5.72	**4.66**
	[0.30]	[1.49]	**[1.13]**
WML EW ret	0.90	7.63	**6.73**
	[0.28]	[2.19]	**[1.94]**
CAPM alpha	3.28	4.71	**1.43**
	[3.12]	[5.18]	**[0.99]**
3-factor alpha	6.11	5.22	**-0.88**
	[7.37]	[5.68]	**[-0.80]**

Panel F: Small stocks (annualized, %)

	Low-Φ^{MOM}	High-Φ^{MOM}	
	1	5	**5−1**
WML VW ret	7.79	13.64	**5.85**
	[2.11]	[4.21]	**[1.70]**
WML EW ret	7.83	15.51	**7.68**
	[2.34]	[5.17]	**[2.45]**
CAPM alpha	8.67	14.01	**5.33**
	[9.12]	[15.57]	**[5.30]**
3-factor alpha	11.88	15.13	**3.25**
	[13.81]	[15.54]	**[3.90]**

Table A.8: Pre-formation characteristics for 5×5 stock portfolios

Note: This table reports the pre-formation characteristics of stocks for each of the 25 portfolios. Panel A reports results for stocks double-sorted on BM ratios and HML betas, Φ^{HML}, where Φ^{HML} is calculated as the shares-weighted average ϕ^{HML} of the underlying funds. Panel B reports results for stocks double-sorted on one-year past return ($r_{t-4,t-1/3}$) and MOM betas, Φ^{MOM}, where Φ^{MOM} is calculated as the shares-weighted average ϕ^{MOM} of the underlying funds. Each panel reports the value-weighted averages of the two sorting variables and one-year mutual fund ownership change. Data are from 1980Q1 to 2018Q4.

Panel A: Pre-formation characteristics for 5×5 stock portfolios sorted on BM ratios and HML betas

		BM							Φ^{HML}					
		Low-Φ^{HML}	⟵	*Fund*	⟶	High-Φ^{HML}			Low-Φ^{HML}	⟵	*Fund*	⟶	High-Φ^{HML}	
		1	2	3	4	5	5−1		1	2	3	4	5	5−1
Low-BM	1	0.12	0.14	0.13	0.10	0.07	-0.05	1	-0.27	-0.10	0.01	0.11	0.27	0.54
↑	2	0.30	0.31	0.32	0.33	0.33	0.03	2	-0.26	-0.08	0.02	0.11	0.27	0.53
Stock	3	0.49	0.49	0.49	0.51	0.51	0.03	3	-0.26	-0.08	0.02	0.11	0.27	0.53
↓	4	0.72	0.72	0.73	0.73	0.74	0.02	4	-0.28	-0.08	0.03	0.11	0.28	0.56
High-BM	5	1.54	1.40	1.29	1.25	1.27	-0.26	5	-0.28	-0.08	0.03	0.12	0.28	0.56
HML		1.42	1.26	1.16	1.15	1.20	-0.21		-0.01	0.02	0.02	0.01	0.01	0.02

Panel B: Pre-formation characteristics for 5×5 stock portfolios sorted on $r_{t-4,t-1/3}$ and MOM betas

		$r_{t-4,t-1/3}$							Φ^{MOM}					
		Low-Φ^{MOM}	⟵	*Fund*	⟶	High-Φ^{MOM}			Low-Φ^{MOM}	⟵	*Fund*	⟶	High-Φ^{MOM}	
		1	2	3	4	5	5−1		1	2	3	4	5	5−1
Low-RET	1	-0.23	-0.22	-0.22	-0.23	-0.24	-0.01	1	-0.10	-0.03	0.01	0.06	0.15	0.24
↑	2	-0.02	-0.02	-0.01	-0.01	-0.01	0.00	2	-0.09	-0.03	0.01	0.06	0.14	0.23
Stock	3	0.13	0.13	0.14	0.14	0.14	0.01	3	-0.09	-0.03	0.01	0.06	0.14	0.23
↓	4	0.30	0.30	0.31	0.32	0.32	0.02	4	-0.09	-0.03	0.01	0.06	0.14	0.23
High-RET	5	0.73	0.69	0.71	0.76	0.95	0.23	5	-0.10	-0.03	0.01	0.06	0.15	0.24
WML		0.96	0.91	0.93	0.99	1.20	0.24		0.00	0.00	0.00	0.00	0.00	0.00

Table A.9: Fund factor loadings and subsequent performance

Note: This table reports the relationship between a mutual fund's factor loadings and its subsequent performance measured by alphas from various factor models. The dependent variables—α_{q+4}^{CAPM}, α_{q+4}^{3F}, α_{q+4}^{4F}—are 1-year-ahead alphas obtained from a 12-month rolling-window regression of a fund's excess returns on a set of risk factors. Alphas are expressed in percentages. High (Low) $\beta_{HML,q}$ is an indicator variable that equals one when the fund's loading on value at quarter q is in the top (bottom) 20% of the distribution. High (Low) $\beta_{MOM,q}$ is an indicator variable that equals one when the fund's loading on momentum at quarter q is in the top (bottom) 20% of the distribution. Other control variables include log fund age, log of total net assets, retail flow, and expense ratio. The data sample is from 1980Q1 to 2018Q4. Standard errors clustered at the quarter and fund levels are reported in parentheses. *, **, *** indicate statistical significance at 10%, 5% and 1% levels, respectively.

	α_{q+4}^{CAPM} (%)				α_{q+4}^{3F} (%)				α_{q+4}^{4F} (%)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Intercept	0.102**	0.126**			0.0116	0.030			0.050	0.060		
	(0.051)	(0.052)			(0.039)	(0.040)			(0.044)	(0.043)		
High ϕ_q^{HML}	0.061		0.051		0.090***		0.088***		0.071***		0.071***	
	(0.045)		(0.045)		(0.026)		(0.026)		(0.026)		(0.026)	
Low ϕ_q^{HML}	0.040		0.038		-0.026		-0.025		-0.023		-0.021	
	(0.041)		(0.043)		(0.030)		(0.031)		(0.027)		(0.027)	
High ϕ_q^{MOM}		0.001		0.004		-0.011		-0.008		-0.024		-0.022
		(0.040)		(0.041)		(0.030)		(0.031)		(0.026)		(0.026)
Low ϕ_q^{MOM}		0.013		0.008		0.010		0.008		0.029		0.026
		(0.038)		(0.037)		(0.033)		(0.032)		(0.033)		(0.032)
$\log(age)_q$	-0.021	-0.021	0.029*	0.020*	0.021	0.020	0.036***	0.036***	0.016	0.016	0.031***	0.032***
	(0.016)	(0.016)	(0.010)	(0.010)	(0.015)	(0.015)	(0.010)	(0.010)	(0.015)	(0.015)	(0.010)	(0.010)
$\log(tna)_q$	-0.013**	-0.013**	-0.014***	-0.014***	-0.019***	-0.018***	-0.016***	-0.016***	-0.018***	-0.018***	-0.017***	-0.017***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.004)	(0.004)	(0.004)	(0.005)	(0.004)	(0.004)
$flow_q$	0.000	0.000	0.000*	0.000*	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$expense_q$	3.806*	3.905*	1.102	1.191	-0.367	-0.501	-1.648	-1.795	-1.384	-1.467	-2.664**	-2.744**
	(2.162)	(2.216)	(1.261)	(1.315)	(1.571)	(1.550)	(1.220)	(1.218)	(1.707)	(1.692)	(1.348)	(1.342)
Date FE			✓	✓			✓	✓			✓	✓
R^2	0.004	0.003	0.107	0.106	0.003	0.001	0.082	0.080	0.002	0.001	0.080	0.079
Observations	237,239	237,239	237,239	237,239	237,239	237,239	237,239	237,239	237,239	237,239	237,239	237,239

Table A.10: Characteristics and returns for portfolios sorted on 4-quarter changes in stock characteristics and funds factor demand

Note: This table reports the average number of stocks (Panels A and B) and subsequent annualized value-weighted portfolio returns (Panels C and D) for each of the 25 double-sorted portfolios. In each quarter, stocks are independently sorted into 25 portfolios based on their 4-quarter changes in BM ratios ($\Delta_4 BM$) or past one-year returns (skipping the most recent month) ($\Delta_4 RET$) and on their stock-level factor demand Φ^{HML} or Φ^{MOM}, where Φ^{HML} or Φ^{MOM} are calculated as the shares-weighted average ϕ^{HML} and ϕ^{MOM} of a stock's underlying funds, respectively. t-statistics are reported in brackets. Data are from 1980Q2 to 2018Q4.

Panel A: Average number of stocks - value

		Low-Φ^{HML}	$\longleftarrow$	*Fund*	$\longrightarrow$	High-Φ^{HML}
		1	2	3	4	5
Low-$\Delta_4 BM$	1	58	75	87	96	102
$\uparrow$	2	94	112	111	110	106
Stock	3	113	124	114	102	90
$\downarrow$	4	94	102	104	103	97
High-$\Delta_4 BM$	5	48	55	66	79	84

Panel B: Average number of stocks - momentum

		Low-Φ^{MOM}	$\longleftarrow$	*Fund*	$\longrightarrow$	High-Φ^{MOM}
		1	2	3	4	5
Low-$\Delta_4 RET$	1	78	79	86	93	95
$\uparrow$	2	108	109	102	91	68
Stock	3	115	117	105	91	62
$\downarrow$	4	109	110	104	92	69
High-$\Delta_4 RET$	5	82	80	87	95	108

Panel C: Annualized portfolio return - value (%)

		Low-Φ^{HML}	$\longleftarrow$	*Fund*	$\longrightarrow$	High-Φ^{HML}	
		1	2	3	4	5	5−1
Low-$\Delta_4 BM$	1	17.5	16.2	12.9	12.5	12.4	-5.1
$\uparrow$	2	16.4	14.2	12.5	11.4	12.8	-3.7
Stock	3	14.4	12.0	11.2	8.8	13.0	-1.4
$\downarrow$	4	10.5	9.9	10.1	11.9	11.7	1.3
High-$\Delta_4 BM$	5	10.0	11.1	9.6	11.9	12.3	2.3
High-Low		**-7.5**	**-5.1**	**-3.3**	**-0.6**	**-0.1**	**7.4**
		[-1.77]	[-1.48]	[-1.04]	[-0.18]	[-0.02]	[1.78]

Panel D: Annualized portfolio return - momentum (%)

		Low-Φ^{MOM}	$\longleftarrow$	*Fund*	$\longrightarrow$	High-Φ^{MOM}	
		1	2	3	4	5	5−1
Low-$\Delta_4 RET$	1	8.7	7.5	9.4	9.0	12.9	4.2
$\uparrow$	2	9.5	8.6	9.9	12.0	15.7	6.2
Stock	3	9.9	10.7	13.0	11.7	18.5	8.7
$\downarrow$	4	9.0	11.9	11.8	14.3	15.0	5.9
High-$\Delta_4 RET$	5	8.7	7.7	11.8	16.8	21.4	12.8
High-Low		**0.0**	**0.3**	**2.4**	**7.8**	**8.5**	**8.6**
		[-0.02]	[0.09]	[0.88]	[2.46]	[3.09]	[2.68]

Table A.11: Alternative performance measures for 5×5 stock portfolios sorted on 4-quarter changes in stock characteristics and stock-level factor demands

Note: This table reports alternative performance measures for each of the 25 double-sorted portfolios. For brevity, we only report the top and bottom portfolios sorted on stock characteristics. In each quarter, stocks are independently sorted into 25 portfolios based on their 4-quarter changes in BM ratios ($\Delta_4 BM$) and stock-level factor demand Φ^{HML} (Panels A1, B1, and C1), or on their 4-quarter changes in past one-year returns (skipping the most recent month) ($\Delta_4 RET$) and stock-level factor demand Φ^{MOM} (Panels A2, B2, and C2). Φ^{HML} or Φ^{MOM} are calculated as the shares-weighted average ϕ^{HML} and ϕ^{MOM} of a stock's underlying funds, respectively. Panels A1 and A2 report equal-weighted annualized returns. Panels B1 and B2 report portfolio alphas based on CAPM. Panel C1 reports alphas from a three-factor model of market, size, and momentum; Panel C2 reports alphas from a three-factor model of market, size, and value. t-statistics are reported in brackets. Data are from 1980Q2 to 2018Q4.

Value

		Low-Φ^{HML}	$\longleftarrow$	*Fund*	$\longrightarrow$	High-Φ^{HML}	
		1	2	3	4	5	5−1
Panel A1: EW portfolio returns (annualized, %)							
Low-$\Delta_4 BM$	1	18.7	18.6	16.0	13.3	14.1	-4.6
High-$\Delta_4 BM$	5	12.7	10.0	9.8	10.5	11.3	-1.4
High-Low		-6.0	-8.5	-6.3	-2.8	-2.8	3.3
t-stats		[-1.74]	[-2.79]	[-2.29]	[-1.18]	[-1.06]	[1.10]
Panel B1: CAPM alpha (annualized, %)							
Low-$\Delta_4 BM$	1	6.6	7.8	5.8	5.7	6.1	-0.5
High-$\Delta_4 BM$	5	-1.6	0.5	0.4	3.1	3.2	4.7
High-Low		-8.2	-7.4	-5.4	-2.6	-2.9	5.3
t-stats		[-7.54]	[-8.57]	[-6.73]	[-3.17]	[-3.43]	[5.01]
Panel C1: MKT+SMB+MOM 3-factor alpha (annualized, %)							
Low-$\Delta_4 BM$	1	2.0	5.8	3.5	4.9	5.2	3.2
High-$\Delta_4 BM$	5	3.7	5.9	4.9	8.4	9.6	5.9
High-Low		1.8	0.1	1.4	3.5	4.4	2.7
t-stats		[2.21]	[0.22]	[2.28]	[5.515]	[6.76]	[2.52]

Momentum

		Low-Φ^{HML}	$\longleftarrow$	*Fund*	$\longrightarrow$	High-Φ^{HML}	
		1	2	3	4	5	5−1
Panel A2: EW portfolio returns (annualized, %)							
Low-$\Delta_4 RET$	1	7.7	7.4	7.8	9.8	12.0	4.3
High-$\Delta_4 RET$	5	12.1	11.6	13.9	17.2	22.6	10.5
High-Low		4.3	4.2	6.1	7.4	10.6	6.2
t-stats		[1.75]	[2.10]	[2.98]	[3.16]	[4.29]	[2.70]
Panel B2: CAPM alpha (annualized, %)							
Low-$\Delta_4 RET$	1	-1.0	-1.8	1.0	0.5	2.2	3.1
High-$\Delta_4 RET$	5	1.2	0.4	3.8	7.6	10.5	9.4
High-Low		2.1	2.2	2.8	7.1	8.4	6.2
t-stats		[2.88]	[2.87]	[4.03]	[8.71]	[11.76]	[7.81]
Panel C2: MKT+SMB+HML 3-factor alpha (annualized, %)							
Low-$\Delta_4 RET$	1	-3.3	-3.3	0.9	1.9	5.5	8.8
High-$\Delta_4 RET$	5	-0.8	-0.4	3.4	9.4	14.1	14.9
High-Low		2.5	2.9	2.4	7.5	8.6	6.1
t-stats		[3.28]	[3.71]	[3.41]	[8.84]	[11.64]	[7.35]

Table A.12: Predicting aggregate factor returns with changes in average mutual fund factor demand
Note: This table reports results from the aggregate factor return predictive regressions

$$\text{Factor Return}_{t+1q} = a + b \times \Delta\phi_t^{s,Aggr} + c \cdot \mathbf{X}_t + \varepsilon_{t+1q}$$

The dependent variables are value (HML) or momentum (MOM) returns in the following quarter. The main predictors are quarterly changes in average mutual fund demand for value and momentum, respectively, where aggregate demand for factor s is measured as the simple average across all mutual funds in our sample $\phi_t^{s,Aggr} \equiv \frac{1}{N}\sum_{j=1}^{N}\phi_{j,t}^{s}$. The data is at the quarterly frequency and covers 1980Q1:2019Q4. Newey-West standard errors with three lags are reported in the parentheses. *, **, *** indicate statistical sign ificance at 10%, 5% and 1% levels, respectively.

	HML_{t+1q}					MOM_{t+1q}				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Intercept	0.01	0.01	0.01	0.00	-0.00	0.02***	0.02***	0.02***	0.01	0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.006)	(0.006)	(0.006)	(0.01)	(0.01)
$\Delta\phi_t^{HML,Aggr}$	0.10	0.07	0.13	0.16	0.18			-0.11		-0.08
	(0.18)	(0.18)	(0.17)	(0.17)	(0.16)			(0.17)		(0.17)
$\Delta\phi_t^{MOM,Aggr}$			-0.55*		-0.64**	0.91***	0.87***	0.92***	0.85**	0.86**
			(0.29)		(0.27)	(0.30)	(0.28)	(0.30)	(0.33)	(0.33)
HML_t		0.18*		0.25**	0.28**				0.15	0.16
		(0.11)		(0.11)	(0.12)				(0.28)	(0.28)
MOM_t				-0.01	0.01		0.10		0.21	0.22
				(0.07)	(0.07)		(0.11)		(0.14)	(0.14)
MKT_t				0.11*	0.11				0.16	0.15
				(0.07)	(0.07)				(0.12)	(0.12)
SMB_t				0.20*	0.21**				0.25	0.24
				(0.11)	(0.10)				(0.16)	(0.16)
CMA_t				-0.12	-0.14				-0.14	-0.14
				(0.15)	(0.16)				(0.29)	(0.30)
RMW_t				0.20**	0.21**				-0.14	-0.15
				(0.09)	(0.09)				(0.13)	(0.13)
R^2	0.00	0.03	0.02	0.09	0.12	0.04	0.05	0.04	0.14	0.14
Observations	160	160	160	160	160	160	160	160	160	160