Factor Demand and Factor Returns[*]

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May 19, 2022

Abstract

We propose a novel source of predictable price pressure resulting from mutual funds' factor rebalancing behavior. When a fund's factor demand is persistent, it needs to rebalance the portfolio's factor exposure, leading to predictable trading at the stock level. This form of predictable trading operates independently from trading induced by retail flows and has distinct implications for cross-sectional return predictability. Consistent with demand-induced price pressure, stocks whose characteristics are well-matched with the underlying funds' factor demand experience more buying pressure and higher returns, whereas mismatched stocks experience more selling and lower returns. We calculate the scale of factor rebalancing and estimate an average factor demand elasticity of -0.23. (*JEL* G12, G23, G40)

[*]We are grateful to Nick Barberis, Thummim Cho, Zhi Da, Xavier Gabaix, Stefano Giglio, Will Goetzmann, Xing Huang, Wenxi Jiang, Marcin Kacperczyk, Leonid Kogan, Ralph Koijen, Augustin Landier, Dong Lou, Toby Moskowitz, Anna Pavlova, Christopher Polk, Veronika Pool, Anna Scherbina, Paul Schultz, Kelly Shue, Taisiya Sikorskaya, Yang Song, Kaushik Vasudevan, Dimitri Vayanos, Michela Verardo, and participants at 2019 RCFS/RAPS Conference at Baha Mar, 2019 CICF, 2019 SGF, 2021 AFA, 2021 MFA, 2021 NFA, 2022 Finance Down Under Conference, Birkbeck, BlackRock, Cambridge, LSE, Notre Dame, Peking University, USI Lugano, and Yale for useful conversations and comments. All errors are our own.

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1 Introduction

A large literature shows that asset prices are affected by institutional investors' demand, even when the demand itself contains little information or imposes no additional risk (see Gabaix and Koijen 2022 for a recent review). Existing evidence of the price impact of institutional demand mostly focuses on an individual stock or the entire stock market. At the stock level, the index inclusion effect suggests that shifts in demand from index-tracking funds affect the returns of stocks added to or deleted from major indices (Harris and Gurel 1986; Shleifer 1986; Wurgler and Zhuravskaya 2002; Chang et al. 2015; Pavlova and Sikorskaya 2020). At the market level, the inelastic market hypothesis posits that money flows in and out of the aggregate market determine the level of equity prices (Gabaix and Koijen 2022).

There is, however, less evidence that links institutional demand with cross-sectional return predictability or the performance of different asset pricing factors—a building block of empirical asset pricing. The existing literature, for example, has examined whether flow-induced demand shifts affect the performance of different factors (Ben-David et al. 2021). However, mutual funds do not just passively scale up or down their existing portfolios based on retail flows—they also rebalance for a variety of other reasons, which can shape cross-sectional return predictability in significant ways. In this paper, we propose a new source of institutional demand that operates regularly and predictably at the factor level, and we show that it has important implications for factor returns.

Our proposed mechanism builds on the premise that mutual funds often target a few well-known factors such as value and momentum and have persistent demand for these factors. This persistence in factor demand, combined with changing stock characteristics, induces a rebalancing motive to maintain a stable factor exposure. When many mutual funds engage in similar rebalancing at about the same time, their trading behavior induces predictable price pressure to the underlying stocks and leads to return predictability in the cross section. Unlike the existing frameworks, a stock's return is now determined not just by its own characteristics, but also by how these characteristics interact with the underlying funds' factor demand.

To fix the idea, consider two value stocks, A and B, with the same book-to-market (B/M) ratio. Stock A has long been a value stock; 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 mostly by value funds while stock B is by growth funds. If the expected return is solely determined by the B/M ratio and is unrelated to the stock's underlying investor demand, the two stocks are expected to earn the same return. However, according to our mechanism of factor rebalancing, stock B will experience lower subsequent returns because the underlying growth funds have a greater incentive to sell, which compresses the stock price.

We find significant support for this mechanism. We start by estimating mutual funds' factor demand and confirming 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 pricing factors, including size, value, and momentum, over the same period.[1] The loading on each factor represents the fund's *persistent* demand for that factor during the 5-year window. These fund-level factor loadings, constructed using a revealed-preference approach based on fund returns, are consistent with other proxies of factor demand and do not rely on the availability or accuracy of self-reported investment objectives. In comparison, holding-based measures only capture a snapshot of fund behavior and are more sensitive to extreme values in stock characteristics and fund manipulation. 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. For example, a fund's loadings on value and momentum show quarterly autocorrelations of 0.95 and 0.94, consistent with persistent factor demand in the time series.

Next, we examine whether persistent factor demand leads to predictable trading from mutual funds—a phenomenon we term "factor rebalancing." Specifically, we focus on value and momentum and examine whether mutual funds rebalance their portfolios to maintain a stable exposure to these two factors. We find evidence in support of factor rebalancing: factor demand interacts with stock characteristics to predict subsequent trading of mutual funds. In particular, when there is a "mismatch" between a stock's characteristic and the underlying funds' factor demand, the stock faces more selling pressure in the subsequent quarter. For instance, growth stocks held by value funds experience greater selling than growth stocks held by growth funds in the subsequent quarter.[2] We find similar selling pressure when a mismatch occurs between a stock's past

[1]Throughout this paper, by momentum, we mean price momentum, as opposed to other momentum-related phenomena such as earnings momentum or factor momentum.

[2]Although the growth stocks held by value funds, in theory, could face buying pressure from other growth funds,

return and the underlying funds' demand for momentum.

If predictable factor rebalancing induces price pressure, possibly due to a downward-sloping demand curve, then it would naturally lead to predictable returns. We confirm this prediction in the data. We first aggregate *fund*-level factor loadings at the *stock* level: for each stock in any given quarter, we calculate the holding-weighted average factor loadings of its underlying funds.[3] The resulting measures, called *factor demand*, represent the average factor loadings of a stock's underlying funds, rather than this stock's own factor loadings. To examine how mutual funds' factor demand interacts with stock characteristics, we then independently double-sort all stocks into 25 (5×5) portfolios based on their own characteristics and their factor demand (from the underlying funds). Out of the 25 value-based portfolios, the two that are most "mismatched"—that is, the one with the highest book-to-market (B/M) ratio but held by funds with the lowest value demand and the one with the lowest B/M 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-matched" portfolios—those with the highest (lowest) B/M ratio *and* held by funds with the highest (lowest) value demand—earn annualized value-weighted returns of 17.0% and 14.0%, respectively.

We identify two additional return patterns from the 25 value-based portfolios. First, we keep the B/M ratio constant and compare portfolios different in their underlying funds' value demand. Among value stocks, those with the highest value demand outperform those with the lowest value demand by an annualized return of 5.5%. In contrast, among growth stocks, those with the lowest value demand outperform those with the highest value demand by an annualized return of 10.4%. Second, we evaluate the conditional performance of the HML strategy based on the underlying funds' value demand. Among stocks held by the most value-prone funds, the HML strategy delivers an annualized return of 7.4%. In sharp contrast, among stocks held by the most growth-prone funds, the HML strategy delivers an annualized return of -8.5%, resulting in a "growth premium." The existence of such a sizable and significant growth premium over the

we find that such buying pressure is limited in the data because many of these stocks are likely to be outside of the empirically small investment universe of the growth funds in the first place. Indeed, Koijen and Yogo (2019) show that, for a median-sized mutual fund, 85 percent of stocks that are currently held were also held in the previous quarter, suggesting that the investment universe is rather stable over time for the same fund.

[3] The stock-level analysis is conducted at the quarterly frequency because mutual fund holdings data are reported quarterly.

last four decades is particularly striking, as it potentially offers an explanation for the seemingly puzzling fact that growth funds are popular despite that value stocks outperform unconditionally (Lettau et al. 2018).

The above return patterns from portfolio sorting are robust to alternative specifications, for example, when we examine equal-weighted portfolio returns and when we examine the CAPM alpha and a three-factor (market, size, and momentum) alpha. Sorting stocks independently into 5×5 portfolios, however, result in some portfolios containing only a few dozen stocks, leading to the concern that some outliers are responsible for the patterns. To address this concern, we instead independently double-sort stocks into 9 (3×3) portfolios. With each portfolio consisting of at least 100 stocks, this alternative sorting method mitigates the concern about power and outliers and yields similar return patterns.

For momentum, we similarly 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, by and large, are consistent with portfolio rebalancing, albeit with a smaller magnitude. We perform a series of subsample analyses to gain additional insights. For example, we show that the return patterns for value are robust 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. The return patterns are more pronounced in the latter sample, among stocks with higher mutual fund ownership, and among large-cap stocks. For momentum, however, the return patterns are stronger among stocks with higher mutual fund ownership, 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 et al. 2013).

To quantify the price impact of factor rebalancing, we estimate price elasticities for different HML and WML 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 discuss a few alternative explanations. First, flow-induced trading cannot explain our findings, because it is either orthogonal to or goes in the opposite direction of the observed return patterns. Second, herding does not appear to be driving the return patterns. For example, contrary to the herding literature, our return patterns in value are more pronounced in large-cap stocks. Third, the documented return patterns cannot be consistently explained by subsequent firm fundamentals. This evidence casts doubt on the notion that the return predictability stems from some funds having private information about future stock fundamentals. Fourth, we discuss and examine explanations based on fund specializations. For example, value funds specialize in picking value stocks, while growth funds specialize in picking growth stocks. We note that, as shown above, this skill-based explanation is not supported by subsequent fundamentals. Furthermore, this explanation is not supported by fund performance. If skills explain the return predictability, then factor-targeting funds such as value and momentum funds should substantially outperform other funds due to their superior stock-picking skills. However, on average, value and momentum funds exhibit annualized four-factor alphas of only 28bps and -8bps, respectively.

A vast literature has linked movements in stock prices to various mutual fund behaviors, such as 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). We share the similar prior that trading without information contents can also 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. 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.

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 characteristics-managed portfolio returns.

By showing that factor demand helps forecast future stock returns, we expand the existing set of cross-sectional stock return predictors. The literature has primarily focused on stocks' own characteristics as return predictors. We show that the characteristics of the underlying investors 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 interact with stock characteristics and fund characteristics and typically find a relatively small difference in returns. We show, however, 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 basic properties of these measures. Section 3 provides evidence for mutual funds' factor rebalancing behavior. Section 4 investigates return predictability and discusses its implications. Section 5 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 show 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.[4] The two datasets are then merged using the MFLinks files 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 only include 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 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.

[4] 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; and net returns and expense ratios are computed as the TNA-weighted averages across all share classes. For other fund characteristics, values from the share class with the largest TNA are used to represent the entire fund.

2.2 Measuring factor demand

For each fund i 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:

$$rret_{i,t+1-k} = \alpha_{i,t} + \beta_{i,t}^{MKT} MKT_{t+1-k} + \beta_{i,t}^{HML} HML_{t+1-k} + \beta_{i,t}^{SMB} SMB_{t+1-k} + \beta_{i,t}^{MOM} MOM_{i,t+1-k}$$

$$+\beta_{i,t}^{CMA} CMA_{t+1-k} + \beta_{i,t}^{RMW} RMW_{t+1-k} + \beta_{i,t}^{flow} flow_{i,t+1-k} + \varepsilon_{i,t,t+1-k}, \tag{1}$$

where $k = 1, 2, ..., 60$. $rret$ represents raw fund returns, 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.[5] We also control for the sensitivity of fund returns to retail flows by including $flow$, where $flow_{i,t} = \frac{TNA_{i,t}}{TNA_{i,t-1}} - (1 + ret_{i,t})$ and ret represents net fund returns. Therefore, for fund i in month t, we obtain seven beta coefficients: $\beta_{i,t}^{MKT}$ to $\beta_{i,t}^{flow}$. We will from now on refer to these coefficients as fund-level factor loading or factor demand interchangeably.[6]

In Equation (1), each $\beta_{i,t}$ measures the loading of fund i's return on a given factor over the last 60 months. Therefore, $\beta_{i,t}$ 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 auto-correlation in $\beta_{i,t}$, an issue we will return to in Section 2.3 when discussing the persistence of factor demand. While other approaches can also be used to measure funds' factor demand, our approach has two advantages. First, factor loadings are based on fund returns and therefore capture trading behavior between two reporting dates. For instance, if we instead measure factor demand for value using the average B/M ratio of end-of-quarter holdings, the resulting measure would provide an up-to-date snapshot of the fund's current exposure to value, but it does not capture fund activities between the two reporting dates thus says little about whether the fund is

[5] 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.

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

actively targeting value (Kacperczyk et al. 2008).[7] Furthermore, such holding-based measures are prone to quarter-end manipulations such as window dressing. Second, compared to mutual fund classifications or investment objectives, which often rely on funds' self-reported investment objectives and can be misreported or missing, our return-based measures are available for all funds with at least five years of return data.

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 think of 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 et al. 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 that are well-known and have been long established. Indeed, the underlying philosophies of value and momentum 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 also discovered more recently and are therefore less likely to be targeted by mutual funds. Indeed, if one looks at the reported investment objectives, many say "value" or "growth," some say "momentum," but very few say "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 B/M ratio and past one-year return change frequently at the stock level. This means that, if a fund targets either of the two strategies, it will have to rebalance regularly.

Table 2 reports the summary statistics of fund-level factor demand. Panel A of Table 2 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 et al. (2018), and a small and negative

[7] Lettau et al. (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.

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 B/M 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, 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[8]. Many of them have a specific investment objective, such as small-cap or growth, and by mandates they need to keep a relatively stable exposure to this factor. Therefore, as the set of stocks considered "small-cap" or "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 when 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 by force of habit. We use the term "habit" loosely and remain agnostic about its underlying causes. Economically, however, a number of factors may contribute to habit, such as persistent beliefs in the

[8] 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.

profitability of a trading strategy, a stable investment philosophy, and persistent use of similar technical analysis.

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

$$\beta^X_{i,q} = a + b \times \beta^X_{i,q-20} + \epsilon_{i,q}, \tag{2}$$

where X represents market, value, size, and momentum (the Carhart four factors).[9] Equation (2) runs a predictive regression by lagging factor loadings for 20 quarters (60 months), which ensures that the estimation windows for the two sides are non-overlapping.[10] We 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 very 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 show 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) run two additional regressions to shed light on 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 therefore is 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.

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

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

Column (6) runs a similar regression for value loadings and finds a similar pattern.[11]

2.4 Aggregate trends

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 factor loadings for size, value, and momentum all increase from 1980 up to the Great Recession, after which they decline. These patterns are roughly consistent with those in Lettau et al. (2018). 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.

3 Factor rebalancing

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

3.1 Transition probability

We start by discussing the necessary conditions for factor rebalancing. 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

[11] In the Online Appendix, Table A.1 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.1 runs additional regressions to show that factor demand is persistent after controlling for active shares (Cremers and Petajisto 2009).

the size strategy: firm size is very stable over time, and 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-prone 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 3.3.

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 B/M ratio.[12] We primarily focus on the diagonal 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 for the momentum strategy. Intuitively, this is because the past one-year return is more volatile than the B/M 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 B/M ratio. Panel D shows the transition probabilities between fund quintiles sorted on fund momentum loadings, where the diagonal terms 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

In this section, we investigate how mutual funds rebalance portfolios based on stock characteristics. The following fund-level regression estimates the marginal effect of a stock's B/M ratio

[12] Tables A.3 and A.4 in the Online Appendix shows more details about transition probabilities at other frequencies.

and past one-year return on mutual fund trading behavior in the next quarter:

$$trade_{i,j,q+1} = \alpha_t + \gamma_1 B/M_{i,q} + \gamma_2 r_{i,q-4,q-\frac{1}{3}} + \gamma_3 ME_{i,q} + \gamma_4 \beta_{i,q} + \varepsilon_{i,j,q+1}, \tag{3}$$

where $trade_{i,j,q+1}$ measures the trading in stock i by fund j in quarter $q+1$. We consider two variables to measure fund-level trading activities: $\Delta Shares_{i,j,q+1}/Shrout_{i,q}$, trading in shares in quarter $q+1$ normalized by stock i's total shares outstanding as of quarter q, and $\Delta Dollars_{i,j,q+1}/ME_{i,q}$, trading in dollars in quarter $q+1$ normalized by stock i's market capitalization as of quarter q. When constructing the two trade measures, we adjust for flow-induced trading (FIT) to isolate the trades from mutual funds' active portfolio rebalancing—which is our focus here—from those driven by retail flows; results are quantitatively similar without FIT adjustments.[13] The independent variables are stock i's characteristics in quarter q, including cross-sectionally demeaned book-to-market ratio, $B/M_{i,q}$; past one-year return (skipping the most recent month), $r_{i,q-4,q-1/3}$; market beta, $\beta_{i,q}$; and market capitalization (in billions), $ME_{i,q}$. To differentiate funds with different trading styles, we run the above regression for subsamples of funds that are either high or low in their factor betas; that is, subsamples of value, growth, momentum, and contrarian funds.

Table 5 reports the regressions results for Equation (3), using $\Delta Shares_{i,j,q+1}/Shrout_{i,q}$ as the dependent variable. In the Online Appendix, Table A.5 reports similar regression results using $\Delta Dollars_{i,j,q+1}/ME_{i,q}$ as the dependent variable. Panel A focuses on value. Columns (1) and (2) show that, consistent with rebalancing on value, the trading of value funds loads positively on the B/M ratio. In contrast, columns (3) and (4) show that the trading of growth funds load negatively on the B/M ratio, although in column (4) the coefficient is no longer statistically significant, possibly due to the inclusion of the past one-year return as a control variable. Panel B repeats

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

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

where $flow_{i,q}$ is the dollar flow to fund i in quarter q scaled by the fund's lagged TNA, and $shares_{i,j,q-1}$ is the number of shares held by fund i 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 a one-dollar sale of the existing portfolio.

the same set of analyses for momentum. Consistent with rebalancing on momentum, columns (1) and (2) show that momentum funds' trades load positively on past one-year return, whereas columns (3) and (4) show that contrarian funds' trades load negatively on past one-year return. Taken together, the portfolio rebalancing evidence suggests that mutual funds exhibit significant persistence in their trading styles, providing empirical support to our proposed mechanism of factor rebalancing.

3.3 Portfolio-level evidence

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 B/M 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 growth funds have an 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 theory, the selling pressure facing stock B can be canceled out if some value funds exhibit an equally strong demand to buy. However, there is ample reason to suspect that the selling pressure dominates the buying pressure. First, many of these "new" value stocks are likely to be outside of the empirically small investment universe of value funds in the first place. Indeed, Koijen and Yogo (2019) show that, for a median-sized mutual fund, 85 percent of stocks that are currently held were also held in the previous quarter and 94 percent were held in the previous 11 quarters, suggesting that the investment universe is highly persistent over time for the same fund. Therefore, the sellers have a strong incentive to sell this particular "mismatched" stock, while the buyers can choose from a large pool of value stocks that may not include stock B. Second, value funds that do not have stock B in their portfolios may not even realize that it is now a value stock, as starting a new position requires attention and takes time (Barber and Odean 2008; Hartzmark 2015). Therefore, on balance, stock B's selling pressure from growth funds is unlikely to be fully offset by value funds.

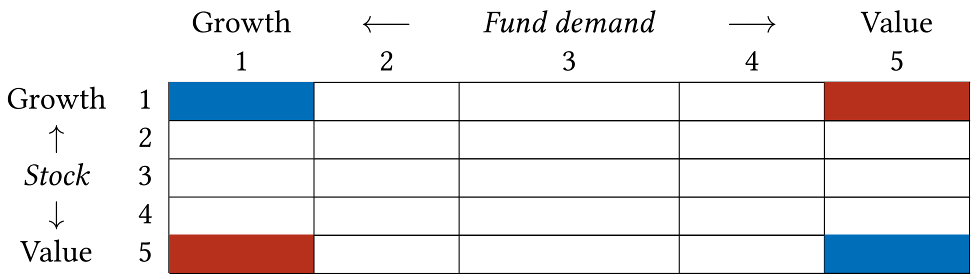

Figure 1: Stock portfolios well-matched and mismatched between own characteristics and underlying funds' demand for value

We test these predictions from factor rebalancing through portfolio-sorting, with the following intuition. Suppose that we double-sort stocks into 25 (5×5) portfolios based on the B/M ratio and the underlying funds' HML demand, as shown in the table below. The top-right corner and the bottom-left corner (both in red) represent two "mismatched" 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 underlying funds in subsequent periods. In comparison, the top-left corner and the bottom-right corner (both in blue) represent two portfolios "well-matched" in stocks' B/M 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.

In Panel A of Table 6, at the end of each quarter, all stocks are independently sorted into 25 portfolios based on their B/M ratios and $\overline{\beta}^{HML}$, where $\overline{\beta}^{HML}$ measures underlying funds' demand for value and is calculated as the shares-weighted average β^{HML} of the underlying funds.[14] 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 "mismatched" portfolios contain enough stocks. This is a common issue associated with the independent sorting procedure.[15] Panel A immediately addresses this concern: both portfolios contain, on average, more than 25 stocks. Therefore, even

[14]One may think that it is the change in the B/M ratio that should matter for mutual funds' rebalancing behavior. However, factor-targeting funds should just care about the level of the B/M ratio rather than its change. A deep value stock that recently experienced a drop in the B/M ratio is still considered a value, not a growth, stock.

[15]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.

the most value-prone funds hold some growth stocks and the most growth-prone funds hold some value stocks, establishing the third condition of factor rebalancing. Similarly, in Panel B, the two "mismatched" portfolios each contain more than 60 stocks.[16] 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 C, which concerns the 25 portfolios sorted on the B/M 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 "mismatched" portfolios—substantially underperform the other two corners—the two "well-matched" portfolios. The "mismatched" 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 B/M 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 HML beta of the underlying funds. The last column (Column "5–1") takes the differences in returns between two extreme portfolios in $\overline{\beta}^{HML}$. Among growth stocks (in the bottom B/M-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 B/M-quintile), those held by growth funds *underperform* by 5.5%. Therefore, a stock's future return depends not only on its own B/M 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 demand. For stocks in the bottom $\overline{\beta}^{HML}$-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 B/M ratio. Once we move away from the bottom $\overline{\beta}^{HML}$-quintile, the usual value premium reappears and reaches 7.4% in the top $\overline{\beta}^{HML}$-quintile. This evidence implies, from the perspective of portfolio

[16]Table A.6 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.

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 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 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.

There are a few possible reasons why our mechanism 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 reduce their exposure to momentum. For example, an average mutual fund has a β^{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 possible counterbalancing force is the disposition effect. As documented by Frazzini (2006), mutual funds exhibit a strong tendency to ride losses and realize gains, which may neutralize the potential price impact from momentum factor rebalancing.

3.4 Additional stock-level evidence and robustness

3.4.1 Flow-induced trading

A competing mechanism that also generates price pressure is flow-induced trading (FIT). 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 the corresponding asset pricing evidence may be ascribed to a flow effect instead. We have shown the robustness of 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 7. For value, the FIT for the HML portfolios (in line "HML") decreases from -0.23% for the low-$\bar{\beta}^{HML}$ stocks to -0.56% for the high-$\bar{\beta}^{HML}$ 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 7. Therefore, FIT cannot explain the documented return predictability from factor rebalancing.

3.4.2 Other measures of portfolio returns

Table 8 considers several alternative measures of portfolio returns. Panels A1 and A2 show that the same patterns hold for equal-weighted returns. Therefore, the documented return predictability is not driven solely by large-cap stocks. In fact, the momentum patterns are more pronounced among small-cap stocks. Panels B1 and B2 consider CAPM alpha and confirm the previous patterns in returns. In Panels C1 and C2, we compute alphas from three-factor models. For value, we use market, size, and momentum while purposely omitting the value factor to avoid the confounding effect from value itself; for momentum, we use market, size, and value. Similar to the case with CAPM alphas, the three-factor alpha patterns remain unchanged for value but weakens for momentum. We partially address this result below in Section 3.4.3.

3.4.3 Subsample analysis

We perform a series of subsample analyses and report the results in Tables 9 and 10. For simplicity, we only report the HML return for different $\overline{\beta}^{HML}$-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 9, 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 in 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 10 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 $\overline{\beta}^{MOM}$-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 11: four-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 9, the return patterns are most robust among stocks with high mutual fund ownership. Panels E and F show that, unlike value strategy, in which large stocks are more profitable than small ones, the momentum strategy works better for small stocks.

3.4.4 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 11. 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. The patterns of mismatched and well-matched portfolios and HML returns, however, remain the same and are robust to alternative asset-pricing models.

3.4.5 Stock-level regression

We also stock-level regressions to test whether the B/M ratio and past one-year return have different predictive power for stock returns conditional on different underlying funds. Specifically, we run the following panel regression:

$$r_{i,q+1} = \gamma_0 + \gamma_1 BM_{i,q} + \gamma_2 r_{i,q-4,q-\frac{1}{3}} + \gamma_3 ME_{i,q} + \gamma_4 {\beta_{i,q}}^{MKT} + \varepsilon_{i,q+1}, \tag{4}$$

where the dependent variable is stock i's return in quarter $q+1$. The independent variables include the book-to-market ratio, $BM_{i,q}$; past one-year return (skipping the most recent month), $r_{i,q-4,q-\frac{1}{3}}$; market beta, $\beta_{i,q}$, and market capitalization (in billions), $ME_{i,q}$. To evaluate whether return predictability improves conditional on mutual funds ownerships of different factor demand, we run this regression for subsamples of stocks that are low and high in their underlying funds' value and momentum betas.

Table 12 reports the results. Panel A shows the results for value, and we focus on the coefficients of the B/M ratio. In Columns (1) and (2), which represent the full-sample results, both coefficients are positive. Consistent with the price implications of factor rebalancing, in the subsample of high $\bar{\beta}^{HML}$ stocks, the coefficient is much greater at 0.0044, which more than quadruples the coefficient in the low $\bar{\beta}^{HML}$ subsample.

Panel B reports results for momentum. In Columns (3) and (4), the coefficients on past one-year returns are negative and close to zero. We suspect that this weak evidence for momentum stems from its weak performance in the second half of our sample, possibly due to momentum crashes (Daniel and Moskowitz 2017). Columns (5) and (6) show that, indeed, once we focus on the first half of the sample where momentum is more pronounced, the coefficient on past return becomes significantly positive in the high $\bar{\beta}^{MOM}$ subsample and insignificantly negative in the low $\bar{\beta}^{MOM}$ subsample.

4 Discussion

In this section, we first provide further stock-level evidence supporting the price impact of factor rebalancing by analyzing how trading from a subset of mutual funds (e.g., value funds) aggregates to the sorted portfolios. We then quantify the magnitude of the factor-level price impact induced by factor rebalancing and estimate corresponding demand elasticities. We finish this section by discussing and ruling out a few alternative explanations for our asset pricing results.

4.1 Whose trading matters?

The evidence presented in Section 3.3 confirms factor rebalancing using trades from mutual funds. A closer examination of our mechanism suggests that different funds play different roles in driving the trading patterns in Panel B of Table 6. To tighten the link between factor rebalancing and the stock-level price impact, it is worth exploring how trading from a subset of mutual funds aggregates to the sorted portfolios. For example, the selling of the bottom-left corner should be primarily driven by growth funds and the selling of the top-right corner by value funds. We now provide a sharper test of factor rebalancing by decomposing the sources of mutual fund ownership changes. Specifically, we examine funds with low and high factor betas separately. For the value (momentum) strategy, in each quarter, we define value (momentum) funds broadly as funds with HML (MOM) beta (estimated in the previous quarter) higher than the cross-sectional median and growth (contrarian) funds as those with HML (MOM) beta lower than the cross-sectional median.

In Panel A of Table 13, we decompose stock-level mutual fund ownership changes into those from value funds and growth funds. The left table shows the behavior of growth funds as a whole and the right table shows the behavior of value funds as a whole. In the left table, most of the actions indeed happen among the low-$\bar{\beta}^{HML}$ stocks. In aggregate, growth funds increase their ownership of the low-BM stocks by 0.35% and decrease their ownership of the high-BM stocks by 0.14%. In the right table, there is similar but weaker evidence: value funds increase their ownership of the high-BM stocks 0.11% more than the low-BM stocks do. This decomposition indicates that growth and value funds indeed trade to maintain a stable factor exposure as prescribed by factor rebalancing. They account for a significant portion of the stocks' mutual fund ownership changes. This evidence from the portfolio level tightens the link between mutual fund factor rebalancing and the stock returns pattern documented in the previous two subsections. The results for the momentum strategy are shown in Panel B of Table 13, where we find supporting evidence similar to that for the factor-rebalancing behavior from momentum and contrarian funds.

4.2 Implied price elasticity

While the portfolio returns we documented above are consistent with factor rebalancing, it would be useful to get a sense of the implied price elasticity based on factor rebalancing. This exercise will help put our work in the broad context of papers that study inelastic demand-induced price pressure. Doing such an exercise requires making additional assumptions about what part of the demand is inelastic. Though we do not take a strong stand on this matter in the previous sections, to operationalize this exercise, we assume that, for example, value funds—defined by having an HML beta above the median—have inelastic positive demand for value stocks and negative demand for growth stocks in their portfolio. When these value funds rebalance their portfolio to maintain a stable exposure to value, they purchase value stocks and liquidate growth stocks. Among stocks held by value funds, the changes in demand of the HML portfolio ($\Delta Demand$) is defined as the difference in quarterly changes in value-fund holdings between the long and short legs.[17] To get the price elasticity associated with these demand changes, we divide $\Delta Demand$ by quarterly returns of this HML portfolio ($\Delta Return$)[18]:

$$Elasticity = -\frac{\Delta Demand}{\Delta Return}. \tag{5}$$

With a flat or perfectly elastic demand curve, the price elasticity approaches $-\infty$, while with downward-sloping or inelastic demand, the estimate approaches zero. Notice that, different from previous studies of price elasticity at the micro (stock) level or macro (market) level, we compute our elasticity estimates at the factor level. We make similar assumptions about inelastic demand for four types of funds—value, growth, contrarian, and momentum—and back out the implied price elasticities for different HML and WML portfolios. We report detailed holding change by these four types of funds for each sorted portfolio and the long-short portfolios in Table 13 in the Online Appendix. The price elasticity estimates are reported in Table 14. Overall, our estimated elasticities are between -0.04 and -0.35, with an average of -0.21. These numbers are substantially larger than those that study micro elasticity, such as Harris and Gurel 1986; Shleifer 1986; Chang, Hong, and Liskovich 2015, but they are close to price elasticities estimated at the factor and market levels (Gabaix and Koijen 2022; Ben-David et al. 2021; Haddad et al. 2021). One potential explanation for such a low price elasticity, similar to that in Gabaix and Koijen (2022), is that among well-known and robust asset-pricing factors, finding a close substitute for a particular

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

[18] 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 long-short portfolios.

factor is difficult—in fact, value and momentum factors complement, rather than substitute, each other. It is arguably more difficult than finding a close substitute for Apple or Google among all stocks.

4.3 Long-term patterns

So far, we have primarily focused on mutual funds' trading behavior in the first quarter post-formation and their implications for stock prices. What happens if we hold the same sorted portfolios for many quarters? Suppose mutual funds rebalance sufficiently quickly while stock characteristics continue to change. In that case, we should expect the predictable trading documented in Section 3 to decrease in subsequent quarters, which would be associated with a narrowing gap in returns between the "well-matched" and "mismatched" portfolios. Figure 3 confirms that this is indeed the long-term pattern in total mutual fund ownership and returns. For both value and momentum, over the next eight quarters, the ownership difference between the "well-matched" and "mismatched" portfolios gradually decreases and the return difference drops to nearly zero. Therefore, mutual funds appear to be rebalancing their factor exposures rather quickly and most of the pricing implications concentrate on the immediate quarter.

4.4 Alternative explanations

In this subsection, we discuss several explanations alternative to factor rebalancing for the stock-level evidence documented in the previous subsections. In a previous section, we 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.

4.4.1 Subsequent stock fundamentals

In the real world, mutual funds trade for various reasons besides factor rebalancing. One such motive is that fund managers may have private information regarding the firm's future fundamentals. Stocks bought by fund managers with such an informational advantage are more likely to have good realized fundamentals in subsequent periods. The stock return dispersion in

Tables 6 may reflect fund managers' better forecasting ability for stock fundamentals.

We evaluate this possibility using stocks' post-formation standardized earnings surprises (SUE) and cumulative abnormal returns (CAR) around earnings announcement dates, where SUE is defined as earnings surprise relative to analysts' forecasts, normalized by the current stock price, and CAR is defined as the size and value-adjusted abnormal returns in a three-day window around an earnings announcement. Table 15 reports the subsequent SUE and CAR for the 25 portfolios sorted on stock characteristics and fund betas. Panels A and B report results for the value strategy: SUEs for the five HML long-short portfolios are all negative and the HML portfolio with high-$\overline{\beta}^{HML}$ has an SUE of -0.86, suggesting that value fund managers make poorer, not better, forecasts for future stock fundamentals. CARs for the five HML portfolios go in the same direction as our return evidence, although the magnitude is much smaller. Panels C and D report results for the momentum strategy. SUEs for the five WML portfolios are positive and the low-$\overline{\beta}^{MOM}$WML portfolio has a higher SUE than high-$\overline{\beta}^{MOM}$, contradicting the return evidence for momentum. The patterns of CAR for the WML portfolios are somewhat close to our return evidence, albeit with a smaller magnitude. One needs to interpret the CAR evidence with caution: the days around an earnings announcement are often associated with higher trading volume and greater attention from fund managers. Therefore, fund managers may decide to complete some of the factor rebalancing during these periods. Since we cannot observe the exact timing of each trade in our data, we leave this question for future research.

In summary, we find no coherent evidence in support of the alternative explanation based on fund managers' forecasting ability for future stock fundamentals. Most notably, subsequent SUE often goes in the wrong direction to explain our results, while CAR has a magnitude that is too small.

4.4.2 Other skill-based explanations

We note that the ability to forecast future fundamentals is just one facet of fund skills. If mutual funds exhibit skills that cannot be inferred from subsequent fundamentals, then our analysis in the previous section would not capture these skills. Indeed, it is possible that value funds specialize in value stocks while growth funds specialize in growth stocks and that their specializations explain differences in returns. However, it is challenging to use this explanation to reconcile some of the more detailed patterns in portfolio returns. For example, growth funds outperform value funds by more than 10% in their selection of growth stocks, a magnitude that seems difficult to rationalize based on the literature on mutual fund performance. Indeed, prominent proxies of mutual fund skill—such as the return gap, active shares, the sensitivity to public information, herding, and active fundamental performance—have generally found a difference in returns of less than 3% per year from between the two extreme deciles (Kacperczyk and Seru 2007; Kacperczyk, Sialm, and Zheng 2008; Cremers and Petajisto 2009; Jiang and Verardo 2018; Jiang and Zheng 2018). Furthermore, this explanation is not supported by fund performance. If skills explain the return predictability, then factor-targeting funds such as value and momentum funds should substantially outperform other funds due to their superior stock-picking skills. However, on average, value and momentum funds exhibit annualized four-factor alphas of only 28bps and -8bps, respectively, as shown by Table A.7 of the Online Appendix.

4.4.3 Herding

It is also possible that our results are driven by mutual fund herding. Wermers (1999) shows that stocks with a large increase in mutual fund ownership in the recent quarter tend to outperform subsequently. In another paper, Dasgupta, Prat, and Verardo (2011) shows that stocks with a persistent increase in mutual fund ownership tend to underperform subsequently. We want to point out that the two mechanisms are not mutually exclusive. In fact, Wermers (1999) speculates that positive feedback trading can be an important source of herding: driven by a common signal=(e.g., past stock returns) positive feedback traders herd—that is, they rush into buying past winners and selling past losers. Similarly, taking the B/M ratio as a common signal could lead to herding on either value or growth stocks. However, subsample analysis suggests that our results are unlikely to be driven entirely by the herding behavior documented in the literature. 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 matters more to small-cap stocks.

5 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 pricing factor, measured by the loading of the fund's returns on the factor's 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 as a whole 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 is at the factor level. Fourth, our results have implications for the mutual fund performance literature, which has primarily focused on the average performance of stocks. We show that further insights can be gained if we condition on stock characteristics.

While we have demonstrated consistent results on trading behavior and return predictability, a few questions remain open. First, while the evidence on return predictability is robust and consistent with factor rebalancing, it is also consistent with skill-based explanations. Therefore, it would be worthwhile to differentiate these two explanations further. Second, to the extent that our asset-pricing results represent profitable trading opportunities to be exploited, it remains unclear why they have sustained for almost 40 years and why some arbitrageurs do not exploit them. Third, 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.8 presents some preliminary evidence on using factor demand for predicting future factor returns. We leave these questions for future research.

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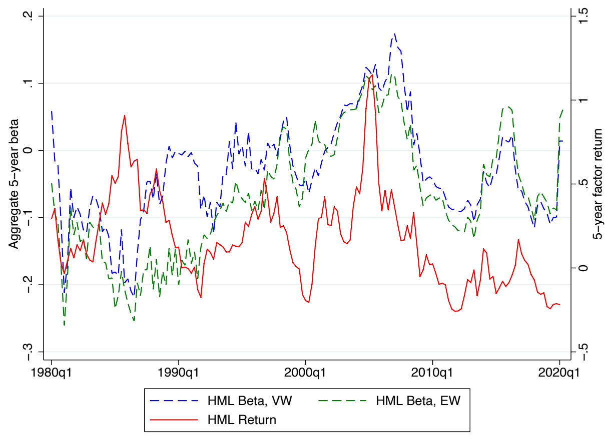
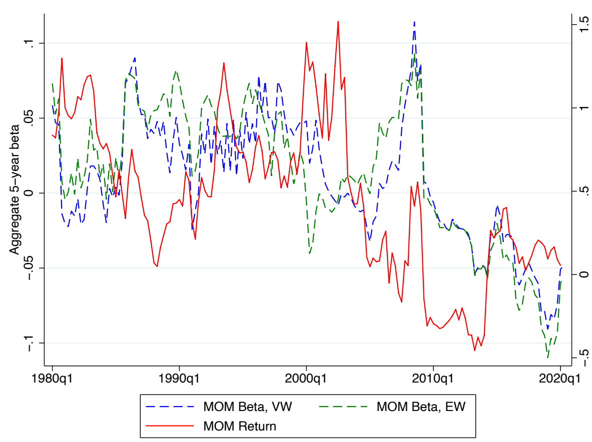
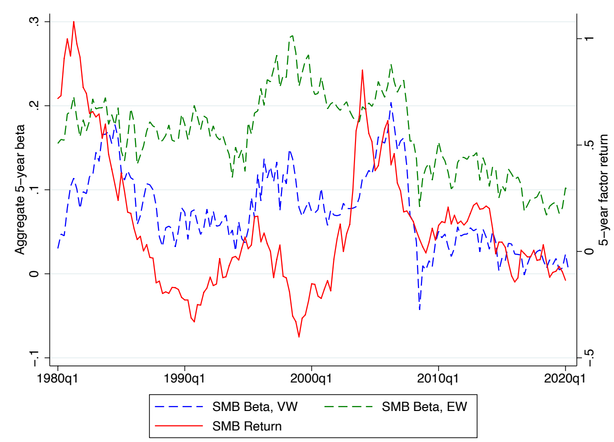


(a) Value



(b) Momentum



(c) Size

Figure 2: Aggregate factor loadings

Note: This figure plots the time series dynamics of factor loadings of the aggregate mutual fund industry from 1980 to 2019. Subfigures A, B and C plot value, momentum and size factors, 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.

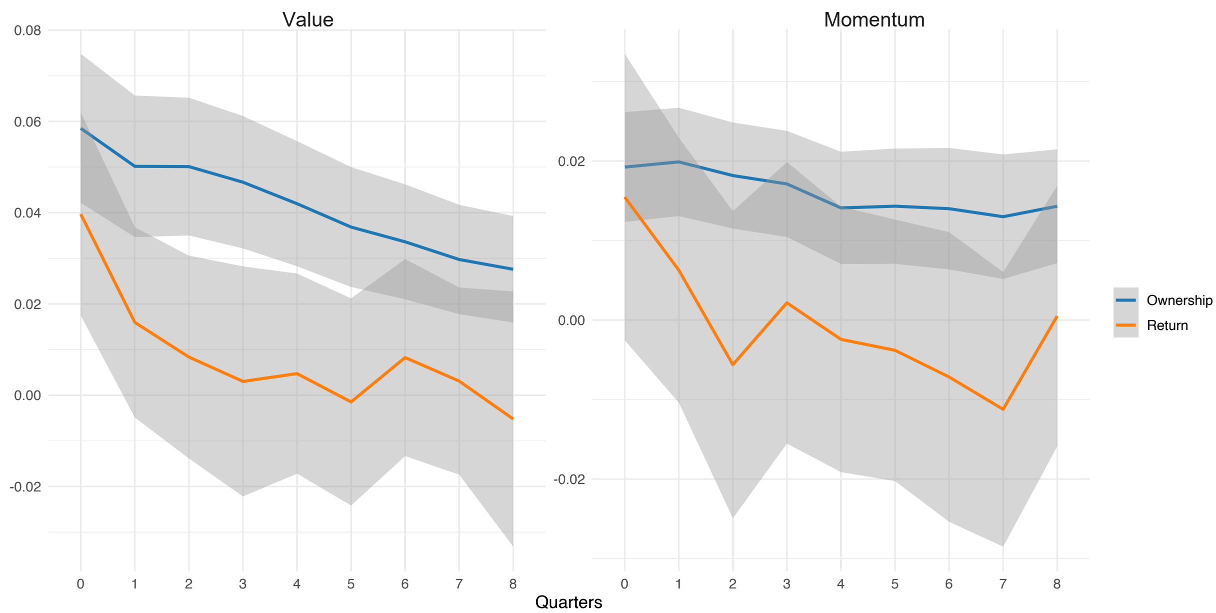


Figure 3: Post-formation Return and Mutual Fund Ownership

Note: This figure plots differences in post-formation quarterly returns and mutual fund ownership between high-minus-low (HML) portfolios with high and low underlying funds' betas. The left figure corresponds to value and the right figure corresponds to momentum. At the beginning of quarter 0, stocks are independently sorted into 25 bins based on B/M (past one-year return) and underlying funds' loading on value (momentum) factor. These portfolios are held for the next 8 quarters. For each fund beta quintile, the HML portfolio goes long in high B/M (past one-year return) stocks and short in low B/M (past one-year return) stocks. The differences in quarterly returns and mutual fund ownership between high and low fund beta HML portfolios are plotted in the figure. The shaded areas depict 95% confidence intervals.

	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 1: Summary statistics for the mutual fund sample

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

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	β^{MKT}	β^{SMB}	β^{HML}	β^{MOM}	β^{CMA}	β^{RMW}	β^{flow}
	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 2: Summary statistics of factor betas

Note: This table summarizes the distribution of factor betas. 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. For each fund i 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:

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

where $k = 1, 2, ..., 60$; $rret$ 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 $flow_{i,t} = \frac{TNA_{i,t}}{TNA_{i,t-1}} - (1 + ret_{i,t})$ and ret represents net fund returns. In Panel A, P5, P25, P50, P75, and P95 correspond to the 5th, 25th, 50th, 75th, and 95th percentiles in the distribution. In Panel B, the classifications of growth, value, small cap, medium cap, and large cap are from the Lipper mutual fund classifications. In Panel C, the classifications of index funds are provided by CRSP.

	(1)	(2)	(3)	(4)	(5)	(6)
	$\beta_{i,q}^{MKT}$	$\beta_{i,q}^{SMB}$	$\beta_{i,q}^{HML}$	$\beta_{i,q}^{MOM}$	$\beta_{i,q}^{SMB}$	$\beta_{i,q}^{HML}$
$\beta_{i,q-20}^{MKT}$	0.348***					
	(0.019)					
$\beta_{i,q-20}^{SMB}$		0.747***			0.424***	
		(0.012)			(0.021)	
$\beta_{i,q-20}^{HML}$			0.369***			0.297***
			(0.015)			(0.021)
$\beta_{i,q-20}^{MOM}$				0.293***		
				(0.019)		
Dummy_size					0.031***	
					(0.009)	
Dummy_size$\times\beta_{i,q-20}^{SMB}$					0.469***	
					(0.024)	
Dummy_BM						-0.039***
						(0.012)
Dummy_BM$\times\beta_{i,q-20}^{HML}$						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 3: Persistence of factor demand

Note: This table examines the persistence of factor demand. $\beta_{i,q}$ represents the loading on a given factor estimated using the five-year window in which q is the last quarter; $\beta_{i,q-20}$ represents the loading to a given factor estimated when $q-20$ is the last quarter of the five-year window. Therefore, $\beta_{i,q}$ and $\beta_{i,q-20}$ do not overlap in their estimation periods. For funds classified as small cap, medium cap, and large cap according to the Lipper mutual fund classifications, *Dummy_size* equals 1; otherwise, it equals 0. For funds classified as value or growth funds according to the Lipper mutual fund classifications, Dummy_BM equals 1; otherwise, it equals 0. All standard errors are double-clustered by fund and quarter. *, **, *** indicate statistical significance at 10%, 5% and 1% levels, respectively.

Panel A: Stock B/M

	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 β^{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: Stock $r_{t-12,t-2}$

	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 β^{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 4: One-year transition probability of stocks characteristics and mutual fund factor loadings

Note: This table reports the probability of a stock and a fund moving from one characteristic quintile to another quintile over one year. Panels A and B pertain to value and Panels C and D pertain to momentum. Stocks are sorted into different quintiles in each quarter based on their book-to-market ratios (B/M) in Panel A and their returns over the last year ($r_{t-12,t-2}$, skipping the most recent month) in Panel C. Funds are sorted into different quintiles in each quarter based on their loadings on HML (β^{HML}) in Panel B and their loadings on MOM (β^{MOM}) in Panel D. One-year transition probability represents the probability of moving from one quintile to another quintile between the current quarter and four quarters later.

Dependent variable: $\Delta Shares_{i,j,q+1}/Shrout_{i,q}$				
Panel A: Value				
	High-$\beta^{HML}_{j,q}$		Low-$\beta^{HML}_{j,q}$	
	(1)	(2)	(3)	(4)
$BM_{i,q}$	0.0159***	0.0116***	-0.0194***	-0.0053
	(0.0037)	(0.0034)	(0.0071)	(0.0055)
$r_{i,q-4,q-1/3}$		0.0005		0.1072***
		(0.0047)		(0.0065)
$\beta_{i,q}$		-0.0289***		0.0247***
		(0.0066)		(0.0090)
$ME_{i,q}$		-0.9863***		-1.482***
		(0.0568)		(0.0921)
R^2	0.0000	0.0025	0.0000	0.0104
Observations	6,575,970	6,548,231	3,615,836	3,584,211
Panel B: Momentum				
	High-$\beta^{MOM}_{j,q}$		Low-$\beta^{MOM}_{j,q}$	
	(1)	(2)	(3)	(4)
$r_{i,q-4,q-1/3}$	0.1027***	0.0980***	-0.0170**	-0.0132*
	(0.0064)	(0.0060)	(0.0081)	(0.0076)
$BM_{i,q}$		-0.0306***		0.0177***
		(0.0059)		(0.0039)
$\beta_{i,q}$		-0.0035		-0.0072
		(0.0051)		(0.0080)
$ME_{i,q}$		-1.286***		-1.51***
		(0.0700)		(0.0947)
R^2	0.0049	0.0082	0.0000	0.0044
Observations	5,875,288	5,845,588	2,778,921	2,763,143

Table 5: Fund-level portfolio rebalancing: FIT-adjusted trading in shares

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 in shares in quarter $q+1$, normalized by stock i's total shares outstanding as of quarter q. The independent variables are stock i's characteristics in quarter q, including the book-to-market ratio (demeaned cross-sectionally), $BM_{i,q}$; past one-year return (skipping the most recent month), $r_{i,q-4,q-1/3}$; market beta, $\beta_{i,q}$; and market capitalization (in billions), $ME_{i,q}$. Panels A and B report results for value and momentum, respectively. Columns (1) and (2) use funds in top quintile of $\beta^{HML}_{j,q}$ (Panel A) or $\beta^{MOM}_{j,q}$ (Panel B). Columns (3) and (4) use funds in bottom quintile of $\beta^{HML}_{j,q}$ (Panel A) or $\beta^{MOM}_{j,q}$ (Panel B). The data sample is from 1980Q1 to 2018Q4. Standard errors are clustered at quarter and fund levels. *, **, *** indicate statistical significance at 10%, 5% and 1% levels, respectively.

Panel A: Average number of stocks - value

		Low-$\overline{\beta}^{HML}$	$\longleftarrow$	*Fund*	$\longrightarrow$	High-$\overline{\beta}^{HML}$
		1	2	3	4	5
Low-B/M	1	220	132	71	41	27
$\uparrow$	2	124	142	110	72	45
Stock	3	61	103	122	115	92
$\downarrow$	4	35	67	106	134	150
High-B/M	5	26	50	92	139	184

Panel B: Average number of stocks - momentum

		Low-$\overline{\beta}^{MOM}$	$\longleftarrow$	*Fund*	$\longrightarrow$	High-$\overline{\beta}^{MOM}$
		1	2	3	4	5
Low-RET	1	131	107	98	87	70
$\uparrow$	2	124	117	104	87	63
Stock	3	106	116	110	95	69
$\downarrow$	4	87	102	108	108	90
High-RET	5	60	68	85	115	165

Panel C: Annualized portfolio return - value (%)

		Low-$\overline{\beta}^{HML}$	$\longleftarrow$	*Fund*	$\longrightarrow$	High-$\overline{\beta}^{HML}$	
		1	2	3	4	5	5−1
Low-B/M	1	17.0	11.9	8.8	10.0	6.6	-10.4
$\uparrow$	2	14.5	14.3	10.6	11.2	10.1	-4.4
Stock	3	17.3	14.1	12.5	10.7	11.7	-5.5
$\downarrow$	4	11.2	15.2	13.9	11.9	13.2	2.0
High-B/M	5	8.5	16.4	15.2	12.8	14.0	5.5
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]

Panel D: Annualized portfolio return - momentum (%)

		Low-$\overline{\beta}^{MOM}$	$\longleftarrow$	*Fund*	$\longrightarrow$	High-$\overline{\beta}^{MOM}$	
		1	2	3	4	5	5−1
Low-RET	1	7.5	7.5	9.9	8.3	12.4	4.9
$\uparrow$	2	10.2	10.9	12.1	11.5	14.0	3.8
Stock	3	10.0	11.4	13.5	12.9	17.2	7.3
$\downarrow$	4	10.5	11.6	11.5	14.4	16.2	5.6
High-RET	5	8.4	8.5	12.7	16.2	19.5	11.1
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 6: Characteristics and returns for portfolios sorted on 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 B/M ratios or past one-year returns (skipping the most recent month) and on their stock-level factor demand $\overline{\beta}^{HML}$ or $\overline{\beta}^{MOM}$, where $\overline{\beta}^{HML}$ or $\overline{\beta}^{MOM}$ are calculated as the shares-weighted average β^{HML} and β^{MOM} of a stock's underlying funds, respectively. Data are from 1980Q2 to 2018Q4.

Flow-induced trading (FIT, %)													
		Low-$\overline{\beta}^{HML}$	$\longleftarrow$	*Fund*	$\longrightarrow$	High-$\overline{\beta}^{HML}$			Low-$\overline{\beta}^{MOM}$	$\longleftarrow$	*Fund*	$\longrightarrow$	High-$\overline{\beta}^{MOM}$
		1	2	3	4	5			1	2	3	4	5
Low-B/M	1	-0.02	-0.07	0.10	0.11	0.42	Low-RET	1	-0.40	-0.42	-0.46	-0.49	-0.25
$\uparrow$	2	-0.40	-0.31	-0.29	-0.05	0.17	$\uparrow$	2	-0.23	-0.38	-0.35	-0.31	-0.27
Stock	3	-0.35	-0.29	-0.17	-0.04	0.18	*Stock*	3	-0.14	-0.33	-0.31	-0.22	-0.19
$\downarrow$	4	-0.24	-0.27	-0.16	-0.19	0.03	$\downarrow$	4	-0.07	-0.18	-0.14	-0.08	0.04
High-B/M	5	-0.25	-0.21	-0.13	-0.29	-0.14	High-RET	5	0.20	-0.10	0.06	0.10	0.42
HML		**-0.23**	**-0.14**	**-0.23**	**-0.39**	**-0.56**	WML		**0.60**	**0.32**	**0.52**	**0.59**	**0.67**

Table 7: 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 B/M ratios or past one-year returns (skipping the most recent month) and on their stock-level factor demand $\overline{\beta}^{HML}$ or $\overline{\beta}^{MOM}$, where $\overline{\beta}^{HML}$ and $\overline{\beta}^{MOM}$ are calculated as the shares-weighted average β^{HML} and β^{MOM} of a stock's underlying funds, respectively. We follow Lou (2012) and define FIT for each stock j in each quarter q as $FIT_{j,q} = \frac{\sum_i shares_{i,j,q-1} \times flow_{i,q} \times PSF}{\sum_i shares_{i,j,q-1}}$, where $flow_{i,q}$ is the dollar flow to fund i in quarter q scaled by the fund's lagged TNA and $shares_{i,j,q-1}$ is the number of shares held by fund i 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 left and right panels report quarterly average FIT for value and momentum-related portfolios, respectively.

Value

		Low-$\overline{\beta}^{HML}$	$\longleftarrow$	*Fund*	$\longrightarrow$	High-$\overline{\beta}^{HML}$	
Panel A1: EW portfolio returns (annualized, %)							
		1	2	3	4	5	5−1
Low-B/M	1	15.7	12.1	9.1	9.9	6.4	-9.3
High-B/M	5	11.8	16.7	16.2	15.0	13.9	2.1
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, %)							
		1	2	3	4	5	5−1
Low-B/M	1	5.0	3.0	1.0	2.8	-2.3	-7.3
High-B/M	5	-2.1	7.2	7.8	5.3	6.3	8.4
HML		-7.1	4.2	6.8	2.5	8.6	15.8
t-stats		[-6.59]	[5.25]	[10.02]	[3.24]	[12.48]	[13.54]
Panel C1: MKT+SMB+MOM 3-factor alpha (annualized, %)							
		1	2	3	4	5	5−1
Low-B/M	1	1.3	0.9	-0.6	1.8	-2.5	-3.8
High-B/M	5	1.8	10.1	10.1	8.0	9.4	7.6
HML		0.5	9.3	10.6	6.3	11.9	11.4
t-stats		[0.46]	[13.41]	[12.27]	[9.75]	[17.81]	[9.91]

Momentum

		Low-$\overline{\beta}^{HML}$	$\longleftarrow$	*Fund*	$\longrightarrow$	High-$\overline{\beta}^{HML}$	
Panel A2: EW portfolio returns (annualized, %)							
		1	2	3	4	5	5−1
Low-RET	1	7.8	8.3	8.0	8.3	10.2	2.4
High-RET	5	12.5	13.4	14.5	18.8	22.7	10.2
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, %)							
		1	2	3	4	5	5−1
Low-RET	1	-2.6	-2.8	1.0	-1.5	0.7	3.3
High-RET	5	0.4	0.0	4.0	6.6	7.8	7.4
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, %)							
		1	2	3	4	5	5−1
Low-RET	1	-5.9	-5.5	0.3	-0.5	3.6	9.5
High-RET	5	0.1	0.1	4.3	8.7	11.4	11.3
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: Alternative performance measures for 5×5 stock portfolios sorted on 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 B/M ratios and stock-level factor demand $\overline{\beta}^{HML}$(Panels A1, B1, and C1), or on their past one-year returns (skipping the most recent month) and stock-level factor demand $\overline{\beta}^{MOM}$ (Panels A2, B2, and C2). $\overline{\beta}^{HML}$ or $\overline{\beta}^{MOM}$ are calculated as the shares-weighted average β^{HML} and β^{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 the brackets. Data are from 1980Q2 to 2018Q4.

Panel A: Pre-1999 (annualized, %)

	Low-$\overline{\beta}^{HML}$	$\longleftarrow$	*Fund*	$\longrightarrow$	High-$\overline{\beta}^{HML}$	
	1	2	3	4	5	5−1
HML VW ret	-2.71	4.11	7.82	1.04	7.57	10.29
	[-0.51]	[0.92]	[1.91]	[0.24]	[2.08]	[2.05]
HML EW ret	0.10	3.31	6.37	3.23	4.41	4.31
	[0.02]	[0.89]	[1.99]	[0.87]	[1.53]	[1.02]
CAPM alpha	1.78	5.76	11.71	3.87	12.87	11.09
	[1.07]	[4.65]	[14.25]	[3.24]	[14.15]	[6.75]
3-factor alpha	9.13	10.98	18.49	9.59	15.06	5.93
	[6.28]	[10.31]	[20.39]	[9.26]	[12.56]	[3.52]

Panel B: Post-1999 (annualized, %)

	Low-$\overline{\beta}^{HML}$	$\longleftarrow$	*Fund*	$\longrightarrow$	High-$\overline{\beta}^{HML}$	
	1	2	3	4	5	5−1
HML VW ret	-13.94	4.91	5.04	4.50	7.17	21.11
	[-2.17]	[1.14]	[1.49]	[1.09]	[1.79]	[2.88]
HML EW ret	-7.65	5.86	7.78	6.85	10.44	18.09
	[-1.32]	[1.51]	[2.31]	[2.55]	[3.19]	[2.93]
CAPM alpha	-14.00	3.75	3.90	2.75	6.48	20.48
	[-7.69]	[3.40]	[3.28]	[3.29]	[6.69]	[10.06]
3-factor alpha	-9.31	6.33	5.27	3.78	8.89	18.20
	[-7.03]	[7.01]	[4.41]	[4.79]	[10.88]	[12.42]

Panel C: High MF ownership (annualized, %)

	Low-$\overline{\beta}^{HML}$	$\longleftarrow$	*Fund*	$\longrightarrow$	High-$\overline{\beta}^{HML}$	
	1	2	3	4	5	5−1
HML VW ret	-10.26	0.30	3.09	2.36	2.75	13.01
	[-2.13]	[0.08]	[1.17]	[0.87]	[0.88]	[2.51]
HML EW ret	-5.61	2.38	1.95	1.41	1.91	7.51
	[-1.19]	[0.73]	[0.82]	[0.55]	[0.68]	[1.54]
CAPM alpha	-8.35	0.13	3.54	1.72	3.02	11.37
	[-6.64]	[0.13]	[4.96]	[2.47]	[3.26]	[7.59]
3-factor alpha	-0.55	7.23	7.20	5.75	5.28	5.83
	[-0.54]	[7.21]	[10.70]	[8.55]	[5.62]	[4.19]

Panel D: Low MF ownership (annualized, %)

	Low-$\overline{\beta}^{HML}$	$\longleftarrow$	*Fund*	$\longrightarrow$	High-$\overline{\beta}^{HML}$	
	1	2	3	4	5	5−1
HML VW ret	-1.78	5.10	8.37	8.05	7.96	9.74
	[-0.44]	[1.64]	[2.80]	[2.32]	[2.21]	[2.14]
HML EW ret	3.03	6.35	9.30	8.74	8.44	5.41
	[0.85]	[2.20]	[3.36]	[2.99]	[2.92]	[1.33]
CAPM alpha	0.11	5.41	8.51	8.79	9.65	9.54
	[0.10]	[5.90]	[9.70]	[7.36]	[10.11]	[8.06]
3-factor alpha	5.79	9.58	12.03	13.84	14.01	8.22
	[6.01]	[12.49]	[12.74]	[11.82]	[15.37]	[7.66]

Panel E: Large stocks (annualized, %)

	Low-$\overline{\beta}^{HML}$	$\longleftarrow$	*Fund*	$\longrightarrow$	High-$\overline{\beta}^{HML}$	
	1	2	3	4	5	5−1
HML VW ret	-7.37	5.48	8.76	0.04	6.22	13.59
	[-1.61]	[1.51]	[3.72]	[0.01]	[2.21]	[2.63]
HML EW ret	-4.29	6.56	8.47	4.83	6.40	10.69
	[-0.99]	[2.08]	[3.57]	[2.07]	[2.34]	[2.34]
CAPM alpha	-5.77	4.86	9.10	-0.15	6.99	12.76
	[-4.57]	[4.58]	[12.62]	[-0.26]	[9.53]	[8.96]
3-factor alpha	1.52	10.20	11.96	3.50	9.22	7.70
	[1.33]	[10.25]	[18.12]	[6.26]	[13.15]	[5.91]

Panel F: Small stocks (annualized, %)

	Low-$\overline{\beta}^{HML}$	$\longleftarrow$	*Fund*	$\longrightarrow$	High-$\overline{\beta}^{HML}$	
	1	2	3	4	5	5−1
HML VW ret	-2.52	0.30	4.50	10.29	4.68	7.20
	[-0.59]	[0.08]	[1.51]	[3.34]	[1.51]	[1.46]
HML EW ret	-1.40	-0.77	4.55	9.55	2.72	4.11
	[-0.35]	[-0.23]	[1.60]	[3.18]	[0.97]	[0.93]
CAPM alpha	0.08	2.52	6.32	12.40	5.71	5.63
	[0.06]	[2.37]	[6.76]	[13.13]	[6.93]	[4.38]
3-factor alpha	7.34	9.79	12.04	15.98	8.70	1.37
	[6.13]	[10.53]	[14.01]	[17.29]	[11.12]	[1.13]

Table 9: Returns for 5×5 stock portfolios double-sorted on B/M ratios and HML betas, subsample analysis

Note: This table reports returns and alphas for each of the 25 portfolios double-sorted on B/M ratios and HML betas, $\overline{\beta}^{HML}$, where $\overline{\beta}^{HML}$ is calculated as the shares-weighted average β^{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 that are above the median mutual fund ownership in each quarter. Panel D uses stocks that are below the median mutual fund ownership in each quarter. Panel E uses stocks that are above the median firm size in each quarter. Panel F uses stocks that are below the median firm size in each quarter. When calculating 3-factor alphas, we control for market, size, and momentum. t statistics are reported in the brackets.

Panel A: Pre-1999 (annualized, %)

	Low-$\overline{\beta}^{MOM}$	$\longleftarrow$	*Fund*	$\longrightarrow$	High-$\overline{\beta}^{MOM}$	
	1	2	3	4	5	5−1
WML VW ret	2.72	4.50	7.81	13.43	15.58	12.87
	[0.66]	[1.08]	[2.00]	[3.01]	[3.78]	[2.69]
WML EW ret	10.38	10.58	12.84	17.60	20.39	10.01
	[3.54]	[3.37]	[4.87]	[5.63]	[6.46]	[3.71]
CAPM alpha	1.89	5.76	6.49	10.23	12.71	10.82
	[1.79]	[5.66]	[6.16]	[8.78]	[13.20]	[11.70]
3-factor alpha	4.32	4.71	5.35	9.38	15.37	11.05
	[4.07]	[4.63]	[5.17]	[8.36]	[17.10]	[8.57]

Panel B: Post-1999 (annualized, %)

	Low-$\overline{\beta}^{MOM}$	$\longleftarrow$	*Fund*	$\longrightarrow$	High-$\overline{\beta}^{MOM}$	
	1	2	3	4	5	5−1
WML VW ret	-0.66	-2.33	-1.95	2.81	-0.73	-0.07
	[-0.12]	[-0.44]	[-0.42]	[0.55]	[-0.13]	[-0.01]
WML EW ret	-0.57	0.10	0.62	3.85	5.13	5.70
	[-0.11]	[0.02]	[0.14]	[0.80]	[1.09]	[1.51]
CAPM alpha	2.34	-0.35	-0.96	4.54	0.73	-1.60
	[1.43]	[-0.22]	[-0.81]	[4.15]	[0.52]	[-0.89]
3-factor alpha	4.15	1.21	-0.05	6.37	3.13	-1.02
	[3.58]	[1.15]	[-0.04]	[5.59]	[2.04]	[-0.76]

Panel C: High MF ownership (annualized, %)

	Low-$\overline{\beta}^{MOM}$	$\longleftarrow$	*Fund*	$\longrightarrow$	High-$\overline{\beta}^{MOM}$	
	1	2	3	4	5	5−1
WML VW ret	0.65	-0.84	1.85	8.83	9.77	9.12
	[0.18]	[-0.25]	[0.53]	[2.35]	[2.53]	[2.27]
WML EW ret	3.78	2.83	5.35	10.20	11.30	7.51
	[1.20]	[1.03]	[1.71]	[3.13]	[3.33]	[2.62]
CAPM alpha	1.02	-0.23	1.49	9.55	10.54	9.52
	[0.97]	[-0.25]	[1.33]	[11.10]	[9.82]	[7.65]
3-factor alpha	4.35	2.51	3.26	11.75	12.49	8.14
	[5.28]	[3.01]	[3.55]	[13.28]	[10.44]	[6.75]

Panel D: Low MF ownership (annualized, %)

	Low-$\overline{\beta}^{MOM}$	$\longleftarrow$	*Fund*	$\longrightarrow$	High-$\overline{\beta}^{MOM}$	
	1	2	3	4	5	5−1
WML VW ret	2.79	2.90	6.45	5.73	5.33	2.55
	[0.77]	[0.69]	[1.78]	[1.46]	[1.45]	[0.66]
WML EW ret	5.70	8.23	8.45	7.75	12.12	6.41
	[1.83]	[2.77]	[2.85]	[2.58]	[3.95]	[2.25]
CAPM alpha	4.81	5.59	7.29	4.55	5.08	0.27
	[4.63]	[3.91]	[7.39]	[4.75]	[5.86]	[0.26]
3-factor alpha	6.73	8.16	8.26	4.50	5.29	-1.43
	[7.25]	[7.15]	[8.17]	[4.46]	[6.38]	[-1.68]

Panel E: Large stocks (annualized, %)

	Low-$\overline{\beta}^{MOM}$	$\longleftarrow$	*Fund*	$\longrightarrow$	High-$\overline{\beta}^{MOM}$	
	1	2	3	4	5	5−1
WML VW ret	1.06	-0.91	1.33	6.33	5.72	4.66
	[0.30]	[-0.28]	[0.42]	[1.88]	[1.49]	[1.13]
WML EW ret	0.90	0.90	2.27	6.57	7.63	6.73
	[0.28]	[0.32]	[0.79]	[2.16]	[2.19]	[1.94]
CAPM alpha	3.28	0.39	1.08	6.06	4.71	1.43
	[3.12]	[0.40]	[1.29]	[7.54]	[5.18]	[0.99]
3-factor alpha	6.11	3.26	2.65	7.37	5.22	-0.88
	[7.37]	[4.22]	[3.40]	[8.27]	[5.68]	[-0.80]

Panel F: Small stocks (annualized, %)

	Low-$\overline{\beta}^{MOM}$	$\longleftarrow$	*Fund*	$\longrightarrow$	High-$\overline{\beta}^{MOM}$	
	1	2	3	4	5	5−1
WML VW ret	7.79	7.88	11.09	14.31	13.64	5.85
	[2.11]	[2.62]	[3.69]	[4.68]	[4.21]	[1.70]
WML EW ret	7.83	9.61	11.76	15.06	15.51	7.68
	[2.34]	[3.37]	[3.87]	[4.99]	[5.17]	[2.45]
CAPM alpha	8.67	9.59	11.62	13.97	14.01	5.33
	[9.12]	[14.86]	[14.31]	[15.18]	[15.57]	[5.30]
3-factor alpha	11.88	11.67	12.55	15.25	15.13	3.25
	[13.81]	[17.68]	[14.42]	[14.58]	[15.54]	[3.90]

Table 10: Returns for 5×5 stock portfolios double-sorted on past returns and MOM betas, subsample analysis

Note: This table reports the return and average number of stocks for each of the 25 portfolios double-sorted on past one-year returns (skipping the most recent month) and MOM betas, $\overline{\beta}^{MOM}$, where $\overline{\beta}^{MOM}$ is calculated as the shares-weighted average β^{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 that are above the median mutual fund ownership in each quarter. Panel D uses stocks that are below the median mutual fund ownership in each quarter. Panel E uses stocks that are above the median firm size in each quarter. Panel F uses stocks that are below the median firm size in each quarter. When calculating 3-factor alphas, we control for market, size, and value. t statistics are reported in the brackets.

Panel A: VW portfolio returns (annualized, %)

		Low-$\overline{\beta}^{HML}$	←*Fund*→	High-$\overline{\beta}^{HML}$	
		1	2	3	3−1
Low-B/M	1	14.12	10.31	8.90	
Stock↕	2	14.26	12.09	11.17	
High-B/M	3	12.70	13.47	13.08	
HML		-1.41	3.17	4.18	5.59
t-stats		[-0.55]	[1.85]	[2.25]	[2.27]

Panel B: EW portfolio returns (annualized, %)

		Low-$\overline{\beta}^{HML}$	←*Fund*→	High-$\overline{\beta}^{HML}$	
		1	2	3	3−1
Low-B/M	1	14.59	11.02	8.94	
Stock↕	2	15.44	13.81	12.64	
High-B/M	3	15.20	15.51	13.76	
HML		0.61	4.49	4.81	4.20
t-stats		[0.25]	[2.73]	[2.65]	[2.11]

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

		Low-$\overline{\beta}^{HML}$	←*Fund*→	High-$\overline{\beta}^{HML}$	
		1	2	3	3−1
Low-B/M	1	1.73	1.56	0.56	
Stock↕	2	5.97	4.96	4.21	
High-B/M	3	5.81	7.31	7.96	
HML		4.07	5.75	7.40	3.33
t-stats		[6.89]	[14.03]	[15.56]	[5.19]

Panel D: Number of stocks

		Low-$\overline{\beta}^{HML}$	←*Fund*→	High-$\overline{\beta}^{HML}$
		1	2	3
Low-B/M	1	477	238	103
Stock↕	2	214	327	278
High-B/M	3	102	266	450

Table 11: Returns and characteristics for 3×3 stock portfolios double-sorted on the B/M ratio demand for value

Note: This table reports returns, alphas and number of stocks for 3×3 stock portfolios double-sorted on the B/M ratio and stock-level demand for value ($\overline{\beta}^{HML}$), where a stock's $\overline{\beta}^{HML}$ is calculated as the shares-weighted average β^{HML} of its underlying funds. Panels A, B and C report the value-weighted returns, equal-weight returns and alphas based on a model of MKT, SMB and MOM for each of the 9 portfolios and the corresponding HML portfolios, respectively. Panel D reports the average number of stocks for each of the portfolios. Quarterly portfolios are from 1980Q2 to 2018Q4.

	Dependent variable: $r_{i,q+1}$							
	Value		Momentum					
	Full sample		Full sample		Pre-1999		Post-1999	
	Low-$\bar{\beta}^{HML}_{i,q}$	High-$\bar{\beta}^{HML}_{i,q}$	Low-$\bar{\beta}^{MOM}_{i,q}$	High-$\bar{\beta}^{MOM}_{i,q}$	Low-$\bar{\beta}^{MOM}_{i,q}$	High-$\bar{\beta}^{MOM}_{i,q}$	Low-$\bar{\beta}^{MOM}_{i,q}$	High-$\bar{\beta}^{MOM}_{i,q}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$BM_{i,q}$	0.0010**	0.0044***	0.0007	0.0025*	0.0003	0.0016**	0.0037	0.0184***
	(0.0004)	(0.0013)	(0.0007)	(0.0013)	(0.0004)	(0.0007)	(0.0025)	(0.0051)
$r_{i,q-4,q-1/3}$	0.0037**	0.0019	-0.0042*	0.0016	-0.0037	0.0190***	-0.0041	-0.0040**
	(0.0017)	(0.0018)	(0.0025)	(0.0016)	(0.0044)	(0.0032)	(0.0027)	(0.0018)
$ME_{i,q}$	-0.2037***	0.1119	-0.0512	-0.2883***	-0.2304	0.2580	-0.0005	-0.2218***
	(0.0399)	(0.0963)	(0.0325)	(0.0512)	(0.2314)	(0.1854)	(0.0315)	(0.0510)
$\beta_{i,q}$	-0.0083***	-0.0103***	-0.0127***	-0.0009	-0.0012	0.0191***	-0.0149***	-0.0163***
	(0.0024)	(0.0014)	(0.0018)	(0.0024)	(0.0027)	(0.0029)	(0.0024)	(0.0030)
R^2	0.0000	0.0013	0.0012	0.0000	0.0000	0.0058	0.0020	0.0028
Observations	69,902	76,254	76,898	69,042	35,045	30,309	41,853	38,733

Table 12: Stock-level cross-sectional regressions

Note: This table reports results from the stock return predictive regressions

$$r_{i,q+1} = \gamma_0 + \gamma_1 BM_{i,q} + \gamma_2 r_{i,q-4,q-\frac{1}{3}} + \gamma_3 ME_{i,q} + \gamma_4 \beta_{i,q} + \varepsilon_{i,q+1},$$

where the dependent variable is stock i's return in quarter $q+1$. The independent variables include the book-to-market ratio, $BM_{i,q}$; past one-year return (skipping the most recent month), $r_{i,q-4,q-\frac{1}{3}}$; market beta, $\beta_{i,q}$; and market capitalization (in billions), $ME_{i,q}$. In Columns (1) and (2), we separately estimate the regressions for stocks whose underlying investors' demand for value (measured by $\bar{\beta}^{HML}_{i,q}$) is in the bottom and top quintiles. In Columns (3) to (8), we perform similar analyses concerning momentum with three sample periods: full sample (Columns (3) and (4)), pre-1999 sample (Columns (5) and (6)), and post-1999 sample (Columns (7) and (8)). Within each sample period, we separately estimate the regressions for stocks whose underlying investors' demand for momentum (measured by $\bar{\beta}^{MOM}_{i,q}$) is in the bottom and top quintiles. Standard errors are clustered by year-quarter. *, **, *** indicate statistical significance at 10%, 5% and 1% levels, respectively.

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

		Growth funds							Value funds				
		Low-$\overline{\beta}^{HML}$	⟵	*Fund*	⟶	High-$\overline{\beta}^{HML}$			Low-$\overline{\beta}^{HML}$	⟵	*Fund*	⟶	High-$\overline{\beta}^{HML}$
		1	2	3	4	5			1	2	3	4	5
Low-B/M	1	**0.34**	0.14	0.10	0.06	0.00	Low-B/M	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	*Stock*	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-B/M	5	**-0.14**	0.02	0.01	0.00	0.01	High-B/M	5	0.13	0.19	0.18	0.23	**0.23**
HML		**-0.48**	**-0.12**	**-0.09**	**-0.06**	**0.01**	HML		**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-$\overline{\beta}^{MOM}$	⟵	*Fund*	⟶	High-$\overline{\beta}^{MOM}$			Low-$\overline{\beta}^{MOM}$	⟵	*Fund*	⟶	High-$\overline{\beta}^{MOM}$
		1	2	3	4	5			1	2	3	4	5
Low-RET	1	**0.21**	0.23	0.23	0.26	0.17	Low-RET	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	*Stock*	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	High-RET	5	0.16	0.24	0.24	0.40	**0.53**
WML		**-0.19**	-0.29	-0.17	-0.22	-0.08	WML		0.18	0.23	0.26	0.39	**0.63**

Table 13: Decomposition of total mutual fund ownership changes

Note: This table reports the average ownership changes from funds with low and high factor betas separately. In each quarter, stocks are independently sorted into 25 portfolios based on their B/M ratios or past one-year returns (skipping the most recent month) and on their $\overline{\beta}^{HML}$ or $\overline{\beta}^{MOM}$, calculated as the shares-weighted average β^{HML} and β^{MOM} of the underlying funds, respectively. We calculate ownership changes for a subset of mutual funds for each portfolio in each quarter and take their time-series averages. For value (momentum) strategy, we define value (momentum) funds as funds with HML (MOM) beta higher than the cross-sectional median and growth (contrarian) funds as those lower than the cross-sectional median. Panels A and B report the decomposition of mutual fund ownership change for value and momentum, respectively.

	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 14: Estimates of price elasticity of demand

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

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

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

		Panel A: SUE (%), value								Panel B: CAR (%), value					
		Low-$\overline{\beta}^{HML}$	$\longleftarrow$	*Fund*	$\longrightarrow$	High-$\overline{\beta}^{HML}$				Low-$\overline{\beta}^{HML}$	$\longleftarrow$	*Fund*	$\longrightarrow$	High-$\overline{\beta}^{HML}$	
		1	2	3	4	5	5−1			1	2	3	4	5	5−1
Low-B/M	1	0.16	0.24	0.24	0.33	0.36	0.20	Low-B/M	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	*Stock*	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-B/M	5	-0.86	-0.63	-0.45	-0.45	-0.49	0.36	High-B/M	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	HML		-0.42	-0.06	0.46	0.50	0.17	0.59

		Panel C: SUE (%), momentum								Panel D: CAR (%), momentum					
		Low-$\overline{\beta}^{MOM}$	$\longleftarrow$	*Fund*	$\longrightarrow$	High-$\overline{\beta}^{MOM}$				Low-$\overline{\beta}^{MOM}$	$\longleftarrow$	*Fund*	$\longrightarrow$	High-$\overline{\beta}^{MOM}$	
		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	Low-RET	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	*Stock*	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	High-RET	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	WML		-0.53	0.14	0.23	-0.15	0.18	0.72

Table 15: Subsequent fundamentals for 5×5 stock portfolios double-sorted on stock characteristics and fund betas

Note: Panels A and B report subsequent fundamentals (SUE and CAR) for the 25 portfolios double-sorted on B/M ratios and HML betas, $\overline{\beta}^{HML}$, where $\overline{\beta}^{HML}$ is calculated as the shares-weighted average β^{HML} of the underlying funds. Panels C and D report subsequent fundamentals (SUE and CAR) for the 25 portfolios double-sorted on B/M ratios and HML betas, $\overline{\beta}^{HML}$, where $\overline{\beta}^{HML}$ is calculated as the shares-weighted average β^{HML} of the underlying funds. Standardized earnings surprise (SUE) is defined as earnings surprise relative to analysts' forecasts, normalized by the current stock price. Cumulative abnormal returns (CAR) is defined as the size and value-adjusted abnormal returns in a three-day window around the earnings announcements.

Online Appendix for

“Factor Demand and Factor Returns”

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

*p<0.1; **p<0.05; ***p<0.01.

Table A.1: Persistence of factor demand for value and momentum

Note: This table examines the persistence of factor demand. $\beta_{i,q}$ represents the loading to a given factor estimated using the five-year window in which q is the last quarter; $\beta_{i,q-20}$ represents the loading to a given factor estimated when $q-20$ is the last quarter of the five-year window. Therefore, $\beta_{i,q}$ and $\beta_{i,q-20}$ do not overlap in their estimation periods. *PureIndex* is an indicator for passive index funds. *AllIndex* is an indicator for all index funds.

	$\beta^{HML}_{i,q}$		$\beta^{MOM}_{i,q}$	
	(1)	(2)	(3)	(4)
$\beta^{HML}_{i,q-20}$	0.886***	1.013***		
	(0.054)	(0.066)		
$\beta^{MOM}_{i,q-20}$			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 $\times \beta^{HML}_{i,q-20}$	-0.546***			
	(0.066)			
ActiveShare (SD) $\times \beta^{HML}_{i,q-20}$		-0.620***		
		(0.084)		
ActiveShare $\times \beta^{MOM}_{i,q-20}$			-0.252***	
			(0.080)	
ActiveShare (SD) $\times \beta^{MOM}_{i,q-20}$				-0.263***
				(0.077)
Quarter FE	Yes	Yes	Yes	Yes
Obs.	125,512	87,000	125,512	87,000
R-squared	0.307	0.364	0.184	0.228

*p<0.1; **p<0.05; ***p<0.01.

Table A.2: Persistence of factor demand for value and momentum, controlling for active shares

Note: This table examines the persistence of factor demand. $\beta_{i,q}$ represents the loading to a given factor estimated using the five-year window in which q is the last quarter; $\beta_{i,q-20}$ represents the loading to a given factor estimated when $q-20$ is the last quarter of the five-year window. Therefore, $\beta_{i,q}$ and $\beta_{i,q-20}$ 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-decleared benchmarks, respectively, from Cremers and Petajisto (2009). The standard errors are clustered at fund and date levels.

Panel A: One-quarter transition, B/M

	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, B/M

	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, $r_{t-12,t-2}$

	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, $r_{t-12,t-2}$

	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.3: 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 (B/M). In Panels C and D, stocks are sorted into different quintiles in each quarter based on their returns over the last year ($r_{t-12,t-2}$, 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, β^{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, β^{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, β^{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, β^{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.4: 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 β^{HML} and Panels C and D report transition probabilities based on β^{MOM}. 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.

Dependent variable: $\Delta Dollar_{i,j,q+1}/ME_{i,q}$				
Panel A: Value				
	Low-$\beta_{j,q}^{HML}$		High-$\beta_{j,q}^{HML}$	
	(1)	(2)	(3)	(4)
$BM_{i,q}$	-0.0068	0.0000	0.0185***	0.0137***
	(0.0048)	(0.0035)	(0.0039)	(0.0035)
$r_{i,q-4,q-1/3}$		0.1011***		-0.0032
		(0.0064)		(0.0046)
$\beta_{i,q}$		0.0197**		-0.0297***
		(0.0088)		(0.0066)
$ME_{i,q}$		-1.505***		-0.9802***
		(0.0939)		(0.0567)
R^2	0.0000	0.0095	0.0000	0.0025
Observations	3,622,974	3,590,458	6,584,249	6,555,659
Panel B: Momentum				
	Low-$\beta_{j,q}^{MOM}$		High-$\beta_{j,q}^{MOM}$	
	(5)	(6)	(9)	(10)
$r_{i,q-4,q-1/3}$	-0.0228***	-0.0195***	0.0963***	0.0923***
	(0.0078)	(0.0074)	(0.0062)	(0.0059)
$BM_{i,q}$		0.0139**		-0.0252***
		(0.0053)		(0.0051)
$\beta_{i,q}$		-0.0121		-0.0062
		(0.0078)		(0.0051)
$ME_{i,q}$		-1.487***		-1.321***
		(0.0941)		(0.0715)
R^2	0.0000	0.0043	0.0042	0.0075
Observations	2,782,034	2,766,048	5,885,403	5,855,197

Table A.5: Fund-level portfolio rebalancing: FIT-adjusted trading in dollars

Note: This table reports how mutual funds rebalance their portfolios based on stock characteristics. The dependent variable, $\Delta Dollars_{i,j,q+1}/ME_{i,q}$, is FIT-adjusted trading in dollars in quarter $q+1$ normalized by stock i's market capitalization as of quarter q. The independent variables are stock i's characteristics in quarter q, including the book-to-market ratio (demeaned cross-sectionally), $BM_{i,q}$; past one-year return (skipping the most recent month), $r_{i,q-4,q-1/3}$; market beta, $\beta_{i,q}$; and market capitalization (in billions), $ME_{i,q}$. Panels A and B report results for value and momentum, respectively. Columns (1) and (2) use funds in top quintile of $\beta_{j,HML}$ (Panel A) or $\beta_{j,MOM}$ (Panel B). Columns (3) and (4) use funds in bottom quintile of $\beta_{j,HML}$ (Panel A) or $\beta_{j,MOM}$ (Panel B). The data sample is from 1980Q1 to 2018Q4. Standard errors are clustered at quarter and fund levels. *, **, *** indicate statistical significance at 10%, 5% and 1% levels, respectively.

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

		B/M							$\overline{\beta}^{HML}$					
		Low-$\overline{\beta}^{HML}$	$\longleftarrow$	*Fund*	$\longrightarrow$	High-$\overline{\beta}^{HML}$			Low-$\overline{\beta}^{HML}$	$\longleftarrow$	*Fund*	$\longrightarrow$	High-$\overline{\beta}^{HML}$	
		1	2	3	4	5	5−1		1	2	3	4	5	5−1
Low-B/M	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-B/M	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 $r_{t-12,t-1}$ and MOM betas

		$r_{t-12,t-1}$							$\overline{\beta}^{MOM}$					
		Low-$\overline{\beta}^{MOM}$	$\longleftarrow$	*Fund*	$\longrightarrow$	High-$\overline{\beta}^{MOM}$			Low-$\overline{\beta}^{MOM}$	$\longleftarrow$	*Fund*	$\longrightarrow$	High-$\overline{\beta}^{MOM}$	
		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.6: 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 B/M ratios and HML betas, $\overline{\beta}^{HML}$, where $\overline{\beta}^{HML}$ is calculated as the shares-weighted average β^{HML} of the underlying funds. Panel B reports results for stocks double-sorted on one-year past return ($r_{t-12,t-1}$) and MOM betas, $\overline{\beta}^{MOM}$, where $\overline{\beta}^{MOM}$ is calculated as the shares-weighted average β^{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.

	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	0.1020**	0.1264**			0.0115	0.0296			0.0498	0.0604		
	(0.0508)	(0.0523)			(0.0394)	(0.0393)			(0.0437)	(0.0429)		
High $\beta_{HML,q}$	0.0610		0.0508		0.0897***		0.0880***		0.0706***		0.0714***	
	(0.0447)		(0.0448)		(0.0263)		(0.0261)		(0.0259)		(0.0255)	
Low $\beta_{HML,q}$	0.0401		0.0379		-0.0258		-0.0252		-0.0229		-0.0213	
	(0.0413)		(0.0426)		(0.0298)		(0.0307)		(0.0265)		(0.0273)	
High $\beta_{MOM,q}$		0.0011		0.0044		-0.0110		-0.0078		-0.0237		-0.0223
		(0.0404)		(0.0410)		(0.0301)		(0.0310)		(0.0255)		(0.0263)
High $\beta_{MOM,q}$		0.0125		0.0082		0.0099		0.0079		0.0287		0.0257
		(0.0381)		(0.0368)		(0.0327)		(0.0322)		(0.0331)		(0.0318)
$\log(age)_q$	-0.0205	-0.0214	0.0198*	0.0189*	0.0207	0.0201	0.0359***	0.0357***	0.0157	0.0160	0.0312***	0.0317***
	(0.0160)	(0.0163)	(0.0102)	(0.0102)	(0.0145)	(0.0146)	(0.0100)	(0.0098)	(0.0154)	(0.0153)	(0.0102)	(0.0099)
$\log(tna)_q$	-0.0128**	-0.0130**	-0.0141***	-0.0143***	-0.0186***	-0.0184***	-0.0163***	-0.0164***	-0.0182***	-0.0180***	-0.0172***	-0.0172***
	(0.0053)	(0.0053)	(0.0048)	(0.0048)	(0.0047)	(0.0048)	(0.0040)	(0.0041)	(0.0044)	(0.0045)	(0.0038)	(0.0038)
$flow_q$	0.0003	0.0003	0.0004*	0.0004*	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0001	0.0001
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0001)	(0.0001)	(0.0002)	(0.0002)
$expense_q$	3.806*	3.905*	1.102	1.191	-0.3668	-0.5005	-1.648	-1.795	-1.384	-1.467	-2.664**	-2.744**
	(2.162)	(2.216)	(1.261)	(1.315)	(1.571)	(1.549)	(1.220)	(1.218)	(1.707)	(1.692)	(1.348)	(1.342)
Date FE			✓	✓			✓	✓			✓	✓
R^2	0.0037	0.0030	0.1067	0.1062	0.0030	0.0011	0.0820	0.0801	0.0022	0.0013	0.0801	0.0792
N	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.7: 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 percentage. 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 are clustered at quarter and fund levels. *, **, *** indicate statistical significance 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)
$\Delta\beta_t^{HML,Aggr}$	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)
$\Delta\beta_t^{MOM,Aggr}$			-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				-0.008	0.006		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	0.0022	0.0330	0.0234	0.0923	0.1209	0.0406	0.0508	0.0424	0.1361	0.1371
Observations	160	160	160	160	160	160	160	160	160	160

Table A.8: Predicting aggregate factor returns with changes in average mutual fund factor demand

Note: This table reports results from the aggregate factor return predictive regressions

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

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 j is measured as the simple average across all mutual funds in our sample $\beta_t^{j,Aggr} \equiv \frac{1}{N}\sum_{i=1}^{N}\beta_{i,t}^{j}$. 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 significance at 10%, 5% and 1% levels, respectively.