Factor Demand and Factor Returns*

Cameron Peng[†]

Chen Wang[‡]

March 8, 2023

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 frequently rebalance its portfolio's factor exposure, leading to stock-level predictable trading and price pressure. We confirm the persistence of factor demand and show that factor rebalancing is prevalent and operates independently from trading induced by retail flows. Consistent with demand-induced price pressure, stocks whose characteristics are mismatched with the underlying funds' factor demand experience lower returns, whereas well-matched stocks experience higher returns. We rule out alternative explanations based on private information, skills, and herding. (*JEL* G12, G23, G40)

^{*}We are grateful to Nick Barberis, Adrian Buss, Thummim Cho, Zhi Da, Chukwuma Dim, 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, Stijn Van Nieuwerburgh, Kaushik Vasudevan, Dimitri Vayanos, Michela Verardo, Sumudu Watugala, Russ Wermers, Ran Xing, 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, 2022 SFS Cavalcade North America, 2022 FIRS, 2022 EFA, Birkbeck, BlackRock, Cambridge, LSE, Notre Dame, Peking University, USI Lugano, and Yale for useful conversations and comments. All errors are our own.

[†]Department of Finance, London School of Economics and Political Science. E-mail: c.peng9@lse.ac.uk [‡]Mendoza College of Business, University of Notre Dame. E-mail: chen.wang@nd.edu

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 individual stocks or the entire stock market.¹ 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 different 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 on the underlying stocks and leads to return predictability in the cross section. Under this framework, a stock's expected 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

¹At 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).

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 it, which compresses the stock price.

We find significant support for this mechanism. We start by estimating mutual funds' factor demand and verifying its persistence over time. Each month, we regress a fund's monthly raw returns over the last 60 months on the monthly returns of several well-known pricing factors, including size, value, and momentum, over the same period. The loading on each factor represents the fund's persistent demand for that factor in the past five years. 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. 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. To be precise, a fund's loadings on value and momentum exhibit quarterly autocorrelations of 0.95 and 0.94 respectively, indicating stable factor demand in the time series. We obtain similar levels of persistence using alternative measures of factor demand, for example, based on the factor exposure of mutual fund holdings.

Next, we examine whether persistent factor demand leads to predictable trading from mutual funds—a phenomenon we term "factor rebalancing." In the paper, we examine both value and momentum; here, we focus on value for brevity. We first show that both value and growth funds trade according to their factor demand through portfolio rebalancing—replacing stocks that no longer align with their factor demand with stocks that do. By aggregating trades to the stock level, we find that factor demand interacts with stock characteristics to predict subsequent trading patterns. In particular, when there is a "mismatch" between a stock's characteristic and the underlying funds' factor demand, this stock will face more selling pressure in the subsequent quarter. For example, growth stocks held by value funds experience greater selling in the subsequent quarter than growth stocks held by growth funds.

In principle, for growth stocks held by value funds, the selling pressure from value funds would be balanced by the buying pressure from growth funds, neutralizing any potential price impact. However, this is not the case empirically. We attribute this finding to the fact that each fund has a limited and persistent investment universe and is sluggish in trading stocks outside its current portfolio (Koijen and Yogo 2019). We provide two pieces of supporting evidence. First, for a median-sized mutual fund, 85 percent of stocks that are currently held were also held in the previous quarter. Second, we show that when acquiring stocks, funds are 2.5 times more likely to increase their existing holdings than to initiate new positions in previously unowned stocks.

If predictable factor rebalancing induces price pressure, it would naturally lead to predictable returns. We confirm this prediction in the data. We first aggregate *fund*-level factor loadings to the *stock* level: for each stock in each quarter, we calculate the holding-weighted average factor loadings of its underlying funds. The resulting measures, termed *factor demand*, represent the average factor loadings of a stock's underlying funds. We then form 25 (5×5) portfolios by independently sorting stocks based on their own characteristics and their factor demand. Out of the 25 value-based portfolios, the two that are most "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 earn annualized value-weighted returns of 17.0% and 14.0%.

The analysis so far assumes that funds rebalance based on the *level* of stock characteristics, but some funds may also rebalance as a response to *changes* in stock characteristics. To demonstrate robustness, we instead double-sort stocks based on changes in stock characteristics (over the previous four quarters) and factor demand, and we document similar return patterns. Interestingly, we also observe some differences across factors: results are quantitatively smaller for value and larger for momentum. This suggests that value rebalancing may be more based on levels while momentum more on changes.

We identify two additional return patterns from the 25 value-based portfolios. First, holding the B/M ratio constant, we 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%. Conversely, growth stocks with low value demand earn higher returns than those with high value demand by 10.4% per year on average. Second, we evaluate the conditional performance of the high-minus-low (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 last four decades is particularly noteworthy, as it may shed light on the puzzling phenomenon that growth funds are popular despite the unconditional underperformance of growth stocks (Lettau et al. 2018).

For momentum, we apply the same procedure and sort all stocks into 25 portfolios based on their past one-year returns (skipping the most recent month) and the underlying funds' momentum demand. The return results are also in line with portfolio rebalancing, albeit with a smaller magnitude.

We test the robustness of our portfolio sorting results to various alternative specifications. First, we measure portfolio performance using equal-weighted portfolio returns and alphas from different factor models (CAPM and three-factor). Second, we reduce the number of portfolios from 25 (5×5) to 9 (3×3) to increase the number of stocks in each portfolio and mitigate concerns that some portfolio may contain too few stocks. Lastly, we show that factor demand, measured as the average characteristic of all stocks in a fund's portfolio, is also highly persistent. We use this holdings-based measure of factor demand to check the robustness of the return evidence. In all cases, we find similar return patterns as in our main analysis, suggesting that our results are not driven by any specific specification choices.

We also perform a series of subsample analysis 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. Relatively speaking, the return patterns are more pronounced in the latter sample, among stocks with higher mutual fund ownership, and among large-cap stocks. For momentum, on the other hand, the return patterns are stronger among stocks with higher mutual fund ownership and when we sort stocks based on changes in past returns, but weaker in the latter sample and among large-cap stocks. Overall, consistent with the literature on the relationship between momentum and value, our 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 (winner-minus-loser) portfolios. To do so, we make additional assumptions about which kind of demand is inelastic. For example, we assume value funds' demand for value stocks is inelastic from quarter to quarter. Our estimated factor-level elasticities fall between -0.04 and -0.35, with an average estimate of -0.23. Overall, these numbers are larger than the estimates at the stock level (Chang, Hong, and Liskovich 2015), but on par with those estimated at the factor and market levels (Gabaix and Koijen 2022; Ben-David et al. 2021; Haddad et al. 2021).

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

A vast literature has linked movements in stock prices to various mutual fund behaviors.² 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.³ We propose a different source of institutional

²For example, flow-induced trading (Coval and Stafford 2007; Lou 2012; Akbas et al. 2015; Edelen et al. 2016; Huang et al. 2019), herding (Lakonishok et al. 1992; Nofsinger and Sias 1999; Wermers 1999; Sias 2004; Dasgupta et al. 2011), positive-feedback trading (Lakonishok et al. 1992; Nofsinger and Sias 1999; Cohen et al. 2002), and behavioral patterns such as the disposition effect and the V-shaped selling schedule (Grinblatt and Han 2005; Frazzini 2006; An and Argyle 2020).

³Earlier 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

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

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

2 Factor demand

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

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.

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 the earlier years, but more in later years.

Other data sources are standard: stock prices, stock returns, and accounting variables are from the CRSP/COMPUSTAT merged database; factor returns are from Kenneth R. French's website.⁵

⁴As in Lou (2012), monthly fund returns are calculated as net returns plus 1/12 of annual fees and expenses; TNA is summed across all share classes; net returns and expense ratios are computed as the TNA-weighted averages across all share classes. For other fund characteristics, values from the share class with the largest TNA are used to represent the entire fund.

⁵Since the annual accounting data was not fully available at the time of data collection, our stock sample ends in 2018.

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:

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

where k = 1, 2, ..., 60. On the left-hand side, *rret* represents raw fund returns. On the righthand side, MKT represents excess market returns, and HML, SMB, MOM, CMA, and RMW represent the returns for value, size, momentum, investment, and profitability strategies, respectively. We require a fund to have at least 60 months of returns data and each rollingwindow estimation to have at least 24 monthly observations.⁶ 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 retrepresents 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.⁷

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 autocorrelation in $\beta_{i,t}$, an issue we will return to in Section 2.3 when discussing the persistence of factor demand. Compared to mutual fund classifications or investment objectives from industry data providers such as Lipper or Wiesenberger, which often rely on funds' self-reported investment objectives and can be misreported or missing, our loading-based measures are available for all funds with at least five years of return data and are less subject to reporting errors.

We have included seven factors on the right-hand side of Equation (1), but our main analysis will be devoted to value and momentum; one can therefore think of the other five factors as

⁶While 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.

⁷We 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.

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.

Another popular way to measure mutual funds' factor exposure is by aggregating stock characteristics based on fund holdings.⁸ Both approaches can capture aspects of the factor demand, with slightly different emphases: our loading-based measures, with a focus on the correlation between fund and factor returns, capture trading activities between two reporting dates; by contrast, holding-based measures provide an up-to-date snapshot of the current exposure (Kacperczyk et al. 2008). To entertain the second possibility, later we will repeat our main analyses using holding-based measures of fund demand to show robustness.

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

⁸Lettau 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.⁹ Many of them have a specific investment objective, such as growth, and by mandates they need to keep a relatively stable exposure to this factor. Therefore, as the set of stocks considered "growth" changes, they will need to rebalance their portfolios. Relatedly, some funds have mandates to beat or stick to a benchmark, often represented by a popular index with stable exposure to certain factors. The incentive to minimize the tracking error (or to maximize the "information ratio") prompts funds to keep a persistent exposure to the underlying factors. Second, even 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 profitability of a trading strategy,

⁹See, 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.

a stable investment philosophy, and persistent use of the same technical analysis method.

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 $\hat{\beta}_{i,q}^X$. 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:

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

where X represents market, value, size, and momentum (the Carhart four factors).¹⁰ 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.¹¹ 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 rather persistent in the time series, suggesting that factor exposure is indeed relatively persistent at the fund level. For example, in Columns (3) and (4), loadings on value and momentum 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. Column (6) runs a similar regression for value loadings and finds a similar pattern.¹²

¹⁰Results for the other three factors are similar and omitted for simplicity.

¹¹We can lag by one more quarter to further ensure that the estimation windows are non-overlapping. Results are essentially unchanged.

¹²In the Online Appendix, Table A.2 runs additional regressions to show that persistent factor demand exists

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).¹³

3 Factor rebalancing

In this section, we present direct evidence of 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 size: because firm size is rather stable over time, trading on size does not involve frequent rebalancing. Second, for a given fund, its factor demand should be sufficiently persistent—and more persistent than the stock characteristic associated with that factor. If factor demand is not persistent, it would mean that funds are not really targeting that factor, which in turn reduces

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

¹³An 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.

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.¹⁴ 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, again, are greater than those in Panel C. Therefore, we confirm that, for value and momentum, fund factor demand is indeed more persistent than stock characteristics.

3.2 Fund-level evidence of factor rebalancing

In this section, we investigate how mutual funds rebalance portfolios based on stock characteristics. Mutual funds need to periodically rebalance their portfolios to maintain a persistent exposure to factors such as value and momentum. It is worth noting that mutual funds may rebalance in response to changes in stock characteristics—the need to get rid of stocks that become mismatched with their investment strategy—as well as levels of stock characteristics—the need to acquire more stocks that align with their investment strategy. Since characteristics such

¹⁴Tables A.4 and A.5 in the the Online Appendix shows more details about transition probabilities at other frequencies.

as the B/M ratio and past one-year return change relatively fast, the level and changes of these characteristics are highly correlated. Therefore, in our analysis, we examine the effects of both.

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

$$trade_{i,j,q+1} = \alpha_t + \gamma_1 \Delta B / M_{i,q} + \gamma_2 \Delta r_{i,q-4,q-\frac{1}{2}} + \gamma_3 \Delta M E_{i,q} + \gamma_4 \Delta \beta_{i,q} + \varepsilon_{i,j,q+1}, \quad (3)$$

where the dependent variable, $trade_{i,j,q+1} \equiv \Delta Shares_{i,j,q+1}/Shrout_{i,q}$, measures percentage trading in stock *i* by fund *j* in quarter q + 1. We adjust the trade measure for flow-induced trading (FIT) to separate the trades from mutual funds' active portfolio rebalancing from those driven by retail flows. Results are quantitatively similar without these adjustments.¹⁵ The independent variables are four-quarter changes in stock *i*'s characteristics, including crosssectionally 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. These subsamples include 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. Panel A of Table 5 focuses on value. We find that value funds' trades load positively on the changes in B/M ratio in columns (1) and (2), consistent with rebalancing on value. In contrast, growth funds' trades load negatively on the changes in B/M ratio in columns (3) and (4). Panel B repeats the same analyses for momentum. We find that momentum funds' trades load positively on changes in past one-year return in columns (1) and (2), consistent with rebalancing on momentum. Conversely, contrarian funds' trades load negatively on changes in

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

¹⁵More specifically, we follow Lou (2012) and define FIT for stock j in quarter q as

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.

past one-year return in columns (3) and (4). All of these coefficients are statistically significant at the 1% level with standard errors clustered at the fund and quarter levels, even after controlling for additional characteristics such as size, investment and profitability. Taken together, these results support our proposed mechanism of factor rebalancing by showing that mutual funds with different styles trade in line with their relevant stock characteristics.

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

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

In Table 6 Panel A, we find that value funds' trades positively load on the level of B/M while growth funds' trades load negatively. In Panel B, we find similar results for momentum and contrarian funds when we examine how they respond to past one-year returns. Results are statistically significant except those of contrarian funds. Overall, evidence from Tables 5 and 6 confirms that mutual funds rebalance their portfolios to maintain their factor exposure and further suggests that the factor rebalancing relies on both levels and changes of stock characteristics.

3.3 Evidence on portfolio returns

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 underlying growth funds have the incentive to sell stock B to maintain their exposure to growth stocks. This means that, compared to stock A, stock B faces more selling pressure from its current investors and will experience lower returns in subsequent periods.

3.3.1 Investment universe

In theory, the selling pressure on stock B could be offset if some value funds have an equally strong demand to buy it. However, we have reasons to believe that, in this case, the selling pressure outweighs the buying pressure. First, many of these "new" value stocks are likely to be outside of the empirically small investment universe of value funds. Figure 3 confirms this observation. In the current quarter, the median fund holds 90% of the positions held in the previous quarter. In fact, more than 15% of the funds do not change their portfolio composition at all in a given quarter.¹⁶ Therefore, the sellers have a strong incentive to sell this "mismatched" stock, while the buyers can choose from a large pool of value stocks that may not include stock B.

Second and relatedly, funds on average tend to trade stocks that are already in their portfolios rather than initiate new positions. To illustrate this, we categorize all quarterly changes in stock positions into five different types: (1) new buy, meaning starting a new position from zero; (2) additional buy, meaning increasing holding for an existing position; (3) partial sell, meaning reducing holding for, but not liquidating, an existing position; (4) liquidation; and (5) no change. These five types of transactions account for 10.4%, 36.1%, 26.9%, 0.04%, and 26.5% of all quarterly changes respectively. Therefore, more than 60% of quarterly changes are additional buys and partial sells, indicating that funds scale up and down positions based on a small investment universe. At the same time, funds are much less likely to start new positions and almost never liquidate.

Third, trading requires attention and time, and value funds that do not have stock B in their portfolios may not even notice that it has become a value stock (Barber and Odean 2008; Hartzmark 2015). Based on all three reasons, we contend that the selling pressure from existing funds is unlikely to be fully offset by trading from the other funds.

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

3.3.2 Main results

We test these predictions from factor rebalancing through portfolio-sorting. To see the intuition, suppose that we double-sort stocks into 25 (5×5) portfolios based on the B/M ratio and the underlying funds' HML demand, as shown in Figure 1 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.

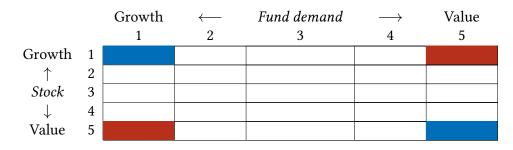


Figure 1: Stock portfolios well-matched and mismatched between own characteristics and underlying funds' demand for value

In Panel A of Table 7, 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.¹⁷ 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.¹⁸ Panel A immediately addresses this

¹⁷One 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.

¹⁸We prefer independent sorting to conditional sorting because a stock (and fund) is classified as value stock

concern: both portfolios contain, on average, more than 25 stocks. Therefore, even 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.¹⁹ 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 $\bar{\beta}^{HML}$. 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 demands. 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

⁽fund) based on its ranking among all stocks (funds), not conditionally within a subgroup.

¹⁹Table A.8 in the Online Appendix reports the pre-formation sorting characteristics of the 25 portfolios. As expected, for both value and momentum, the two sorting variables are monotonically distributed across the portfolios and exhibit substantial cross-quantile dispersions in both directions, eliminating concerns that stocks' investor base may be homogeneous.

reaches 7.4% in the top $\overline{\beta}^{HML}$ -quintile. This evidence implies, from the perspective of portfolio management, that a value strategy conditional on value funds enhances the unconditional value strategy. Moreover, the growth premium we document can justify the persistent popularity of growth funds despite the 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 the price effect of factor rebalancing is weaker in momentum than in value. Most notably, after the momentum crash documented by Daniel and Moskowitz (2017), mutual funds significantly 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.

3.3.3 Sorting based on changes in stock characteristics

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

To test this alternative mechanism, we repeat the previous portfolio sorting exercise by

replacing the current B/M ratio or past year return with the change in the B/M ratio or past one-year return over the last four quarters. Table 8 reports the results. We find similar results, with different magnitudes: results are weaker for value and stronger for momentum. Therefore, we also establish that factor rebalancing can also stem from trading responses to changes in stock characteristics. Furthermore, comparing the two sets of results suggests that value rebalancing may be more based on the level while momentum rebalancing may be more on changes.²⁰

3.3.4 Holding-based measures of factor demand

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

$$BM_{j,q}^{fund} = \frac{\sum_{i} Dollar_{i,j,q} \times BM_{i,q}}{\sum_{i} Dollar_{i,j,q}},$$
(5)

and

$$RET_{j,q}^{fund} = \frac{\sum_{i} Dollar_{i,q} \times RET_{i,q}}{\sum_{i} Dollar_{i,j,q}},$$
(6)

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

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

$$\overline{BM}_{i,q} = \frac{\sum_{i} shares_{i,j,q} \times BM_{j,q}^{fund}}{\sum_{i} shares_{i,j,q}},$$
(7)

²⁰A stronger test of this dynamic argument would control for current stock characteristics such as the B/M ratio. This, for example, can be done through a triple-sorting exercise. We do not do it in Table 8, because the correlation between the level and the change is too high that it leaves a rather limited scope for triple-sorting. Indeed, the correlation between the B/M ratio and its one-year change is 0.36, and the correlation between the past one-year return and its one-year change is 0.72. More detailed results are included in Table A.11 of the Online Appendix.

and

$$\overline{RET}_{i,q} = \frac{\sum_{i} shares_{i,j,q} \times RET_{j,q}^{fund}}{\sum_{i} shares_{i,j,q}}.$$
(8)

With these two holding-based stock-level factor demand measures, we redo the portfolio analysis as in Section 3.3. Table 9 summarizes returns from these alternative portfolio sorts. To highlight the impact of factor rebalancing on well-matched and mismatched stocks, we focus on the high-minus-low portfolios, HML and WML, across the stock-level factor demand. The results are largely consistent with those in Table 7. For example, the value-weighted HML return is 8.5% per annum in stocks with the highest \overline{BM} and only 0.3% in stocks with the lowest \overline{BM} , indicating a difference of 8.2% (t = 1.6).

3.4 Robustness checks

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 postformation FIT for the 25 sorted portfolios and report the results in Table 10. For value, the FIT for the HML portfolios (in line "HML") decreases from -0.23% for the low- $\bar{\beta}^{HML}$ stocks to -0.56% for the high- $\bar{\beta}^{HML}$ stocks, a direction opposite to that of our factor-rebalancing results in Table 7. For momentum, all WML portfolios (in line "WML") have a positive FIT but with a similar level, which clearly does not line up well with the dispersion in WML returns we document in Table 10. Therefore, FIT cannot account for the documented return predictability from factor rebalancing.

3.4.2 Other measures of portfolio returns

Table 11 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 weaken 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 12 and 13. 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 7.

In Table 12, Panels A and B study two subperiods: 1980 to 1999 and 2000 to 2018. In both subperiods, the HML strategy, measured either by raw returns or portfolio alphas, performs substantially better conditional on stocks held by value funds. Overall, the difference doubles in the second half of the sample. Panels C and D sort stocks based on their mutual fund ownership. More specifically, in each quarter, before beginning to sort stocks into 25 portfolios, we first sort them into high or low mutual fund ownership using the median mutual fund ownership as the cutoff. Overall, return patterns are robust in both subsamples, although, perhaps as expected, the results are stronger in the subsample of high mutual fund ownership. Panels E and F sort stocks based on size. In each quarter, stocks are first sorted—as in Panels C and D—into large or small based on their firm size before being sorted into 25 portfolios. Results are robust in both subsamples, but more pronounced for larger stocks.

Table 13 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 14: 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 12, the return patterns are most robust among stocks with high mutual fund ownership. Panels E and F show that, unlike the value strategy, in which large stocks are more profitable than small ones, the momentum strategy works better for small stocks.

3.4.4 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 14. 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.

4 Additional evidence on trading and price elasticity

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

4.1 Whose trading matters?

In the previous section, we focused on the 5×5 double-sorted portfolios and demonstrated how funds of different factor demands are driving trading activities in different portfolios. For example, the selling of the bottom-left corner portfolio is primarily driven by growth funds, whereas the selling of the top-right corner portfolio is driven by value funds. The evidence from Section 3.2 supports the mechanism of factor rebalancing by examining trades made by all mutual funds collectively. To strengthen the connection between factor rebalancing and stock returns, we examine the trading patterns of funds with low and high factor demand, respectively. For the value strategy, in each quarter, we classify value funds as those with HML beta higher than the cross-sectional median and growth funds as those with HML beta lower than the cross-sectional median. The same classification is made for momentum and contrarian funds for the momentum strategy.

In Panel A of Table 15, we decompose stock-level mutual fund ownership changes into those from value funds and growth funds. The left table reports the trading of growth funds and the right table reports the trading of value funds. As evidenced in the left table, most of the trading comes from low- $\bar{\beta}^{HML}$ stocks (Column 1). On 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%. On the right of Panel A, there is a similar but weaker pattern for value funds: they increase their ownership of the high-BM stocks by 0.11% more than the low-BM stocks (Column 5). The results for the momentum strategy are shown in Panel B of Table 15. The trading activities of momentum funds appear to be stronger: momentum funds increase their ownership of the winner stocks by 0.63% more than the loser stocks (Column 5 on the right).

4.2 Implied price elasticity

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

Take value as an example. We further assume that value funds—defined as having an HML beta above the median—have inelastic, positive demand for value stocks and inelastic, negative demand for growth stocks in their investment universe. For stocks demanded mostly by value

funds, $\Delta Demand$ of the HML portfolio is defined as the difference between the long and short legs in quarterly value-fund ownership changes.²¹ To get the price elasticity associated with these demand changes, we divide $\Delta Demand$ by quarterly returns of this HML portfolio ($\Delta Return$):²²

$$Elasticity = -\frac{\Delta Demand}{\Delta Return}.$$
(9)

With a flat or perfectly elastic demand curve, the price elasticity approaches $-\infty$, while with downward-sloping or inelastic demand, the estimate approaches zero. We make similar assumptions about inelastic demand for all four types of funds-value, growth, contrarian, and momentum-and calculate the implied price elasticities for various HML and WML portfolios. $\Delta Demand$ from these four types of funds are taken from Columns 1 and 5 in Table 15.

The price elasticity estimates are reported in Table 16. Overall, our estimated elasticities range from -0.04 to -0.35, with an average of -0.21. It is worth noting that our estimation of price elasticity is at the factor level, which is different from prior studies that focus on the micro (stock) level or macro (market) level. Compared to the literature, our results indicate that the price elasticity at the factor level is significantly higher than those found in studies of micro elasticity (Harris and Gurel 1986; Shleifer 1986; Chang et al. 2015), but it is similar to the estimates obtained at the factor and market levels (Gabaix and Koijen 2022; Ben-David et al. 2021; Haddad et al. 2021). One potential reason for such a low price elasticity is the lack of a close substitute for well-known and robust factors such as value, size, and momentum. In fact, among these factors value and momentum tend to complement, rather than substitute, each other. In contrast, it is arguably easier to find a close substitute for a particular stock like Apple or Google among all stocks.

4.3 Long-term patterns

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

²¹To get the percentage changes in holding, we scale the number of shares by the total shares outstanding.

 $^{^{22}}$ In order to isolate the part of HML return that is attributed to factor rebalancing rather than other factors that drive the average HML return, we define $\Delta Return$ as the difference between the HML return and the average HML return across all five high-minus-low portfolios.

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

Figure 4 confirms this intuition. The left panel plots long-term gaps in mutual fund ownership and cumulative returns between two HML portfolios (corresponding to 5-1 HML portfolio in Table 7). The right panel plots the same difference for momentum (corresponding to 5-1 WML portfolio in Table 7). The figures start at quarter 0, when the portfolios are formed. For both value and momentum, over the next eight quarters, the ownership gap between the two highminus-low portfolios gradually dissipates and the cumulative return difference rapidly drops to zero within 8 quarters, becoming indistinguishable from zero. This pattern of longer-term return reversal is consistent with the findings of many other studies on price impact, such as Lou (2012). Therefore, mutual funds appear to rebalance their factor exposures rather quickly and most of the pricing impact concentrates on the immediate quarter.

5 Alternative explanations

In this section, we address a few alternative explanations that may explain the stock-level evidence we document in the previous sections. Section 3.4 has already ruled out flow-induced trading as a potential explanation for our results. We now turn to explanations based on stocks' subsequent fundamentals, fund manager skills, and mutual fund herding behavior.

5.1 Subsequent stock fundamentals

In the real world, mutual funds can trade for various reasons beyond simple factor rebalancing. One such motive is that fund managers may have access to private information about firm fundamentals. This means that stocks purchased by fund managers with this informational advantage are more likely to perform well in the future. Under this view, the return dispersion shown in Table 7 may instead indicate fund managers' superior ability to forecast firm fundamentals.

We assess this possibility by examining stocks' post-formation standardized earnings

surprises (SUE) and cumulative abnormal returns (CAR) around earnings announcement dates, where SUE is calculated as the difference between actual earnings and analysts' forecasts, normalized by the current stock price, and CAR represents the size and value-adjusted abnormal returns in a three-day window surrounding the earnings announcement. The results for 25 portfolios sorted based on stock characteristics and fund betas are presented in Table 17. If the fund managers' ability to forecast fundamentals is the main driver of the documented return predictability, we should expect SUEs and CARs to line up with our return patterns.

Panels A and B report the results for value. In Panel A, across the five HML portfolios, their SUEs are all negative and similar in magnitude. In Panel B, the CARs for the five HML portfolios roughly align with our return evidence, but the magnitude is much smaller and can account for only a tiny fraction of the return dispersion. Panels C and D show the results for momentum, where the pattern of SUEs for the five WML portfolios contradict our return evidence for momentum. Specifically, the low- $\overline{\beta}^{MOM}$ WML portfolio has a higher SUE than high- $\overline{\beta}^{MOM}$. The monotonicity of CAR for the WML portfolios is similar to our return evidence, though again with a smaller magnitude. Therefore, we do not find evidence that the return patterns documented in Table 7 can be explained by subsequent firm fundamentals.

5.2 Other skill-based explanations

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

Moreover, since the funds we consider are deliberately pursuing their respective strategies, they are unlikely to hold stocks that are not aligned with their investment philosophies. If their specializations explain the return predictability, it should also be reflected in the magnitude of *fund* performance. That is, growth funds and value funds should outperform compared to other unspecialized funds. However, this claim is not supported by the data. Despite targeting profitable factors, value and momentum funds exhibit annualized four-factor alphas of only 28bps and - 8bps, respectively. Growth and contrarian funds, on the other hand, do not exhibit statistically significant alphas (see Table A.10 in the Online Appendix). This evidence is at odds with the notion that fund skills are responsible for the results we document.

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

5.3 Herding

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

6 Conclusion

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

Our results have implications for several strands of the literature. First, to the best of our knowledge, this factor rebalancing is novel to the literature. The economic significance of our results is sufficiently large that our mechanism warrants more attention. Second, we enlarge the set of predictors for stock returns by showing that fund characteristics such as factor loadings can be used to forecast conditional factor returns. Third, we contribute to the literature that links asset demand to price dynamics. Most previous research has examined price impacts at either the stock or the market level. Our analysis 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.13 presents some preliminary evidence on using factor demand for predicting future factor returns. We leave

these questions for future research.

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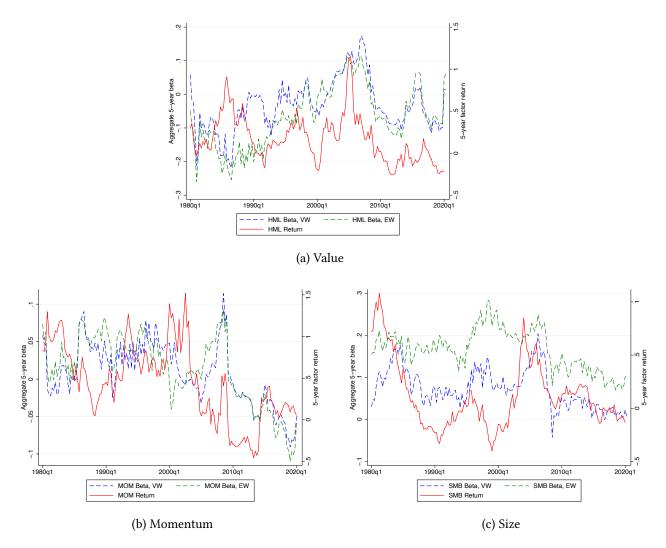
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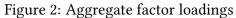
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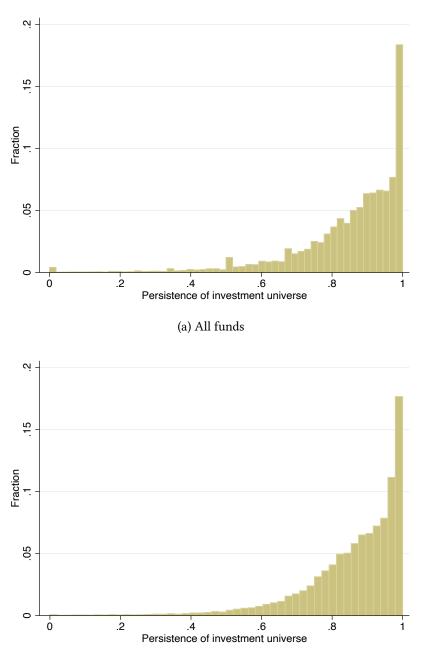
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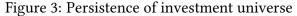




Note: This figure plots the time series dynamics of factor loadings of the aggregate mutual fund industry from 1980 to 2019. Subfigures A, B and C plot value, momentum and size factors, respectively. In each subfigure, the blue dashed line represents the TNA-weighted beta, the green dashed line represents the equal-weighted beta, and the red solid line represents the past five-year return of the corresponding factor.



(b) Funds holding at least 100 positions



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

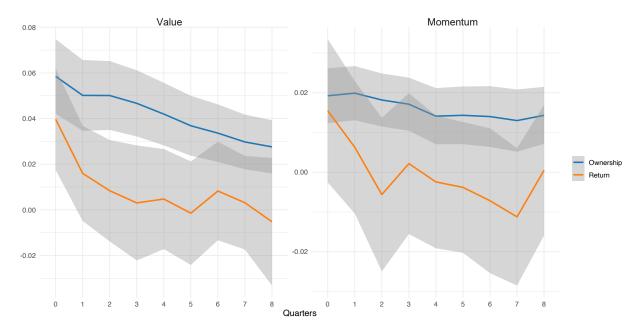


Figure 4: Long-term Long-Short Portfolio Returns and Mutual Fund Ownership Note: This figure plots long-term gaps in mutual fund ownership and cumulative returns between two long-short portfolios for value and momentum. The left and right panels correspond to value (HML) and momentum (WML), respectively.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

			l A: Our san	-		Panel B: Lo		
			5 million)		s return			6 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 presents summary statistics of our sample of US domestic equity mutual funds, for each year in the period from 1980 to 2019. We exclude international, fixed income, and precious metal funds, and restrict the sample to funds with equity holdings to TNA ratio between 0.80 and 1.05, and with a minimum fund size of \$1 million. We obtain fund size, monthly returns, and capital flows data from the CRSP survivorship-bias-free mutual fund database, and fund holdings data from the Thomson Reuters Mutual Fund Holdings database. The two databases are merged using the MFLinks file provided by WRDS. The number of mutual funds at the end of each year is reported as *# of funds*, and total net assets under management are reported as *TNA* in millions of US dollars. Panels A and B show summary statistics for our main sample and the sample used by Lou (2012), respectively.

	$\frac{(1)}{\beta^{MKT}}$	(2) β^{SMB}	(3) β^{HML}	$\frac{(4)}{\beta^{MOM}}$	(5) β^{CMA}	$\frac{(6)}{\beta^{RMW}}$	(7) β^{flow}
	μ	1-	1-	1	1	1	Μ
Maria				Summary			0.01
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
Р5	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	: Summa	ry statisti	ics by fui	nd 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
				unds vs. 1			
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 for mutual funds. 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. We require that a fund should have at least 60 months of returns data and that each rolling window contain at least 24 monthly observations. Panel A reports the mean, standard deviation and percentiles of factor betas across all funds. Panel B reports the mean factor betas by Lipper mutual fund classifications. Panel C reports the mean factor betas by index fund status provided by CRSP.

	$\frac{(1)}{\beta_{i,q}^{MKT}}$	$(2) \\ \beta^{SMB}_{i,q}$	$(3) \\ \beta_{i,q}^{HML}$	$(4) \\ \beta^{MOM}_{i,q}$	(5) $\beta_{i,q}^{SMB}$	$\frac{(6)}{\beta_{i,q}^{HML}}$
$\beta_{i,q-20}^{MKT}$	0.348^{***} (0.019)					
$\beta_{i,q-20}^{SMB}$	(0.017)	0.747*** (0.012)			0.424^{***} (0.021)	
$eta_{i,q-20}^{HML}$		(0.012)	0.369*** (0.015)		(0.021)	0.297^{***} (0.021)
$\beta_{i,q-20}^{MOM}$			()	0.293*** (0.019)		()
Dummy_size				(1111)	0.031*** (0.009)	
$Dummy_size imes eta_{i,q-20}^{SMB}$					0.469*** (0.024)	
Dummy_BM						-0.039*** (0.012)
$Dummy_BM \times \beta_{i,q-20}^{HML}$						0.234*** (0.027)
Quarter FE	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark
Observations R^2	153,331 0.235	153,331 0.568	153,331 0.236	153,331 0.184	153,331 0.639	153,331 0.255

Table 3: Persistence of factor demand

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

	I	Panel A	: Stock	B/M			Panel B: Fund β^{HML}						
	1	2	3	4	5		1	2	3	4	5		
1	0.68	0.23	0.06	0.03	0.01	1	0.74	0.20	0.04	0.02	0.01		
2	0.16	0.50	0.24	0.07	0.02	2	0.19	0.53	0.21	0.06	0.02		
3	0.03	0.21	0.45	0.25	0.07	3	0.04	0.21	0.51	0.20	0.04		
4	0.01	0.05	0.22	0.48	0.23	4	0.01	0.06	0.20	0.56	0.17		
5	0.01	0.01	0.05	0.22	0.72	5	0.01	0.02	0.04	0.18	0.75		
	Panel C: Stock $r_{t-4,t-1/3}$ Panel D: Fund β^{MOM}												
	1	2	$\frac{0 \text{ cm} r_{t-}}{3}$	$\frac{4,t-1/3}{4}$	5		1	2	3	4	5		
1	_				Ū	1	-						
1	0.25	0.20	0.18	0.18	0.19	1	0.75	0.18	0.04	0.02	0.01		
2	0.19	0.22	0.23	0.22	0.14	2	0.15	0.56	0.21	0.06	0.02		
	0.17	0.23	0.25	0.22	0.14	3	0.04	0.20	0.51	0.22	0.04		
3	0.17						0.00	0.07	0.01		0.48		
3 4	0.17	0.22	0.23	0.21	0.15	4	0.02	0.06	0.21	0.54	0.17		

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

Dep	endent varia	ble: $\Delta Shares_i$	$_{j,q+1}/Shrow$	$t_{i,q}$
Panel A: Value				
	Low- $\beta_{j,q}^{HN}$	^{IL} (growth)	High- β_j^H	A_{q}^{MML} (value)
	(1)	(2)	(3)	(4)
$\Delta BM_{i,q}$	-0.1727***	-0.1785***	0.0572***	0.0632***
	(0.0277)	(0.0289)	(0.0163)	(0.0181)
$\Delta \beta_{i,q}$		0.0631***		0.0283***
		(0.0144)		(0.0109)
$\Delta ME_{i,q}$		-4.513***		-2.694***
		(0.6257)		(0.5139)
$\Delta OP_{i,q}$		-0.0067		-0.0064**
- , 1		(0.0045)		(0.0028)
$\Delta INV_{i,q}$		-0.0224***		-0.0183***
-72		(0.0047)		(0.0046)
\mathbb{R}^2	0.0013	0.0029	0.0004	0.0012
Observations	3,459,937	3,235,392	6,528,279	5,465,578
Panel B: Momer		(contrarian)	High- $\beta_{j,q}^{MOI}$	M (momentum
$\Delta r_{i,q-4,q-1/3}$	-0.0638***	-0.0384***	0.0365***	0.0351***
-i,q-4,q-1/3	(0.0102)	(0.0098)	(0.0114)	(0.0116)
$\Delta BM_{i,q}$	(0.0101)	0.1054***	(01011)	-0.0659***
_ <i>i,q</i>		(0.0272)		(0.0191)
$\Delta \beta_{i,q}$		0.0319**		0.0311**
- $>$ i,q		(0.0152)		(0.0135)
$\Delta ME_{i,q}$		-1.643**		-4.727***
_ <i>i,q</i>		(0.6690)		(0.5280)
$\Delta OP_{i,q}$		-0.0060		-0.0018
$ \cdot$ \cdot \cdot \cdot \cdot \cdot \cdot \cdot \cdot \cdot		(0.0043)		(0.0037)
$\Delta INV_{i,q}$		-0.0248***		-0.0185***
<i>i</i> , <i>q</i>		(0.0062)		(0.0044)
\mathbb{R}^2	0.0012	0.0022	0.0006	0.0021

Table 5: Fund-level portfolio rebalancing: FIT-adjusted trading in shares and changes in stock characteristics

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

Dep	pendent vari	able: $\Delta Shares_{i}$	$_{i,j,q+1}/Shrow$	$\mu t_{i,q}$
Panel A: Value				
	Low- $\beta_{j,q}^{H1}$	ML (growth)	High- β_j^I	$\mathcal{A}_{,q}^{MML}$ (value)
	(1)	(2)	(3)	(4)
$BM_{i,q}$	-0.0194*	-0.0194*	0.0159**	0.0173**
	(0.0113)	(0.0109)	(0.0074)	(0.0077)
$\beta_{i,q}$		0.0171		-0.0239**
		(0.0122)		(0.0110)
$ME_{i,q}$		-1.453***		-0.9648***
		(0.1520)		(0.1062)
$OP_{i,q}$		-0.0284***		-0.0048**
71		(0.0040)		(0.0021)
$INV_{i,q}$		0.1273^{***}		0.0983***
		(0.0116)		(0.0115)
R^2	0.0001	0.0103	0.0001	0.0043
Observations	3,615,836	3,400,955	6,575,970	5,531,588
Panel B: Mome	entum			
	Low- $\beta_{j,q}^{MOI}$	^M (contrarian)	High- $\beta_{j,q}^{MOI}$	M (momentum
$r_{i,q-4,q-1/3}$	-0.0170	-0.0103	0.1027***	0.0962***
	(0.0133)	(0.0124)	(0.0162)	(0.0152)
$BM_{i,q}$		0.0230***		-0.0178**
/ 1		(0.0060)		(0.0087)
$\beta_{i,q}$		-0.0074		-0.0185
		(0.0132)		(0.0114)
$ME_{i,q}$		-1.495***		-1.271***
.,1		(0.1274)		(0.1362)
$OP_{i,q}$		-0.0166***		-0.0140***
/ ±		(0.0031)		(0.0029)
$INV_{i,q}$		0.1387***		0.1234***
· / 1		(0.0125)		(0.0117)
R^2	0.0001	0.0072	0.0049	0.0122

Table 6: Fund-level portfolio rebalancing: FIT-adjusted trading in shares and stock characteristics Note: This table reports how mutual funds rebalance their portfolios based on stock characteristics. The dependent variable, $\Delta Shares_{i,j,q+1}/Shrout_{i,q}$, is FIT-adjusted trading 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, $\beta_{i,q}$; market capitalization (in billions), $ME_{i,q}$; operating profitability, $OP_{i,q}$; and investment, $INV_{i,q}$. Panels A and B report results for value and momentum, respectively. Columns (1) and (2) use funds in top quintile of $\beta_{j,q}^{HML}$ (Panel A) or $\beta_{j,q}^{MOM}$ (Panel B). Columns (3) and (4) use funds in bottom quintile of $\beta_{j,q}^{HML}$ (Panel A) or $\beta_{j,q}^{MOM}$ (Panel B). The data sample is from 1980Q1 to 2018Q4. Standard errors are clustered at the quarter and fund levels. *, **, *** indicate statistical significance at 10%, 5% and 1% levels, respectively. Intercepts are omitted.

		$\operatorname{Low-}\overline{\beta}^{HML}$	~	Fund	\rightarrow	High- $\overline{\beta}^{HML}$		
		1 1 1	2	3	4	5		
Low-B/M	1	220	132	71	41	27	-	
↑	2	124	142	110	72	45		
Stock	3	61	103	122	115	92		
Ļ	4	35	67	106	134	150		
High-B/M	5	26	50	92	139	184		
		Panel B: Avera	ge numbe	er of stoc	ks - mor	nentum		
		$\frac{1}{1} \operatorname{Low} - \overline{\beta}^{MOM}$	<i>~</i>	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: Annu	alized po	rtfolio re	eturn - va	due (%)		
		$\operatorname{Low-}\overline{\beta}^{HML}$	\leftarrow	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	[-2.47
\uparrow	2	14.5	14.3	10.6	11.2	10.1	-4.4	[-1.34
Stock	3	17.3	14.1	12.5	10.7	11.7	-5.5	[-1.77
\downarrow	4	11.2	15.2	13.9	11.9	13.2	2.0	[0.65]
High-B/M	5	8.5	16.4	15.2	12.8	14.0	5.5	[1.51]
HML		-8.5	4.5	6.4	2.8	7.4	15.9	
		[-2.02]	[1.46]	[2.43]	[0.95]	[2.72]	[3.52]	
	Pa	nel D: Annualiz	zed portfo	olio retur	n - mom			
		$\operatorname{Low-}\overline{\beta}^{MOM}$	<i>←</i>	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	[1.46]
\uparrow	2	10.2	10.9	12.1	11.5	14.0	3.8	[1.19]
Stock	3	10.0	11.4	13.5	12.9	17.2	7.3	[2.82
\downarrow	4	10.5	11.6	11.5	14.4	16.2	5.6	[2.44
High-RET	5	8.4	8.5	12.7	16.2	19.5	11.1	[3.36
		1.0	1.0	2.8	7.9	7.2	6.2	
WML		1.0	1.0	2.0	1.9	1.4	0.2	

Table 7: 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 valueweighted 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 $\overline{\beta}^{MOM}$, which are the shares-weighted average HML and MOM loadings of a stock's underlying funds. Data are from 1980Q2 to 2018Q4.

	$\operatorname{Low-}\overline{\beta}^{HML}$	<i>~</i>	Fund	\longrightarrow	$\operatorname{High-}\overline{\beta}^{HML}$	
	1	2	3	4	5	5 - 1
VW return	-7.5	-5.1	-3.3	-0.6	-0.1	7.4
	[-1.77]	[-1.48]	[-1.04]	[-0.18]	[-0.02]	[1.78]
EW return	-6.0	-8.5	-6.3	-2.8	-2.8	3.3
	[-1.74]	[-2.79]	[-2.29]	[-1.18]	[-1.06]	[1.10]
CAPM alpha	-8.2	-7.4	-5.4	-2.6	-2.9	5.3
	[-7.54]	[-8.57]	[-6.73]	[-3.17]	[-3.43]	[5.01]
3-factor alpha	1.8	0.1	1.4	3.5	4.4	2.7
	[2.21]	[0.22]	[2.28]	[5.52]	[6.76]	[2.52]

Panel A: Annualized long-short portfolio return for value

Panel B: Annualized long-short portfolio return for momentum

	$\operatorname{Low-}\overline{\beta}^{MOM}$	<i>~</i>	Fund	\longrightarrow	$\mathrm{High}\text{-}\overline{\beta}^{MOM}$	
	1	2	3	4	5	5 - 1
VW return	0.0	0.3	2.4	7.8	8.5	8.6
	[-0.02]	[0.09]	[0.88]	[2.46]	[3.09]	[2.68]
EW return	4.3	4.2	6.1	7.4	10.6	6.2
	[1.75]	[2.10]	[2.98]	[3.16]	[4.29]	[2.70]
CAPM alpha	2.1	2.2	2.8	7.1	8.4	6.2
	[2.88]	[2.87]	[4.03]	[8.71]	[11.76]	[7.81]
3-factor alpha	2.5	2.9	2.4	7.5	8.6	6.1
-	[3.28]	[3.71]	[3.41]	[8.84]	[11.64]	[7.35]

Table 8: Returns for portfolios sorted on changes in stock characteristics and funds factor demand Note: This table reports the performance of portfolios sorted on changes in stock characteristics and funds factor demand. In Panel A, each quarter, we independently sort all stocks into 5×5 portfolios based on their changes in B/M ratios over the last four quarters, denoted by $\Delta_4 B/M$, and their stock-level factor demand $\overline{\beta}^{HML}$, where $\overline{\beta}^{HML}$ is calculated as the shares-weighted average β^{HML} of a stock's underlying funds. Each cell reports the subsequent return for each of the five long-short portfolios that long the portfolio high in $\Delta_4 B/M$ and short the portfolio low in $\Delta_4 B/M$. In Panel B, each quarter, we independently sort all stocks into 5×5 portfolios based on their changes in past one-year returns (skipping the most recent month) over the last four quarters, denoted by $\Delta_4 RET$, and their stock-level factor demand $\overline{\beta}^{MOM}$, where $\overline{\beta}^{MOM}$ is calculated as the shares-weighted average β^{MOM} of a stock's underlying funds. Each cell reports the subsequent return for each of the five long-short portfolios that long the portfolio high in $\Delta_4 RET$ and short the portfolio low in $\Delta_4 RET$. In both panels, we report annualized value- and equal-weighted returns, CAPM alphas, and 3-factor alphas. Data are from 1980Q1 to 2018Q4.

Pan	Panel A: Annualized long-short portfolio return for value								
	Low- \overline{BM}	<i>←</i>	Fund	\longrightarrow	High- \overline{BM}				
	1	2	3	4	5	5 - 1			
VW return	0.3	2.7	5.2	8.6	8.5	8.2			
	[0.05]	[1.01]	[2.17]	[3.07]	[2.56]	[1.59]			
EW return	0.5	3.7	7.2	10.0	7.1	6.5			
	[0.12]	[1.48]	[2.95]	[3.57]	[2.54]	[1.36]			
CAPM alpha	-0.4	1.9	5.3	10.7	11.8	12.2			
	[-0.32]	[2.77]	[8.68]	[15.22]	[14.63]	[9.49]			
3-factor alpha	6.5	5.1	8.0	12.7	13.6	7.2			
	[5.52]	[8.26]	[13.27]	[17.63]	[16.46]	[5.64]			

Panel B: Annualized long-short portfolio return for momentum

	Low- \overline{RET}	\leftarrow	Fund	\longrightarrow	High- \overline{RET}	
	1	2	3	4	5	5-1
VW return	2.8	-0.4	-1.8	4.1	7.6	4.8
	[0.88]	[-0.12]	[-0.54]	[1.26]	[2.04]	[1.15]
EW return	5.9	2.6	3.2	5.4	11.8	6.0
	[2.10]	[0.97]	[1.22]	[2.11]	[3.91]	[1.95]
CAPM alpha	4.0	2.1	0.3	6.6	7.9	3.9
	[4.82]	[2.63]	[0.30]	[8.10]	[8.21]	[3.67]
3-factor alpha	5.2	3.0	0.5	7.7	11.2	6.0
	[6.12]	[3.70]	[0.56]	[9.61]	[12.11]	[5.72]

Table 9: Returns for portfolios sorted on stock characteristics and holdings-based factor demand Note: This table reports the performance of portfolios sorted on stock characteristics and holdings-based mutual fund factor demand. In Panel A, each quarter, we independently sort all stocks into 5×5 portfolios based on their B/M ratios and their stock-level mutual fund factor demand \overline{BM} , where \overline{BM} is calculated as the shares-weighted average BM^{fund} of a stock's underlying funds and BM^{fund} is the dollar-weighted average B/M ratio of a fund's holdings. Each cell reports the subsequent return for each of the five High-minus-Low portfolios. In Panel B, each quarter, we independently sort all stocks into 5×5 portfolios based on their past one-year returns (skipping the most recent month) and their stock-level factor demand \overline{RET} , where \overline{RET} is calculated as the shares-weighted average RET^{fund} of a stock's underlying funds and RET^{fund} is the dollar-weighted average past one-year return of a fund's holdings. Each cell reports the subsequent return for each of the five Winners-minus-Losers portfolios. In both panels, we report annualized value- and equal-weighted returns, CAPM alphas and 3-factor alphas. Data are from 1980Q1 to 2018Q4.

	Panel A: Flow-induced trading (FIT, %) - value										
		$\operatorname{Low-}\overline{eta}^{HML}$	\leftarrow	Fund	\longrightarrow	High- $\overline{\beta}^{HML}$					
		1	2	3	4	5					
Low-B/M	1	-0.02	-0.07	0.10	0.11	0.42					
\uparrow	2	-0.40	-0.31	-0.29	-0.05	0.17					
Stock	3	-0.35	-0.29	-0.17	-0.04	0.18					
\downarrow	4	-0.24	-0.27	-0.16	-0.19	0.03					
High-B/M	5	-0.25	-0.21	-0.13	-0.29	-0.14					
HML		-0.23	-0.14	-0.23	-0.39	-0.56					

Panel B: Flow-induced trading (FIT, %) - momentum	Panel B: Flo	w-induced	l trading (FIT	. %)	- momentun
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		$\operatorname{Low-}\overline{\beta}^{MOM}$	\leftarrow	Fund	\longrightarrow	High- $\overline{\beta}^{MOM}$
		1	2	3	4	5
Low-RET	1	-0.40	-0.42	-0.46	-0.49	-0.25
\uparrow	2	-0.23	-0.38	-0.35	-0.31	-0.27
Stock	3	-0.14	-0.33	-0.31	-0.22	-0.19
\downarrow	4	-0.07	-0.18	-0.14	-0.08	0.04
High-RET	5	0.20	-0.10	0.06	0.10	0.42
WML		0.60	0.32	0.52	0.59	0.67

Table 10: 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 stock j in 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 panels report quarterly average FIT for value and momentum-related portfolios, respectively.

		Panel A1: EW portfolio returns (annua)	v V portfoli	Value olio returns		ized, %)		1		Pane	Panel A2: EW portfolio returns (annualized, %)	portfolic	tfolio returns	(annuali	zed, %)		i
		TWH ^D		EJ		LT: ~L		1		-	$TWH^{\underline{U}}$		E		UI: ~h 7 / ML		
	7	row-p	↓ c	гипа 2	<u></u>	d-ugur ₅	. ע			ГО	d-wor	ļ	runa 2	↑ -	ngn- <i>p</i>	ר ע	
1 1	Ļ		7 7 7 7 7	- Fo	F C			[126]	Tan 1		1 0 1	3 C		۲ c o	0.01		
Low-B/M	-	7.61	12.1	9.1	9.9	6.4	-9.3	[-2.64]	LOW-KEI	_	8.7	8.3	8.0	8.3	10.2	2.4	0.93
High-B/M	5	11.8	16.7	16.2	15.0	13.9	2.1	[0.66]	High-RET	-2	12.5	13.4	14.5	18.8	22.7	10.2	[4.30]
HML		-3.9	4.6	7.1	5.1	7.5	11.4		MML		4.7	5.2	6.5	10.5	12.5	7.8	
t-stats		[-1.04]	[1.72]	[1.72] [3.06]	[2.24]	[3.42]	[2.99]		t-stats		[1.53]	[1.90]	[1.90] $[2.41]$	[3.56]	[4.27]	[3.33]	
		Panel B1	: CAPM ɛ́	Panel B1: CAPM alpha (annualized,		%)				. –	Panel B2: CAPM alpha (annualized, %)	CAPM a	lpha (an	nualized,	(%		
	[$Low - \overline{\beta}^{HML}$	↓	Fund	Î	$\operatorname{High}_{\overline{\beta}}^{HML}$		1		Lo	$Low - \overline{\beta}^{HML}$	↓	Fund	Î	$\operatorname{High}_{\overline{\beta}}^{HML}$		1
		1	2	3	4	5	5 - 1				1	2	3	4	5	5 - 1	
Low-B/M	1	5.0	3.0	1.0	2.8	-2.3	-7.3	[-8.94]	Low-RET	1	-2.6	-2.8	1.0	-1.5	0.7	3.3	[4.28]
High-B/M	5	-2.1	7.2	7.8	5.3	6.3	8.4	[11.50]	High-RET	2	0.4	0.0	4.0	6.6	7.8	7.4	[10.66]
HML		-7.1	4.2	6.8	2.5	8.6	15.8		MML		3.0	2.9	3.0	8.1	7.1	4.2	
t-stats		[-5.64]	[5.20] $[8.01]$	[8.01]	[3.58]	[11.80]	[12.12]		t-stats		[2.93]	[2.84]	[3.59]	[10.02]	[7.79]	[3.44]	
$P_{\hat{s}}$	anel	Panel C1: MKT+SMB+MOM 3-factor alpha (annualized, $\%$)	1B+MOM	[3-factor	alpha (an	nualized, %)			Pai	nel C2:	MKT+SM	B+HML	3-factor	alpha (an	Panel C2: MKT+SMB+HML 3-factor alpha (annualized, %)		
		$\operatorname{Low}_{\beta}^{HML}$	\downarrow	Fund	Ť	$\operatorname{High}_{\overline{\beta}}^{HML}$		1		Lo	$Low - \overline{\beta}^{HML}$	\downarrow	Fund	Î	$\operatorname{High}_{\overline{\beta}}^{HML}$		1
		1	2	3	4	5	5 - 1				1	2	3	4	5	5 - 1	
Low-B/M	-	1.1	0.8	-1.2	1.5	-2.7	-3.8	[-5.07]	Low-RET		-5.9	-5.5	0.3	-0.5	3.6	9.5	[17.53]
High-B/M	5	2.6	10.1	10.4	7.8	9.2	6.6	[10.76]	High-RET	5	0.1	0.1	4.3	8.7	11.4	11.3	[15.16]
HML		1.5	9.3	11.7	6.2	11.9	10.4		MML		6.0	5.6	4.0	9.2	7.8	1.8	
t-stats		[1.51]	[12.80]	[13.54]	[10.68]	[17.67]	[9.26]		t-stats		[7.68]	[6.81]	[5.15]	[10.82]	[7.59]	[1.79]	

 $\overline{\beta}^{HML}$ (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 the shares-weighted average HML and MOM loadings of a stock's underlying funds. Panels A1 and A2 report equal-weighted annualized 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 returns. Panels B1 and B2 report portfolio alphas based on CAPM. Panel C1 reports alphas from a three-factor model of market, size, and momentum; Panel C2 reports alphas from a three-factor model of market, size, and value. t statistics are reported in the brackets (t statistics for alphas are Newey-West adjusted with Table 11: Alternative pertormatice measures for 5×5 stock portuoilos softed on stock characteristics and stock-level factor demands 4 lags). Data are from 1980Q2 to 2018Q4.

	$\text{Low-}\overline{\beta}^{HML}$	$\frac{\text{annualized, \%}}{\text{High-}\overline{\beta}^{HML}}$			$\frac{1}{10000000000000000000000000000000000$	$\frac{\text{(annualized, \%)}}{\text{High-}\overline{\beta}^{HML}}$	/
	1 Low-p	5	5-1		1	$1 \text{ lign-}\beta$	5-1
HML VW ret	-2.71	7.57	- 10.29	HML VW ret	-13.94	7.17	21.11
	[-0.51]	[2.08]	[2.05]		[-2.17]	[1.79]	[2.88]
HML EW ret	0.10	4.41	[2.03] 4.31	HML EW ret	-7.65	10.44	[2.88] 18.09
	[0.02]	[1.53]	[1.02]		[-1.32]	[3.19]	[2.93]
CAPM alpha	1.78	12.87	11.09	CAPM alpha	-14.00	6.48	20.48
	[1.07]	[14.15]	[6.75]	Crii în alpha	[-7.69]	[6.69]	[10.06]
3-factor alpha	9.13	15.06	5.93	3-factor alpha	-9.31	8.89	18.20
	[6.28]	[12.56]	[3.52]	5-lactor alpha	[-7.03]	[10.88]	[12.42]
	[0.20]	[12.50]	[3.32]		[-7.03]	[10.00]	[12.42]
Panel C: Hig	h MF owners	ship (annualize	ed, %)	Panel D: Lo	ow MF owner	ship (annualize	ed, %)
	$\text{Low-}\overline{\beta}^{HML}$	High- $\overline{\beta}^{HML}$			$\text{Low-}\overline{\beta}^{HML}$	High- $\overline{\beta}^{HML}$	
	1	5	5-1		1	5	5-1
HML VW ret	-10.26	2.75	13.01	HML VW ret	-1.78	7.96	9.74
	[-2.13]	[0.88]	[2.51]		[-0.44]	[2.21]	[2.14]
HML EW ret	-5.61	1.91	7.51	HML EW ret	3.03	8.44	5.41
	[-1.19]	[0.68]	[1.54]		[0.85]	[2.92]	[1.33]
CAPM alpha	-8.35	3.02	11.37	CAPM alpha	0.11	9.65	9.54
_	[-6.64]	[3.26]	[7.59]	_	[0.10]	[10.11]	[8.06]
3-factor alpha	-0.55	5.28	5.83	3-factor alpha	5.79	14.01	8.22
-	[-0.54]	[5.62]	[4.19]	-	[6.01]	[15.37]	[7.66]
Panel E:	Large stocks	(annualized, %	5)		Panel F: Sma	all stocks (annu	ualized, %)
	$\text{Low-}\overline{\beta}^{HML}$	High- $\overline{\beta}^{HML}$	·		Low- $\overline{\beta}^{HML}$	High- $\overline{\beta}^{HML}$	
	1	5	5-1		1	5	5-1
HML VW ret	-7.37	6.22	13.59	HML VW ret	-2.52	4.68	7.20
	[-1.61]	[2.21]	[2.63]		[-0.59]	[1.51]	[1.46]
HML EW ret	-4.29	6.40	10.69	HML EW ret	-1.40	2.72	4.11
	[-0.99]	[2.34]	[2.34]		[-0.35]	[0.97]	[0.93]
CAPM alpha	-5.77	6.99	12.76	CAPM alpha	0.08	5.71	5.63
-	[-4.57]	[9.53]	[8.96]	-	[0.06]	[6.93]	[4.38]
3-factor alpha	1.52	9.22	7.70	3-factor alpha	7.34	8.70	1.37
	[1.33]	[13.15]	[5.91]	•	[6.13]	[11.12]	[1.13]

Table 12: Returns for 5×5 stock portfolios double-sorted on B/M ratios and stock-level value demand, subsample analysis

Note: This table reports returns and alphas for 25 portfolios double-sorted on B/M ratios and stock-level value demand, $\overline{\beta}^{HML}$, 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 above the median mutual fund ownership in each quarter. Panel D uses stocks below the median mutual fund ownership in each quarter. Panel E uses stocks above the median firm size in each quarter. Panel E uses stocks above the median firm size in each quarter. The alphas are calculated using a 3-factor model of market, size, and momentum. *t* statistics are reported in the bracket (*t* statistics for alphas are Newey-West adjusted with 4 lags). Data are from 1980Q2 to 2018Q4.

Panel	$\text{Low-}\overline{\beta}^{MOM}$	High- $\overline{\beta}^{MOM}$			$\frac{\text{B: Post-1999}}{\text{Low-}\overline{\beta}^{MOM}}$	High- $\overline{\beta}^{MOM}$	
	1 Low-p	5	5-1		11	5	5-1
WML VW ret	2.72	15.58	12.87	WML VW ret	-0.66	-0.73	-0.07
WINL WWICC	[0.66]	[3.78]	[2.69]	wivil v w ict	[-0.12]	[-0.13]	[-0.01]
WML EW ret	10.38	20.39	10.01	WML EW ret	-0.57	5.13	5.70
WINL LW ICI	[3.54]	[6.46]	[3.71]		[-0.11]	[1.09]	[1.51]
CAPM alpha	1.89	12.71	10.82	CAPM alpha	2.34	0.73	-1.60
	[1.79]	[13.20]	[11.70]	C/II W alpha	[1.43]	[0.52]	[-0.89]
3-factor alpha	4.32	15.37	11.05	3-factor alpha	4.15	3.13	-1.02
J-lactor alpha	[4.07]	[17.10]	[8.57]	5-lactor alpha	[3.58]	[2.04]	[-0.76]
Panel C: Hi	oh MF owner	ship (annualize	ed. %)	Panel D: Lo	ow MF owner	ship (annualize	d. %)
	$\overline{\text{Low-}\overline{\beta}^{MOM}}$	$\frac{1}{\text{High}-\overline{\beta}^{MOM}}$			$\operatorname{Low-}\overline{\beta}^{MOM}$	$\frac{1}{\text{High}-\overline{\beta}^{MOM}}$	u , <i>i</i>
	1 Low-p		5-1		11	πιgn-ρ 5	5-1
WML VW ret	0.65	9.77	- 3-1 9.12	WML VW ret	2.79	5.33	$-\frac{3-1}{2.55}$
wivil v w let	[0.18]	[2.53]	[2.27]	while www.ret	[0.77]	[1.45]	2.55 [0.66]
WML EW ret	3.78	11.30	[2.27] 7.51	WML EW ret	5.70	12.12	[0.00] 6.41
w will have let	[1.20]	[3.33]	[2.62]	WINL LW ICt	[1.83]	[3.95]	[2.25]
CAPM alpha	1.02	10.54	[2.02] 9.52	CAPM alpha	4.81	5.08	0.27
CAI M aipila	[0.97]	[9.82]	9.52 [7.65]	CAI W aipila	[4.63]	[5.86]	[0.26]
3-factor alpha	4.35	12.49	[7.03] 8.14	3-factor alpha	[4.03] 6.73	5.29	-1.43
	[5.28]	[10.44]	[6.75]	5-lactor alpha	[7.25]	[6.38]	[-1.68]
Panel F	Large stock	s (annualized, %	3		Panel F: Sma	ll stocks (annua	alized %
T uller E	$\overline{\text{Low-}\overline{\beta}^{MOM}}$	$\frac{1}{\text{High}} - \overline{\beta}^{MOM}$)	-	$\operatorname{Low}-\overline{\beta}^{MOM}$	$\frac{1}{\text{High}} - \overline{\beta}^{MOM}$	uiizeu, 70,
	1 Low-p		5 1		1 Low-p		5-1
1171 AT 17117 and		5.72	5-1 - 4.66	MANAL MAN and	7.79	13.64	-
WML VW ret	1.06			WML VW ret			5.85
WML EW ret	[0.30] 0.90	[1.49] 7.63	[1.13]	WML EW ret	[2.11]	[4.21]	[1.70]
WINL EW ret			6.73	WML EW ret	7.83	15.51	7.68
CADMalaka	[0.28]	[2.19]	[1.94]	CADMalaka	[2.34]	[5.17]	[2.45]
CAPM alpha	3.28	4.71	1.43	CAPM alpha	8.67	14.01	5.33
	[3.12]	[5.18]	[0.99]	0.6 1 1 1	[9.12]	[15.57]	[5.30]
3-factor alpha	6.11	5.22	-0.88	3-factor alpha	11.88	15.13	3.25
	[7.37]	[5.68]	[-0.80]		[13.81]	[15.54]	[3.90]

Table 13: Returns for 5×5 stock portfolios double-sorted on past one-year returns and stock-level momentum demand, subsample analysis

Note: This table reports returns and alphas for 25 portfolios double-sorted on past one-year returns (skipping the most recent month) and stock-level momentum demand, $\overline{\beta}^{MOM}$, 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 above the median mutual fund ownership in each quarter. Panel D uses stocks below the median mutual fund ownership in each quarter. Panel E uses stocks above the median firm size in each quarter. Panel F uses stocks below the median firm size in each quarter. The alphas are calculated using a 3-factor model of market, size, and value. *t* statistics are reported in the bracket (*t* statistics for alphas are Newey-West adjusted with 4 lags). Data are from 1980Q2 to 2018Q4.

Par	nel 4	A: VW portfol	io returns (a			
		$\text{Low-}\overline{\beta}^{HML}$	\leftarrow Fund \rightarrow	High- $\overline{\beta}^{HML}$		
		1	2	3	3 - 1	
Low-B/M	1	14.12	10.31	8.90	-5.2	[-1.97]
Stock	2	14.26	12.09	11.17	-3.1	[-1.31]
High-B/M	3	12.70	13.47	13.08	0.4	[0.04]
		1 4 1	0.17	4 1 0	5 50	
HML		-1.41	3.17	4.18	5.59	
		[-0.55]	[1.85]	[2.25]	[2.27]	

Panel B: EW portfolio returns (annualized, %)

		$\text{Low-}\overline{\beta}^{HML}$	\leftarrow Fund \rightarrow	High- $\overline{\beta}^{HML}$		
		1	2	3	3 - 1	
Low-B/M	1	14.59	11.02	8.94	-5.65	[-2.64]
$Stock \updownarrow$	2	15.44	13.81	12.64	-2.80	[-1.40]
High-B/M	3	15.20	15.51	13.76	-1.44	[-0.61]
HML		0.61	4.49	4.81	4.20	
		[0.25]	[2.73]	[2.65]	[2.11]	

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

i uner ev			r o raovor arj	pina (annaannae	.,,	
		$\operatorname{Low-}\overline{\beta}^{HML}$	\leftarrow Fund \rightarrow	High- $\overline{\beta}^{HML}$		
		1	2	3	3 - 1	
Low-B/M	1	1.74	1.86	0.90	-0.84	[-2.45]
Stock‡	2	5.84	4.39	4.49	-1.36	[-10.67]
High-B/M	3	6.43	7.43	8.24	1.81	[-1.72]
HML		4.69	5.58	7.34	2.65	
		[7.77]	[13.00]	[17.34]	[4.30]	
		Panel D: N	umber of sto			
		$\operatorname{Low-}\overline{\beta}^{HML}$	\leftarrow Fund \rightarrow	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 14: 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 value demand $(\bar{\beta}^{HML})$, where $\bar{\beta}^{HML}$ is the shares-weighted average β^{HML} of the underlying funds. Panels A, B and C report the value-weighted returns, equal-weight returns and alphas based on a 3-factor model of market, size and momentum for each of the 9 portfolios and the corresponding HML portfolios, respectively. Panel D reports the average number of stocks for each portfolios. t statistics are reported in the bracket (t statistics for alphas are Newey-West adjusted with 4 lags). Data are from 1980Q2 to 2018Q4.

		5	Growth fur	funds					Vâ	Value funds	lds	
I	$\operatorname{Low}-\overline{\beta}^{HML}$		Fund	\uparrow	$\mathrm{High}_{\overline{eta}}^{HML}$		Γ	$\operatorname{Low-}\overline{\beta}^{HML}$	\downarrow	Fund	Ţ	$\mathrm{High}_{\overline{eta}}^{HML}$
	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
\rightarrow 2	0.18	0.08	0.06	0.07	-0.01	\rightarrow 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
\downarrow	0.09	0.07	0.06	0.02	0.00	\downarrow		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
anel B: Decom	position of m	utual fu	and owne	rship c	Panel B: Decomposition of mutual fund ownership change (%) for momentum	omentum						
		Cont	Contrarian funds	unds					Mom	Momentum funds		
I	$\operatorname{Low-}\overline{\beta}^{MOM}$	\downarrow	Fund	Î	$\mathrm{High}_{-}\overline{eta}^{MOM}$		ΓC	$\operatorname{Low}_{-\overline{eta}}^{MOM}$	\downarrow	Fund	Î	$\mathrm{High}_{-\overline{eta}}^{MOM}$
	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
\uparrow 2	0.16	0.15	0.17	0.20	0.21	\rightarrow 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
\downarrow	0.01	0.00	0.04	0.10	0.11	\downarrow		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	MML		0.18	0.23	0.26	0.39	0.63

calculated as the shares-weighted average β^{HML} and β^{MOM} of the underlying funds, respectively. In each quarter, value (momentum) funds are defined as Note: This table reports average ownership changes from funds with low and high factor betas for 25 sorted portfolios of stocks. In each quarter, stocks are funds with HML (MOM) beta higher than the cross-sectional median and growth (contrarian) funds are defined as those lower than the cross-sectional median. We calculate ownership changes from these funds in the subsequent quarter for each portfolio and report their time-series averages. Panels A and B report independently sorted into 25 portfolios based on their B/M ratios or past one-year returns (skipping the most recent month) and on their β^{HML} or β^{MOM} Table 15: Decomposition of total mutual fund ownership changes ownership changes for value and momentum, respectively.

	HM	/L 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
	W	AL 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 16: Estimates of price elasticity of demand

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

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

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

Pan.	el A: SU	E (%), v	alue	- <i>HMH</i>				Pan -HML	el B: CA	K (%), v	alue	-HMH	
-ββ.	\downarrow	Fund	Ť	$\operatorname{High}_{\beta}$				$Low-\beta^{mm}$	\downarrow	Fund	Î	High- β^{mu}	
1	2	3	4	5	5 - 1			1	2	3	4	5	5 - 1
0.16	0.24	0.24	0.33	0.36	0.20	Low-B/M		0.39	0.12	-0.38	-0.31	-0.14	-0.53
0.12	0.17	0.15	0.15	0.20	0.08	\leftarrow	2	0.37	0.15	-0.07	-0.13	-0.18	-0.55
-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
-0.15	-0.02	-0.06	0.04	0.07	0.22	\rightarrow	4	-0.14	0.30	-0.08	0.12	0.03	0.17
-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
-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 (?	%), mon	nentum					Panel D): CAR (%), mon	nentum		
$ow - \overline{\beta}^{MOM}$	\downarrow	Fund	Î	$\operatorname{High}_{\overline{eta}}^{MOM}$				$Low - \overline{\beta}^{MOM}$	\downarrow	Fund	Ť	$\mathrm{High}_{\overline{eta}}^{MOM}$	
1	2	3	4	5	5 - 1			1	2	3	4	5	5 - 1
-1.12	-0.90	-0.64	-0.51	-0.44	0.68	Low-RET		0.05	-0.19	-0.06	0.26	0.20	0.15
-0.21	-0.16	-0.07	-0.04	-0.08	0.13	\leftarrow	2	-0.01	0.06	0.20	0.14	-0.03	-0.02
0.04	0.10	0.09	0.14	0.14	0.10	Stock	33	-0.09	0.01	-0.03	0.19	0.23	0.32
0.26	0.23	0.30	0.21	0.20	-0.06	\rightarrow	4	-0.04	-0.03	-0.09	0.13	0.47	0.51
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
1.79	1.49	1.17	0.98	0.90	-0.89	MML		-0.53	0.14	0.23	-0.15	0.18	0.72
	$\begin{array}{c} {\rm Pant}\\ {\rm Low}-\overline{\beta}^{HML}\\ 1\\ 0.16\\ 0.12\\ -0.04\\ -0.15\\ -0.15\\ -0.15\\ -0.15\\ -0.12\\ 1\\ 1\\ 1\\ 1\\ -1.12\\ -0.21\\ 0.04\\ 0.26\\ 0.68\\ 0.68\end{array}$	$\begin{array}{c c} & Fanel A: SU1 \\ Low-\overline{\beta}^{HML} & \leftarrow \\ 1 & 2 \\ 0.16 & 0.24 \\ 0.12 & 0.17 \\ -0.04 & 0.18 \\ -0.15 & -0.02 \\ -0.02 & -0.63 \\ -1.02 & -0.63 \\ randle C: SUE (\% \\ Low-\overline{\beta}^{MOM} & \leftarrow \\ 1 & 2 \\ 1 & 2 \\ -0.21 & -0.16 \\ 0.04 & 0.10 \\ 0.68 & 0.60 \\ 1.79 & 1.49 \end{array}$	$\begin{array}{c c} F_{anel A: SUE}(\overline{\%}), v \\ \hline Low-\overline{\beta}^{HML} & \longleftarrow Fund \\ 1 & 2 & 3 \\ 0.16 & 0.24 & 0.24 \\ 0.12 & 0.17 & 0.15 \\ -0.04 & 0.18 & 0.16 \\ -0.15 & -0.06 & -0.69 \\ -1.02 & -0.63 & -0.69 \\ -1.02 & -0.67 & -0.69 \\ -1.02 & -0.61 & -0.69 \\ \hline I & 2 & 3 \\ 1 & 2 & 3 \\ -1.12 & -0.90 & -0.64 \\ -0.21 & -0.16 & -0.07 \\ 0.04 & 0.10 & 0.09 \\ 0.68 & 0.60 & 0.53 \\ 0.68 & 0.60 & 0.53 \\ \end{array}$	$\begin{array}{rrrr} I.A: SUE (\%), va \\ \leftarrow Fund \\ 2 & 3 \\ 0.24 & 0.24 \\ 0.17 & 0.15 \\ 0.18 & 0.16 \\ -0.02 & -0.06 \\ -0.63 & -0.45 \\ -0.63 & -0.69 \\ \hline \\ \hline \\ rSUE (\%), mome \\ \leftarrow Fund \\ \hline \\ \hline \\ rund \\ \hline \\ rund \\ \hline \\ rund \\ \hline \\ rund \\ 0.60 & 0.53 \\ 0.60 & 0.53 \\ \hline \end{array}$	I.A: SUE ($\%$), value \leftarrow Fund \rightarrow 2 3 4 2 3 4 0.24 0.24 0.33 0.17 0.15 0.15 0.18 0.16 0.20 -0.02 -0.06 0.04 -0.63 -0.45 -0.45 -0.87 -0.69 -0.78 -0.87 -0.69 -0.78 -0.87 -0.69 -0.78 -0.90 -0.64 -0.78 2 3 4 -0.90 -0.64 -0.14 0.10 0.09 0.14 0.10 0.053 0.30 0.10 0.53 0.31 0.46 0.17 0.93	I.A: SUE (%), value \leftarrow Fund \rightarrow High- $\overline{\beta}^{HML}$ 2 3 4 5 0.24 0.24 0.33 0.36 0.17 0.15 0.15 0.20 0.18 0.16 0.20 0.12 -0.02 -0.06 0.04 0.07 -0.63 -0.45 -0.49 -0.78 -0.87 -0.69 -0.78 -0.86 -0.87 -0.69 -0.78 -0.49 -0.87 -0.69 -0.78 -0.46 -0.93 -0.45 -0.45 -0.49 -0.87 -0.69 -0.78 -0.86 -0.93 -0.45 -0.46 -0.49 -0.87 -0.69 -0.78 -0.86 -0.99 -0.64 -0.44 -0.44 -0.10 0.09 0.47 0.47 1.49 1.17 0.98 0.90	I.A: SUE (%), value High- $\overline{\beta}^{HML}$ 2 3 4 5 5-1 2 3 4 5 5-1 2 3 4 5 5-1 0.17 0.15 0.15 0.20 0.08 0.17 0.15 0.15 0.20 0.08 0.18 0.16 0.20 0.12 0.15 -0.02 -0.06 0.04 0.07 0.22 -0.63 -0.45 -0.49 0.36 1 -0.63 -0.45 -0.49 0.36 1 -0.63 -0.45 -0.49 0.36 1.6 -0.87 -0.69 -0.78 -0.86 0.16 -0.87 -0.69 -0.78 -0.86 0.16 -0.87 -0.69 -0.78 -0.86 0.16 2 3 4 5 5-1 2 3 4 5 5-1 -0.16 0.07 -0.04 0.10 0.06 0.10 0.09 0.14 0.10	I.A: SUE (%), value High- $\overline{\beta}^{HML}$ 2 3 4 5 5-1 2 3 4 5 5-1 2 3 4 5 5-1 0.17 0.15 0.15 0.20 0.08 \uparrow 2 0.17 0.15 0.15 0.20 0.08 \uparrow 2 0.18 0.16 0.20 0.12 0.15 Stock 3 0.18 0.16 0.20 0.15 Stock 3 -0.63 -0.45 -0.49 0.36 High-B/M 5 -0.63 -0.45 -0.49 0.36 High-B/M 5 -0.63 -0.45 -0.49 0.36 High-B/M 5 -0.87 -0.49 0.36 0.16 P/M 5 -0.87 -0.44 0.036 0.16 P/M 5 -0.99 -0.64 -0.74 0.68 0.16 2 2 3 4 5 5 2 2 2 0.14 <td>I.A: SUE (%), value Low.bML Low-B/ML 2 3 4 5 5-1 Low-B/M 1 2 3 4 5 5-1 Low-B/M 1 1 2 3 4 5 5-1 Low-B/M 1 1 1 0.24 0.24 0.33 0.36 0.20 0.08 \uparrow 2 0 0 0.17 0.15 0.15 0.12 0.15 Stock 3 0</td> <td>I.A: SUE (%), value Low.bML Low-B/ML 2 3 4 5 5-1 Low-B/M 1 2 3 4 5 5-1 Low-B/M 1 1 2 3 4 5 5-1 Low-B/M 1 1 1 0.24 0.24 0.33 0.36 0.20 0.08 \uparrow 2 0 0 0.17 0.15 0.15 0.12 0.15 Stock 3 0</td> <td>I.A: SUE (%), value Low.bML Low-B/ML 2 3 4 5 5-1 Low-B/M 1 2 3 4 5 5-1 Low-B/M 1 1 2 3 4 5 5-1 Low-B/M 1 1 1 0.24 0.24 0.33 0.36 0.20 0.08 \uparrow 2 0 0 0.17 0.15 0.15 0.12 0.15 Stock 3 0</td> <td>I.A: SUE (%), value Fanel 15: CAK (%), value \leftarrow Fund \rightarrow High-$\overline{\beta}^{HML}$ Low-$\overline{\beta}^{HML}$ \leftarrow Fund 2 3 4 5 5-1 1 2 3 0.24 0.24 0.33 0.36 0.20 0.08 \uparrow 1 2 3 0.17 0.15 0.15 0.20 0.08 \uparrow 2 0.37 0.12 -0.38 0.17 0.15 0.12 0.15 $Stock$ 3 0.26 -0.03 0.18 0.16 0.20 0.12 0.22 \downarrow 4 0.37 0.15 -0.03 -0.63 -0.45 -0.49 0.36 0.16 0.26 -0.03 -0.63 -0.45 -0.49 0.36 0.14 0.37 0.15 -0.06 -0.63 -0.45 -0.49 0.36 -0.46 -0.12 -0.03 -0.26 -0.03 -0.87 -0.69 -0.14 0.28 -0.42 -0.06</td> <td>I.A: SUE (%), value Fanel B: CAK (%), value \leftarrow Fund \rightarrow High-$\overline{\beta}^{HML}$ Fanel B: CAK (%), value 2 3 4 5 5-1 1 2 3 4 High-$\overline{\beta}^{HML}$ 0.24 0.24 0.35 0.20 0.08 \uparrow 2 0.37 0.13 -0.03 -0.13 0.17 0.15 0.12 0.03 0.12 0.03 0.017 -0.13 -0.013 -0.113 0.18 0.16 0.20 0.03 0.23 0.017 0.03 -0.17 -0.13 -0.05 -0.49 0.36 0.16 HML -</td>	I.A: SUE (%), value Low.bML Low-B/ML 2 3 4 5 5-1 Low-B/M 1 2 3 4 5 5-1 Low-B/M 1 1 2 3 4 5 5-1 Low-B/M 1 1 1 0.24 0.24 0.33 0.36 0.20 0.08 \uparrow 2 0 0 0.17 0.15 0.15 0.12 0.15 Stock 3 0	I.A: SUE (%), value Low.bML Low-B/ML 2 3 4 5 5-1 Low-B/M 1 2 3 4 5 5-1 Low-B/M 1 1 2 3 4 5 5-1 Low-B/M 1 1 1 0.24 0.24 0.33 0.36 0.20 0.08 \uparrow 2 0 0 0.17 0.15 0.15 0.12 0.15 Stock 3 0	I.A: SUE (%), value Low.bML Low-B/ML 2 3 4 5 5-1 Low-B/M 1 2 3 4 5 5-1 Low-B/M 1 1 2 3 4 5 5-1 Low-B/M 1 1 1 0.24 0.24 0.33 0.36 0.20 0.08 \uparrow 2 0 0 0.17 0.15 0.15 0.12 0.15 Stock 3 0	I.A: SUE (%), value Fanel 15: CAK (%), value \leftarrow Fund \rightarrow High- $\overline{\beta}^{HML}$ Low- $\overline{\beta}^{HML}$ \leftarrow Fund 2 3 4 5 5-1 1 2 3 0.24 0.24 0.33 0.36 0.20 0.08 \uparrow 1 2 3 0.17 0.15 0.15 0.20 0.08 \uparrow 2 0.37 0.12 -0.38 0.17 0.15 0.12 0.15 $Stock$ 3 0.26 -0.03 0.18 0.16 0.20 0.12 0.22 \downarrow 4 0.37 0.15 -0.03 -0.63 -0.45 -0.49 0.36 0.16 0.26 -0.03 -0.63 -0.45 -0.49 0.36 0.14 0.37 0.15 -0.06 -0.63 -0.45 -0.49 0.36 -0.46 -0.12 -0.03 -0.26 -0.03 -0.87 -0.69 -0.14 0.28 -0.42 -0.06	I.A: SUE (%), value Fanel B: CAK (%), value \leftarrow Fund \rightarrow High- $\overline{\beta}^{HML}$ Fanel B: CAK (%), value 2 3 4 5 5-1 1 2 3 4 High- $\overline{\beta}^{HML}$ 0.24 0.24 0.35 0.20 0.08 \uparrow 2 0.37 0.13 -0.03 -0.13 0.17 0.15 0.12 0.03 0.12 0.03 0.017 -0.13 -0.013 -0.113 0.18 0.16 0.20 0.03 0.23 0.017 0.03 -0.17 -0.13 -0.05 -0.49 0.36 0.16 HML -

Fundamentals are measured by standardized earnings surprise (SUE) and cumulative abnormal returns (CAR), and aggregated to the portfolio level by valueweighting stock-level quantities. SUE is defined as earnings surprise relative to analysts' forecasts, normalized by the current stock price. CAR is defined as the size and value-adjusted abnormal returns in a three-day window around the earnings announcements. Panels A and B report results for value. Panels C and D Note: This table reports the subsequent fundamentals for the 25 portfolios sorted on B/M ratios (past one-year return) and stock-level value (momentum) demand. Table 17: Subsequent fundamentals for 5×5 stock portfolios double-sorted on stock characteristics and fund betas report results for momentum.

Online Appendix for

"Factor Demand and Factor Returns"

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

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

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

	β_{i}^{H}	ML	β_{ia}^{M}	OM
	(1)	(2)	(3)	(4)
$\beta_{i,q-20}^{HML}$	0.478^{***} (0.014)	0.475^{***} (0.014)		
$\beta_{i,q-20}^{MOM}$	(0.011)	(0.022)	0.421*** (0.017)	0.418*** (0.017)
AllIndex $AllIndex imes eta_{i,q-20}^{HML}$	0.021* (0.012) -0.143*** (0.039)		-0.037*** (0.005)	
PureIndex $PureIndex imes eta_{i,q-20}^{HML}$		0.020 (0.012) -0.141*** (0.041)		-0.039*** (0.005)
$AllIndex imes eta_{i,q-20}^{MOM}$			-0.189^{***} (0.048)	
$PureIndex imes eta_{i,q-20}^{MOM}$			· · · ·	-0.187*** (0.050)
Quarter FE Obs. R ²	Yes 95,876 0.310	Yes 95,876 0.309	Yes 95,876 0.271	Yes 95,876 0.271

Table A.2: 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. *, **, *** indicate statistical significance at 10%, 5% and 1% levels, respectively.

	$\beta_{i,e}^H$		$\beta_{i,a}^M$	<i>IOM</i>
	(1)	(2)	(3)	(4)
$\beta_{i,q-20}^{HML}$	0.886***	1.013***		
<i>i i</i> , <i>q</i> -20	(0.054)			
$\beta_{i,q-20}^{MOM}$			0.535***	0.596***
, _{2,} q 20			(0.064)	(0.062)
ActiveShare	-0.007		-0.030***	
	(0.024)		(0.010)	
ActiveShare (SD)		-0.013		-0.023***
		(0.024)		(0.007)
ActiveShare $ imes eta_{i,q-20}^{HML}$	-0.546***			
	(0.066)			
ActiveShare (SD) $ imes eta_{i,q-20}^{HML}$		-0.620***		
		(0.084)		
ActiveShare $\times \beta_{i,q-20}^{MOM}$			-0.252***	
			(0.080)	
ActiveShare (SD) $\times \beta_{i,q-20}^{MOM}$				-0.263***
				(0.077)
Quarter FE	Yes	Yes	Yes	Yes
Obs.	125,512	87,000	125,512	87,000
R^2	0.307	0.364	0.184	0.228

Table A.3: 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. *, **, *** indicate statistical significance at 10%, 5% and 1% levels, respectively.

	Panel A	A: One-	quarte	r transit	ion, B/M		Panel	B: One-	-year tr	ansitior	1, B/M
	1	2	3	4	5		1	2	3	4	5
1	0.86	0.12	0.01	0.00	0.00	1	0.68	0.23	0.06	0.03	0.01
2	0.10	0.72	0.16	0.02	0.00	2	0.16	0.50	0.24	0.07	0.02
3	0.00	0.14	0.67	0.17	0.01	3	0.03	0.21	0.45	0.25	0.07
4	0.00	0.01	0.16	0.69	0.14	4	0.01	0.05	0.22	0.48	0.23
_									~ ~ =		
5	0.00	0.00	0.01	0.14	0.85	5	0.01	0.01	0.05	0.22	0.72
		One-qu	arter t	ransitio	n, $r_{t-4,t-1/3}$	-		One-ye	ear tran	nsition, <i>i</i>	$r_{t-4,t-1/}$
	nel C:	One-qu 2	arter t	ransition 4	$\frac{n, r_{t-4,t-1/3}}{5}$	-	nel D:	One-ye	ear tran 3	nsition, <i>n</i>	$\frac{r_{t-4,t-1/2}}{5}$
Pa 1		One-qu	arter t	ransitio	n, $r_{t-4,t-1/3}$	-		One-ye	ear tran	nsition, <i>i</i>	$r_{t-4,t-1/}$
Pa 1 2	nel C: 1 0.61	One-qu 2 0.23	arter t 3 0.09	ransition 4 0.05	$\frac{n, r_{t-4,t-1/3}}{5} \\ 0.02$	Pa 1	nel D: 1 0.25	One-ye	ear tran 3 0.18	nsition, 7 4 0.18	$\frac{r_{t-4,t-1/2}}{5}$
	nel C: 0 1 0.61 0.23	One-qu 2 0.23 0.36	arter t <u>3</u> 0.09 0.25	ransition 4 0.05 0.12	$ \begin{array}{r} n, r_{t-4,t-1/3} \\ 5 \\ 0.02 \\ 0.04 \end{array} $	Pa 1 2	nel D: 1 0.25 0.19	One-ye 2 0.20 0.22	ear tran 3 0.18 0.23	nsition, <i>n</i> 4 0.18 0.22	$r_{t-4,t-1/}{5 \over 0.19 \over 0.14}$

Table A.4: Transition probability of stocks

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

	1	2	3	4	5		1	2	3	4	5
1	0.88	0.11	0.01	0.00	0.00	1	0.74	0.20	0.04	0.02	0.01
2	0.11	0.75	0.13	0.01	0.00	2	0.19	0.53	0.21	0.06	0.02
3	0.01	0.13	0.73	0.12	0.01	3	0.04	0.21	0.51	0.20	0.04
4	0.00	0.01	0.12	0.76	0.10	4	0.01	0.06	0.20	0.56	0.17
-	0.00	0.00	0.01	0.10	0.89	E	0.01	0.02	0.04	0.18	0.75
5 D-	0.00	0.00				5 D-					
	I				$\frac{0.89}{n, \beta^{MOM}}$					usition,	
	inel C:	One-qu	arter t	ransitio	n, β^{MOM}		nel D:	One-ye	ear tran	isition,	β^{MOM}
Pa	inel C:	One-qı 2	arter t	ransitio 4	n, β^{MOM} 5	Pa	nel D: 1	One-ye	ear tran 3	sition, 4	$\frac{\beta^{MOM}}{5}$
Pa 1	inel C: 1 0.89	One-qu 2 0.10	harter t $\frac{3}{0.01}$	ransitio 4 0.00	$\frac{n, \beta^{MOM}}{5}$	Pa 1	nel D: 1 0.75	One-ye 2 0.18	ear tran 3 0.04	sition, 4 0.02	$\frac{\beta^{MOM}}{5}$
Pa 1 2	nnel C: 1 0.89 0.09	One-qu 2 0.10 0.77	arter t <u>3</u> 0.01 0.13	ransitio 4 0.00 0.01	n, β^{MOM} 5 0.00 0.00	Pa 1 2	nel D: 1 0.75 0.15	One-ye 2 0.18 0.56	ear tran 3 0.04 0.21	nsition, 4 0.02 0.06	$\frac{\beta^{MOM}}{5}$ 0.01 0.02

Table A.5: Transition probability of funds

Note: This table reports the probability of a fund moving from one factor beta quintile to another quintile over time. Funds are sorted into different quintiles in each quarter based on their factor betas, which are estimated by regressing fund returns on factor returns in a five-year rolling window. Panels A and B report transition probabilities based on 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.

Dep	oendent varia	able: $\Delta Shares_{i}$	$_{i,j,q+1}/Shrow$	$\mu t_{i,q}$
Panel A: Value				
	Low- $\beta_{j,q}^{HI}$	ML (growth)	High- β_j^H	$A_{,q}^{MML}$ (value)
	(1)	(2)	(3)	(4)
$BM_{i,q}$	-0.0194**	-0.0185**	0.0159**	0.0181**
	(0.0076)	(0.0074)	(0.0072)	(0.0076)
$\beta_{i,q}$		0.0148^{**}		-0.0239***
		(0.0068)		(0.0065)
$ME_{i,q}$		-1.443***		-0.9635***
., 1		(0.0792)		(0.0647)
$OP_{i,q}$		-0.0445***		-0.0067**
.,1		(0.0054)		(0.0030)
$INV_{i,q}$		0.1582***		0.1193***
. / 1		(0.0096)		(0.0091)
R^2	0.0001	0.0103	0.0001	0.0043
Observations	3,615,836	3,400,955	6,575,970	5,531,588
Panel B: Mome	entum			
	Low- $\beta_{j,q}^{MOI}$	M (contrarian)	High- $\beta_{j,q}^{MOI}$	M (momentum)
$r_{i,q-4,q-1/3}$	-0.0170*	-0.0097	0.1027***	0.0965***
	(0.0095)	(0.0086)	(0.0060)	(0.0056)
$BM_{i,q}$		0.0233***		-0.0164***
		(0.0060)		(0.0054)
$\beta_{i,q}$		-0.0080		-0.0198***
		(0.0083)		(0.0056)
$ME_{i,q}$		-1.494***		-1.265***
- 7 2		(0.0902)		(0.0621)
$OP_{i,q}$		-0.0244***		-0.0233***
- 7 - 2		(0.0045)		(0.0036)
$INV_{i,q}$		0.1661***		0.1527***
- 7 - 7		(0.0106)		(0.0084)
R^2	0.0001	0.0072	0.0049	0.0122

Table A.6: Fund-level portfolio rebalancing: FIT-adjusted trading in shares and stock characteristics

Note: This table reports how mutual funds rebalance their portfolios based on stock characteristics. The dependent variable, $\Delta Shares_{i,j,q+1}/Shrout_{i,q}$, is FIT-adjusted trading 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, $\beta_{i,q}$; market capitalization (in billions), $ME_{i,q}$; operating profitability, $OP_{i,q}$; and investment, $INV_{i,q}$. Panels A and B report results for value and momentum, respectively. Columns (1) and (2) use funds in top quintile of $\beta_{j,q}^{HML}$ (Panel A) or $\beta_{j,q}^{MOM}$ (Panel B). Columns (3) and (4) use funds in bottom quintile of $\beta_{j,q}^{HML}$ (Panel B). The data sample is from 1980Q1 to 2018Q4. Standard errors are clustered at the fund level. *, **, *** indicate statistical significance at 10%, 5% and 1% levels, respectively. The intercepts are omitted.

Dep	endent varial	ble: $\Delta Shares_i$	$_{j,q+1}/Shrow$	$t_{i,q}$
Panel A: Value				
	Low- $\beta_{j,q}^{HN}$	^{<i>IL</i>} (growth)	High- β_j^H	A_{q}^{MML} (value)
	(1)	(2)	(3)	(4)
$\Delta BM_{i,q}$	-0.1365***	-0.1651***	0.0815***	0.0832***
	(0.0139)	(0.0156)	(0.0154)	(0.0173)
$\Delta \beta_{i,q}$		0.0603***		0.0258***
		(0.0055)		(0.0042)
$\Delta M E_{i,q}$		-4.435***		-2.501***
		(0.2945)		(0.1738)
$\Delta OP_{i,q}$		-0.0083***		-0.0057***
.,1		(0.0021)		(0.0017)
$\Delta INV_{i,q}$		-0.0256***		-0.0178***
		(0.0029)		(0.0036)
\mathbb{R}^2	0.0007	0.0025	0.0007	0.0013
Observations	3,435,607	3,232,590	6,396,422	5,390,468
Panel B: Momer	ntum			
	Low- $\beta_{j,q}^{MON}$	(contrarian)	High- $\beta_{j,q}^{MOI}$	M (momentum)
$\Delta r_{i,q-4,q-1/3}$	-0.0638***	-0.0384***	0.0365***	0.0351***
,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,	(0.0060)	(0.0053)	(0.0041)	(0.0037)
$\Delta BM_{i,q}$		0.1054^{***}		-0.0659***
71		(0.0227)		(0.0089)
$\Delta \beta_{i,q}$		0.0319***		0.0311***
		(0.0069)		(0.0039)
$\Delta ME_{i,q}$		-1.643***		-4.727***
		(0.1792)		(0.2822)
$\Delta OP_{i,q}$		-0.0060**		-0.0018
· / I		(0.0029)		(0.0014)
$\Delta INV_{i,q}$		-0.0248***		-0.0185***
-14		(0.0048)		(0.0022)
\mathbb{R}^2	0.0012	0.0022	0.0006	0.0021
Observations	2,697,639	2,349,658	5,595,247	4,995,286

Table A.7: Fund-level portfolio rebalancing: FIT-adjusted trading in shares and changes in stock characteristics

Note: This table reports how mutual funds rebalance their portfolios based on stock characteristics. The dependent variable, $\Delta Shares_{i,j,q+1}/Shrout_{i,q}$, is FIT-adjusted trading 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 4-quarter change in characteristics (between q - 4 and q), including the book-to-market ratio, $\Delta BM_{i,q}$; past one-year return (skipping the most recent month), $\Delta r_{i,q-4,q-1/3}$; market beta, $\Delta \beta_{i,q}$; market capitalization (in billions); operating profitability, $\Delta OP_{i,q}$; and investment, $\Delta INV_{i,q}$. $DeltaME_{i,q}$. Panels A and B report results for value and momentum, respectively. Columns (1) and (2) use funds in top quintile of $\beta_{j,q}^{HML}$ (Panel A) or $\beta_{j,q}^{MOM}$ (Panel B). Columns (3) and (4) use funds in bottom quintile of $\beta_{j,q}^{HML}$ (Panel A) or $\beta_{j,q}^{MOM}$ (Panel B). The data sample is from 1980Q1 to 2018Q4. Standard errors are clustered at the fund level. *, **, *** indicate statistical significance at 10%, 5% and 1% levels, respectively. The intercepts are omitted.

				B/M							$\overline{\beta}^{HM}$	L		
		$Low-\overline{\beta}^{HML}$		Fund	\rightarrow	High- $\overline{\beta}^{HML}$	•		$\text{Low-}\overline{\beta}^{HML}$	<i>—</i>	Fund	\rightarrow	High- $\overline{\beta}^{HML}$	
		1	2	3	4	5	5 - 1		1	2	3	4	5	5-
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	0.5
1	2	0.30	0.31	0.32	0.33	0.33	0.03	2	-0.26	-0.08	0.02	0.11	0.27	0.5
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	0.5
\downarrow	4	0.72	0.72	0.73	0.73	0.74	0.02	4	-0.28	-0.08	0.03	0.11	0.28	0.5
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	0.5
HML		1.42	1.26	1.16	1.15	1.20	-0.21		-0.01	0.02	0.02	0.01	0.01	0.0
		Panel B: Pre	e-forma			stics for 5×5	stock po	rtfolio	os sorted on r_t	-4,t-1/3	and M	OM be	tas	
			e-forma	r_{t-4}	aracteri		stock po			-4,t-1/3	$\overline{\beta}^{M}$	ОМ		
		Panel B: Pre	e-forma ←			stics for 5×5 stics for $\overline{5} \times \overline{5}$ stics for $\overline{5} \times \overline{5} \times \overline{5}$ stics for $\overline{5} \times \overline{5} \times \overline{5}$ stics for $\overline{5} \times \overline{5} \times \overline{5} \times \overline{5} \times \overline{5}$ stics for $\overline{5} \times \overline{5} \times \overline$	stock po			-4,t-1/3	and M $\overline{\beta}^{M}$ Fund	ОМ	tas High- $\overline{\beta}^{MOM}$	
			e-forma	r_{t-4}	t - 1/3		5-1		$\frac{1}{1} \text{Low} - \overline{\beta}^{MOM}$	$\xrightarrow{-4,t-1/3}$	$\overline{\beta}^{M}$	ОМ		5-
Low-RET	1		<i>~</i>	r _{t-4} , Fund	$t \rightarrow 1/3$	$\mathrm{High}\text{-}\overline{\beta}^{MOM}$				~	$\overline{\beta}^{M}$ Fund	\longrightarrow	$\mathrm{High}\text{-}\overline{\beta}^{MOM}$	5-
Low-RET ↑	1 2	$\frac{1}{1} Low - \overline{\beta}^{MOM}$	$\stackrel{\longleftarrow}{\sim}_2$	r_{t-4} , Fund 3	$\stackrel{t-1/3}{\longrightarrow}$	High- $\overline{\beta}^{MOM}$	5-1		Low- $\overline{\beta}^{MOM}$	$\leftarrow 2$	$\overline{\beta}^{M}$ Fund 3	\xrightarrow{OM} 4	High- $\overline{\beta}^{MOM}$	0.2
Low-RET ↑ Stock			←	r_{t-4} Fund 3 -0.22	$ \begin{array}{c} t-1/3 \\ \longrightarrow \\ 4 \\ \hline -0.23 \end{array} $	High- $\overline{\beta}^{MOM}$ 5 -0.24	5-1 -0.01	1	$ Low-\overline{\beta}^{MOM} 1 -0.10 $	← 2 -0.03	$ \frac{\overline{\beta}^{M}}{Fund} \\ 3 \\ 0.01 $	$ \xrightarrow{OM} \\ 4 \\ \hline 0.06 $	$\frac{\text{High-}\overline{\beta}^{MOM}}{5}$	
\uparrow	2		<2 -0.22 -0.02	r_{t-4} Fund 3 -0.22 -0.01	$ \begin{array}{c} t-1/3 \\ \hline \\ 4 \\ \hline \\ -0.23 \\ -0.01 \end{array} $	High- $\overline{\beta}^{MOM}$ 5 -0.24 -0.01	5—1 -0.01 0.00	1 2	Low- \overline{eta}^{MOM} 1 -0.10 -0.09	<2 -0.03 -0.03	$\overline{\beta}^{M}$ Fund 3 0.01 0.01	$ \begin{array}{c} \longrightarrow \\ 4 \\ \hline 0.06 \\ 0.06 \end{array} $	High- $\overline{\beta}^{MOM}$ 5 0.15 0.14	0.2 0.2
\uparrow	2 3		< -0.22 -0.02 0.13	$\begin{array}{c} r_{t-4,}\\ Fund\\ 3\\ -0.22\\ -0.01\\ 0.14 \end{array}$	$ \begin{array}{c} t-1/3 \\ \hline 4 \\ \hline -0.23 \\ -0.01 \\ 0.14 \end{array} $	$\begin{array}{c} \text{High-}\overline{\beta}^{MOM} \\ 5 \\ -0.24 \\ -0.01 \\ 0.14 \end{array}$	5-1 -0.01 0.00 0.01	1 2 3	Low- $\overline{\beta}^{MOM}$ 1 -0.10 -0.09 -0.09	< -0.03 -0.03 -0.03	$\overline{\beta}^{M}$ Fund 3 0.01 0.01 0.01	$\begin{array}{c} \longrightarrow \\ 4 \\ \hline 0.06 \\ 0.06 \\ 0.06 \end{array}$	$\begin{array}{c} \text{High-}\overline{\beta}^{MOM} \\ 5 \\ 0.15 \\ 0.14 \\ 0.14 \end{array}$	0.2 0.2 0.2

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

Note: This table reports the 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 $(r_{t-4,t-1/3})$ 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.

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

Table A.9: Stock-level cross-sectional regressions

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

$$r_{i,q+1} = \gamma_0 + \gamma_1 B M_{i,q} + \gamma_2 r_{i,q-4,q-\frac{1}{2}} + \gamma_3 M E_{i,q} + \gamma_4 \beta_{i,q} + \varepsilon_{i,q+1}$$

where the dependent variable is stock *i*'s return in quarter q + 1. The independent variables include the bookto-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 $\bar{\beta}_{i,q}^{HML}$) 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 $\bar{\beta}_{i,q}^{MOM}$) is in the bottom and top quintiles. Standard errors are clustered by year-quarter. *, **, *** indicate statistical significance at 10%, 5% and 1% levels, respectively.

		$\alpha^{CA_1}_{q+4}$	$\alpha_{q+4}^{CAPM} \left(\%\right)$			α^{3F}_{q+}	$lpha_{q+4}^{3F}$ (%)			$\alpha_{q+4}^{4F}~(\%)$	t (%)	
	(1)	(2)	(3)	(4)	(5)	(9)	(2)	(8)	(6)	(10)	(11)	(12)
Intercept	0.1020^{**} (0.0508)	0.1264^{**} (0.0523)			0.0115 (0.0394)	0.0296 (0.0393)			0.0498 (0.0437)	0.0604 (0.0429)		
High $\beta_{HML,q}$	0.0610 (0.0447)		0.0508 (0.0448)		0.0897*** (0.0263)		0.0880^{***} (0.0261)		0.0706*** (0.0259)		0.0714^{***} (0.0255)	
$\mathrm{Low}\ \beta_{HML,q}$	0.0401 (0.0413)		0.0379 (0.0426)		-0.0258 (0.0298)		-0.0252 (0.0307)		-0.0229 (0.0265)		-0.0213 (0.0273)	
High $\beta_{MOM,q}$	~	0.0011	~	0.0044	~	-0.0110		-0.0078	~	-0.0237	~	-0.0223
High $eta_{MOM,q}$		(0.0404) 0.0125		(0.0410) 0.0082		(0.0301) 0.0099		(0.0310) 0.0079		(0.0255) 0.0287		(0.0263) 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		0.0357^{***}	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)	(6600.0)
$\log(tna)_q$	-0.0128^{**}	-0.0130^{**}	-0.0141^{***}	-0.0143^{***}	-0.0186^{***}	-0.0184^{***}		-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		factor los	hinge and	סווהסמלווס	10. Fund factor loadings and subsequent nerformance	00400			

	ed b	
ce	celationship between a mutual fund's factor loadings and its subsequent performance measured b	1 ^{4}E 2 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
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Table A.10: Fund factor loadings and subsequent performance	/een	4 FJ
Ξ	betw	-
	ship	CAPM $3F$
	tion	PM
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is in the top (bottom) 20% of the distribution. High (Low) $\tilde{\beta}_{MOM,q}$ 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 The dependent variables $-\alpha_{q+4}^{CAPM}$, α_{q+4}^{4F} , α 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 qby alphas from various factor models. from 1980Q1 to 2018Q4. Standard errors are clustered at the quarter and fund levels. *, **, *** indicate statistical significance at 10%, 5% and 1% levels, respectively. Note: This table reports the re

	$Low-\overline{\beta}^{m}$		Fund	Ť	$High-\overline{\beta}^{mu}$			Ц	$\operatorname{Low}_{-\overline{\beta}^{MOM}}$	\downarrow	Fund	Î	$\mathrm{High}_{-\overline{eta}}{}^{MOM}$	
	- 1	2	33	4) v				. –	2	3	4		
$\mathrm{Low-}\Delta_4 B/M$	1 58	75	87	96	102		$\mathrm{Low} ext{-}\Delta_4RET$	- -	78	62	86	93	95	I
~	2 94	112	111	110	106		~	2	108	109	102	91	68	
Stock	3 113	124	114	102	06		Stock	3	115	117	105	91	62	
\rightarrow	4 94	102	104	103	67		\rightarrow	4	109	110	104	92	69	
$\mathrm{High}\text{-}\Delta_4B/M$	5 48	55	99	79	84		$\operatorname{High-}\Delta_4 RET$	5	82	80	87	95	108	
Pai	Panel C: Annualized portfolio return -	ized portfolic	o return -	value (%)			Panel I): Anr	Panel D: Annualized portfolio return - momentum (%)	tfolio ret	urn - me	omentui	m (%)	
	$1.0W - \overline{R}^{HML}$	\rightarrow TW	Fund	Ì↑	$High-\overline{\beta}^{HML}$				$1.0W - \overline{B}^{MOM}$	\downarrow	Fund	Î	$\operatorname{High}_{\overline{B}}^{MOM}$	1
	1	2	ŝ	4	- ro	5 - 1				2	ŝ	4	2 2	5 - 1
$\mathrm{Low-}\Delta_4 B/M$	1 17.5	16.2	12.9	12.5	12.4	-5.1	$\mathrm{Low} ext{-}\Delta_4 RET$		8.7	7.5	9.4	9.0	12.9	- 4.2
~	2 16.4	14.2	12.5	11.4	12.8	-3.7	~	2	9.5	8.6	9.9	12.0	15.7	6.2
Stock	3 14.4	12.0	11.2	8.8	13.0	-1.4	Stock	3	9.9	10.7	13.0	11.7	18.5	8.7
\rightarrow	4 10.5	9.6	10.1	11.9	11.7	1.3	\rightarrow	4	9.0	11.9	11.8	14.3	15.0	5.9
High- $\Delta_4 B/M$	5 10.0	11.1	9.6	11.9	12.3	2.3	$\operatorname{High-}\Delta_4 RET$	5	8.7	7.7	11.8	16.8	21.4	12.8
High-Low	-7.5	-5.1	-3.3	-0.6	-0.1	7.4	High-Low		0.0	0.3	2.4	7.8	8.5	8.6
ŀ	[-1.77]		[-1.48] [-1.04]	[-0.18]	[-0.02]	[1.78]	I		[-0.02]	[0.09]	[0.88]	[2.46]	[3.09]	[2.68]

of the 25 double-sorted portfolios. In each quarter, stocks are independently sorted into 25 portfolios based on their 4-quarter changes in B/M ratios ($\Delta_4 B/M$) or past one-year returns (skipping the most recent month) ($\Delta_4 RET$) 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. 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

	nnualized, %)	$\longrightarrow \operatorname{High}-\overline{\beta}^{HML}$	4 5 5-1	9.8 12.0 4.3	17.2 22.6 10.5	7.4 10.6 6.2	[3.16] [4.29] [2.70]		uizea, %)	$\stackrel{\text{unzeq. \%}}{\longrightarrow} \text{High-}\overline{\beta}^{HML}$	$ \xrightarrow{\text{High}-\overline{\beta}^{HML}} 4 5 5-1 $	High- $\overline{\beta}^{HML}$ 5 2.2	High- \overline{eta}^{HML} 5 2.2 10.5	$\begin{array}{c} \operatorname{High}_{-\overline{\beta}^{HML}} \\ 5 \\ 2.2 \\ 10.5 \\ 8.4 \end{array}$	High- $\overline{\beta}^{HML}$ 5 2.2 10.5 8.4 [11.76] [High- $\overline{\beta}^{HML}$ 5 2.2 10.5 8.4 [11.76] alized, \gg)					
Momentum	olio returns (a	Fund	2 3	7.4 7.8	11.6 13.9	4.2 6.1	[2.10] $[2.98]$	alaha (annus	I	Fund		$\begin{array}{c c} & - & - & - \\ \hline \leftarrow & Fund \\ 2 & 3 \\ -1.8 & 1.0 \end{array}$	$\begin{array}{c c} & - & - \\ \hline & - & Fund \\ \hline & 2 & 3 \\ -1.8 & 1.0 \\ 0.4 & 3.8 \end{array}$	$\begin{array}{c c} & & & \\ \hline & & & \\ \hline & & & \\ \hline & & & \\ 1.8 & 1.0 \\ 0.4 & 3.8 \\ 0.4 & 3.8 \\ 2.2 & 2.8 \end{array}$	$\begin{array}{c c} & \leftarrow & Fund \\ \hline 2 & 3 \\ -1.8 & 1.0 \\ 0.4 & 3.8 \\ 2.2 & 2.8 \\ [2.87] & [4.03] \end{array}$	L = 1 = 1 = 1 = 1 = 1 = 1 = 1 = 1 = 1 =	Fund 2 3 2 3 1.8 1.0 0.4 3.8 2.2 2.8 .87] [4.03] ML 3-factor alp -	Fund 2 3 2 3 1.8 1.0 0.4 3.8 0.5 2.2 2.2 2.8 2.3 2.8 2.1 [4.03] 11 3.5 12 5.2 2.3 2.8 11 3.5 2 3 2 3	$\begin{array}{cccc} & & & & & & \\ \hline & & & & & & \\ \hline & & & &$	$\begin{array}{cccccccccccccccccccccccccccccccccccc$	← Fund -1.8 1.0 0.4 3.8 0.4 3.8 0.4 3.8 2.2 2.8 2.87] [4.03] ML 3-factor alp ← Fund 2.3 0.9 0.4 3.4 2.4 2.9 2.4
W	Panel A2: EW portfolio returns (annualized, %)	$\operatorname{Low}_{\overline{\beta}^{HML}} \neq$	1	7.7	12.1 1	4.3	[1.75] [2	Panel B2: CAPM alpha (annualized, %)		$\operatorname{Low}-\overline{\beta}^{HML} \leftrightarrow$	$\operatorname{Low}_{-\overline{eta}}^{HML} \leftarrow 1$					Low- $\overline{\beta}^{HML}$ \leftarrow 1 -1.0 1.2 2.1 [2.88] [2 MKT+SMB+Hh	$\begin{array}{c} \text{Low-}\overline{\beta}^{HML} & \leftarrow \\ 1 & -1.0 & - \\ 1.2 & 0 & 2.1 \\ 2.1 & 2.1 & 2.1 \\ 2.88 & 2.1 & 2.1 \\ 2.88 & 120 & - 2 \\ \hline 2.88 & 120 & - 2 \\ \hline 1000-\overline{\beta}^{HML} & \leftarrow \end{array}$	$\begin{array}{c} \operatorname{Low}_{-\overline{\beta}}^{HAL} \leftarrow \\ 1 \\ -1.0 \\ 1.2 \\ 2.1 \\$	$\begin{array}{c} \text{Low-}\overline{\beta}^{HML} & \leftarrow \\ 1 \\ -1.0 \\ 1.2 \\ 2.1 \\ 2.1 \\ 2.1 \\ 2.1 \\ 2.1 \\ 2.1 \\ 2.1 \\ -3.3 \\ -3.3 \end{array}$	$\begin{array}{c} \text{Low-}\overline{\beta}^{HML} & \leftarrow \\ 1 \\ -1.0 \\ -1.2 \\ 1.2 \\ 1.2 \\ 2.1 \\ 2.1 \\ 2.1 \\ 2.1 \\ 2.1 \\ 2.1 \\ 2.1 \\ 2.1 \\ 2.3 \\ -3.3 \\ -0.8 \end{array}$	$\begin{array}{c} \text{Low-}\overline{\beta}^{HML} & \leftarrow \\ 1 & 1 \\ -1.0 & -1 \\ 2.1 & 2.1 \\ 2.88 & 2.1 \\ 2.88 & 2.1 \\ 2.88 & -2.8 \\ -0.8 & -2.5 \\ 2.5 & 3 \end{array}$
	Pan			Low- $\Delta_4 RET$ 1	High- $\Delta_4 RET$ 5	High-Low	t-stats					Low- $\Delta_4 RET$ 1	Low- $\Delta_4 RET$ 1 High- $\Delta_4 RET$ 5			Low- $\Delta_4 RET$ 1 High- $\Delta_4 RET$ 5 High-Low t-stats Panel C2:	Low- $\Delta_4 RET$ 1 High- $\Delta_4 RET$ 5 High-Low t-stats Panel C2:	Low- $\Delta_4 RET$ 1 High- $\Delta_4 RET$ 5 High-Low t-stats Panel C2:	Low- $\Delta_4 RET$ 1 High- $\Delta_4 RET$ 5 High-Low t-stats Panel C2: Low- $\Delta_4 RET$ 1	Low- $\Delta_4 RET$ 1 High- $\Delta_4 RET$ 5 High-Low t-stats Panel C2: Low- $\Delta_4 RET$ 1 High- $\Delta_4 RET$ 5	Low- $\Delta_4 RET$ 1 High- $\Delta_4 RET$ 5 High-Low t-stats Panel C2: Panel C2: High- $\Delta_4 RET$ 1 High-Low
			5 - 1	-4.6	-1.4	3.3	[1.10]				5 - 1	5-1 -0.5	5-1 -0.5 4.7	5-1 -0.5 4.7 5.3	- 5-1 -0.5 4.7 5.3 5.3	5-1 -0.5 4.7 5.3 5.3 [5.01]	5-1 -0.5 4.7 5.3 5.3 [5.01]	5-1 -0.5 4.7 5.3 5.3 5-1	5-1 -0.5 4.7 5.3 5.3 5-1 3.2	$\begin{array}{c} 5-1 \\ -0.5 \\ 4.7 \\ 5.3 \\ 5.01 \\ 3.2 \\ 5.9 \\ 5.9 \end{array}$	$\begin{bmatrix} 5-1 \\ -0.5 \\ 4.7 \\ 5.3 \\ 5.3 \\ 5.1 \\ 3.2 \\ 5.9 \\ 5.9 \end{bmatrix}$
	1, %)	$\operatorname{High}_{\overline{\partial}}^{HML}$	IJ.	14.1	11.3	-2.8	[-1.06]			$\operatorname{High}_{\overline{\beta}}^{HML}$	$\mathrm{High}_{-}\overline{eta}^{HML}$	$\mathrm{High}_{-\overline{\partial}^{HML}}$ 5 6.1	$\mathrm{High} \cdot \overline{eta}^{HML}$ 5 6.1 3.2	High- $\overline{\beta}^{HML}$ 5 6.1 3.2 -2.9	High- $\overline{\beta}^{HML}$ 5 5 6.1 3.2 -2.9 [-3.43]	High- $\overline{\beta}^{HML}$ 6.1 6.1 3.2 -2.9 [-3.43] ialized, \approx)	$\begin{array}{c} \text{High} -\overline{\beta}^{HML} \\ \text{6.1} \\ \text{6.1} \\ \text{3.2} \\ \text{3.2} \\ \text{-2.9} \\ \text{[-3.43]} \\ \text{talized, } \overline{x} \\ \text{High} -\overline{\beta}^{HML} \end{array}$	$\begin{array}{c} \text{High} -\overline{\beta}^{HML} \\ \text{6.1} \\ \text{6.1} \\ \text{3.2} \\ \text{3.2} \\ \text{3.2} \\ \text{-2.9} \\ \text{[-3.43]} \\ \text{[-3.43]} \\ \text{talized, } \overline{x} \\ \text{High} -\overline{\beta}^{HML} \\ \text{5} \end{array}$	$\begin{array}{c} \text{High} -\overline{\beta}^{HML} \\ \text{6.1} \\ \text{6.1} \\ \text{6.1} \\ \text{3.2} \\ \text{3.2} \\ \text{-2.9} \\ \text{[-3.43]} \\ \text{[-3.43]} \\ \text{1alized, } \overline{x} \\ \text{High} -\overline{\beta}^{HML} \\ \text{High} -\overline{\beta}^{-1} \\ \text{5.2} \end{array}$	High- $\overline{\beta}^{HML}$ 6.1 6.1 3.2 -2.9 [-3.43] [-	High- $\overline{\beta}^{HML}$ 6.1 6.1 3.2 -2.9 [-3.43] high- $\overline{\beta}^{HML}$ High- $\overline{\beta}^{HML}$ 9.6 9.6
	nnualizeo	Î	4	13.3	10.5	-2.8	[-1.18]	alized, %)		Î	↓ 4	$\downarrow 4$ 5.7	$\begin{array}{c} \downarrow \\ 4\\ 5.7\\ 3.1 \end{array}$	$\begin{array}{c} \downarrow \\ 4 \\ 5.7 \\ 3.1 \\ -2.6 \end{array}$	→ 4 5.7 3.1 -2.6 [-3.17]	→ 4 5.7 3.1 -2.6 [-3.17] pha (annu	 → 4 5.7 5.7 3.1 3.1 3.1 3.1 5.7 5.8 5.7 5.7 5.7 5.8 5.7 5.8	$ \begin{array}{c} & \downarrow \\ & 4 \\ & 5.7 \\ & 5.7 \\ & 3.1 \\ & 3.1 \\ & -2.6 \\ & [-3.17] \\ & 17 \\ \hline & \downarrow \\ & \downarrow \end{array} $	$ \begin{array}{c} & \downarrow \\ & 4 \\ & 5.7 \\ & 5.7 \\ & 3.1 \\ & 3.1 \\ & -2.6 \\ & -2.$	→ 4 5.7 3.1 3.1 -2.6 [-3.17] [-3.17] [-3.17] + 4 4 4 4 8.4	$ \begin{array}{c} & \downarrow \\ & 4 \\ & 5.7 \\ & 5.7 \\ & 3.1 \\ & 3.1 \\ & -2.6 \\ & -2.$
1	returns (a.	Fund	3	16.0	9.8	-6.3	[-2.29]	pha (annualized, %)		Fund	Fund 3	Fund 3 5.8	Fund 3 5.8 0.4	Fund 3 5.8 0.4 -5.4		Fund 3 5.8 0.4 -5.4 [-6.73]	Fund 3 5.8 0.4 -5.4 [-6.73] factor alt Fund	Fund 3 5.8 0.4 -5.4 [-6.73] factor alt Fund 3	Fund 3 5.8 0.4 -5.4 [-6.73] factor alt Fund 3.5 3.5	Fund 3 5.8 0.4 0.4 -5.4 [-6.73] [-6.73] factor alt <i>Fund</i> 3 3.5 4.9	Fund 3 5.8 0.4 -5.4 [-6.73] -factor alt Fund 3 3 3.5 4.9
value	portfolio 1	\downarrow	2	18.6	10.0	-8.5	[-2.79]	CAPM al		↓	5 ↓		Ť			← 2 2 0.5 -7.4 [-8.57] 3+MOM 3	← 2 2 0.5 -7.4 [-8.57] 3+MOM 3	$\begin{array}{c} \leftarrow \\ 2 \\ 7.8 \\ 0.5 \\ 0.5 \\ -7.4 \\ [-8.57] \\ 3+MOM 3 \end{array}$	← 2 2 7.8 0.5 -7.4 [-8.57] 3+MOM 3 2 2 2 2 2 8.8	← 2 2 0.5 -7.4 [-8.57] 3+MOM 3: 3+MOM 3: 5.8 5.9	$\begin{array}{c} \leftarrow \\ 2 \\ 7.8 \\ -7.4 \\ [-8.57] \\ 3+MOM 3. \\ 6 \\ - \\ 5.8 \\ 5.9 \\ 5.9 \end{array}$
	Panel A1: EW portfolio returns (annualized, %)	$Low - \overline{\beta}^{HML}$	1	18.7	12.7	-6.0	[-1.74]	Panel B1: CAPM alj		$Low - \overline{\beta}^{HML}$	$\frac{Low-\overline{eta}^{HML}}{1}$	$\begin{array}{c c} \operatorname{Low}_{-\overline{\beta}^{HML}} \\ 1 \\ 6.6 \end{array}$		L	L		$\begin{array}{c c} \operatorname{Low}-\overline{\beta}^{H,ML}\\ \hline & & \\ \hline & & \\ & &$	$\begin{array}{c c} \operatorname{Low} & \overline{\beta}^{HML} \\ \hline & & \\ & &$	$\begin{array}{c c} \text{Low}-\overline{\beta}^{H,ML}\\ \hline \text{Low}-\overline{\beta}^{H,ML}\\ \text{6.6}\\ -1.6\\ -1.6\\ -1.54\\ [-7.54]\\ [-7.54]\\ \text{C1:} \text{MKT+SME}\\ \hline \text{Low}-\overline{\beta}^{H,ML}\\ 1\\ \hline \end{array}$	$\begin{array}{c c} \operatorname{Low} -\overline{\beta}^{H,ML} \\ \hline & 1 \\ \hline & 0.6 \\ -1.6 \\ -1.6 \\ -1.6 \\ -8.2 \\ \hline & -8.2 \\ -8.2 \\ \hline & -7.54 \end{bmatrix}$	$\begin{array}{c c} \operatorname{Low} -\overline{\beta}^{H,ML} \\ \hline & & \beta \\ \hline & & \beta \\ & & 6.6 \\ & & 6.6 \\ & & -1.6 \\ & & -1.6 \\ & & -1.6 \\ \hline & & -1.6 \\ & & -1.6 \\ \hline & & & & -1.6 \\ \hline & & & & -1.6 \\ \hline & & & & & -1.6 \\ \hline & & & & & -1.6 \\ \hline & & & & & & -1.6 \\ \hline & & & & & & & -1.6 \\ \hline & & & & & & & & -1.6 \\ \hline & & & & & & & & & & -1.6 \\ \hline & & & & & & & & & & & & \\ \hline & & & &$
	Γ.			Low- $\Delta_4 B/M$ 1	High- $\Delta_4 B/M$ 5	High-Low	t-stats					B/M 1	B/M 1 B/M 5			(B/M = 1) (B/M = 5) (B/M = 5) (B/M = 5) (B/M = 1) (B/M = 1)	$\frac{B/M}{1B/M} = \frac{1}{5}$ Low ts Panel	Low- $\Delta_4 B/M$ 1 High- $\Delta_4 B/M$ 5 High-Low t-stats Panel	Low- $\Delta_4 B/M$ 1 High- $\Delta_4 B/M$ 5 High-Low t-stats Panel	Low- $\Delta_4 B/M$ 1 High- $\Delta_4 B/M$ 5 High-Low t-stats Panel (Panel 0 High- $\Delta_4 B/M$ 1	$pw-\Delta_4 B/M$ 1 $pw-\Delta_4 B/M$ 5 High-Low t-stats panel $pw-\Delta_4 B/M$ 1 $pw-\Delta_4 B/M$ 5 High-Low

Table A.12: Alternative performance measures for 5×5 stock portfolios sorted on 4-quarter changes in stock characteristics and stock-level factor demands

stock-level factor demand $\overline{\beta}^{HML}$ (Panels A1, B1, and C1), or on their 4-quarter changes in past one-year returns (skipping the most recent month) ($\Delta_4 RET$) and stock-level factor demand $\overline{\beta}^{MOM}$ (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 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 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 sorted on stock characteristics. In each quarter, stocks are independently sorted into 25 portfolios based on their 4-quarter changes in B/M ratios ($\Delta_4 B/M$) and underlying funds, respectively. Panels A1 and A2 report equal-weighted annualized returns. Panels B1 and B2 report portfolio alphas based on CAPM. Panel C1 are reported in the brackets. Data are from 1980Q2 to 2018Q4.

	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)
\mathbb{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.13: Predicting aggregate factor returns with changes in average mutual fund factor demand

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

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.