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Factor Demand and Factor Returns*

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Abstract

A mutual fund's demand for a pricing factor, measured by the loading of the fund's returns on the factor's returns, is persistent over time. When stock characteristics are time-varying and change frequently, persistence in factor demand generates a need for rebalancing. This rebalancing motive, in turn, leads to predictable trading from mutual funds and contributes to cross-sectional return predictability. In particular, when there is a "mismatch" between a stock's characteristic and the underlying funds' demand for that characteristic, the "mismatched" stock will face selling pressure from the underlying funds and subsequently earn lower returns. Double-sorting on stocks' characteristics and mutual funds' factor demand refines value and momentum strategies, generating abnormal returns that cannot be explained by subsequent fundamentals or retail trading flows.

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1 Introduction

Mutual funds face a variety of constraints in their choice of asset holdings.[1] A particular constraint is faced by mutual funds with a specific investment objective: value funds, for example, are expected to hold stocks with a high book-to-market (B/M) ratio while momentum funds are expected to buy stocks that have done well over the past year. Even without these constraints, mutual funds may often choose to target one or several trading strategies in constructing their portfolios, either to take advantage of well-known pricing factors or to simplify the complex process of investment decision-making. Overall, it seems reasonable to expect a mutual fund's demand for a given factor to be persistent over time.

Persistence in factor demand, combined with time-varying stock characteristics, generates a need to rebalance. Just as a long-short trading strategy needs to frequently reassign stocks into different legs of the portfolio, mutual funds targeting a factor will also need to rebalance their holdings regularly to achieve their desired exposure. For example, imagine a value fund that only holds stocks with a B/M ratio above one. As stocks change in their B/M ratios over time, the value fund will need to sell stocks with a B/M ratio that has dropped below one and replace them with stocks whose B/M ratio has risen above one. If such factor-rebalancing occurs at a large scale, it would lead to systematic trading by mutual funds as a whole. Crucially, the direction and magnitude of these trades would be forecastable based on stocks' characteristics and funds' factor demand. If aggregate trading from mutual funds is contemporaneously associated with some price impacts, these predictable trading activities would contribute to improved return predictability.

In this paper, we show that such factor rebalancing exists and has important consequences for stock prices. We use standard datasets such as the Thomson Reuters mutual fund holdings database and the Center for Research in Security Prices (CRSP) survivor-bias-free US mutual fund database for our analysis. Our sample spans from 1980 to 2019 and we primarily focus on US equity funds.

We start our analysis by estimating mutual funds' factor demand. Each month, we

[1] An extreme version of this constraint is given by passive index funds: when the constituents of an index change, these funds, due to their mandates, will need to rebalance accordingly to minimize the deviation of their portfolios to the index's composition.

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.[2] The loading on a given factor—which we call *fund*-level factor beta or factor loading interchangeably through the paper—represents the fund's demand for that factor during the 5-year window. These fund-level factor loadings are consistent with other proxies of factor demand, such as Lipper mutual fund classifications, but they do not rely on the availability or accuracy of funds' self-reported investment objectives. Instead, they are constructed using a reveal-preference approach and only require observing fund returns for five years. Although factor loadings, by construction, are positively auto-correlated due to overlapping estimation windows, we demonstrate strong persistence even for loadings that are estimated five years apart. Overall, a mutual fund's demand for a given factor, measured by its factor loading, is very persistent over time.

We next examine whether factor rebalancing takes place and leads to predictable trading from mutual funds. Specifically, we focus on value and momentum and examine whether mutual funds rebalance to maintain a stable exposure to the value and momentum factors. We first aggregate *fund*-level factor loadings at the *stock* level by calculating, for each stock in each quarter, the holding-weighted average factor loadings of the underlying funds.[3] These *stock*-level factor loadings represent the average factor loading of the underlying funds, not a stock's own loading on that factor. All stocks are then independently double-sorted into 25 (5×5) portfolios based on their own characteristics and their stock-level factor loadings. For instance, for value, we double-sort stocks into 25 portfolios based on their own B/M ratios and their stock-level loadings on the HML (high-minus-low) factor, the latter of which are holding-weighted averages of fund-level HML loadings.[4]

Evidence from mutual fund trading supports factor rebalancing. In particular, when there is a "mismatch" between a stock's characteristic and the underlying funds' factor demand, the stock faces more selling pressure from mutual funds as a whole in the subsequent quarter.

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

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

[4]Throughout this paper, we use the HML factor and the value factor interchangeably. Similarly, we use the WML (winners-minus-losers) factor and the momentum (MOM) factor interchangeably.

For instance, compared to growth stocks held by growth funds, growth stocks held by value funds experience greater selling in the subsequent quarter; likewise, compared to value stocks held by value funds, value stocks held by growth stocks also experience more selling. We find similar selling pressure when a "mismatch" occurs between a stock's past return and the underlying funds' demand for momentum. Therefore, factor rebalancing induces predictable trading in a way that is distinct from that of other sources of trading, such as flow-induced trading (FIT).

Earlier literature has shown that the demand curve for stocks is downward-sloping and trading pressure induces price impacts. If predictable trading from mutual funds has a similar price impact, then predictable trading implies predictable returns. Indeed, this is what we find from analyzing the 25 portfolios' subsequent returns. Out of the 25 value-based portfolios, the two that are most "mismatched"—that is, the one with the highest B/M ratio but held by the most growth-prone funds and the one with the lowest B/M ratio but held by the most value-prone funds—earn the lowest annualized value-weighted returns (8.5% and 6.6%, respectively). In comparison, the two most "well-matched" portfolios—that is, the one with the lowest B/M ratio and held by the most growth-prone funds and the one with the highest B/M ratio and held by the most value-prone funds—earn an annualized value-weighted return of 17.0% and 14.0%, respectively.

With double-sorting, there are two other ways to interpret the patterns of the portfolio returns across the 25 value-based portfolios. The first way is to keep the B/M ratio constant and compare across the underlying funds' HML betas. Among growth stocks, those held by the most growth-prone funds outperform those held by the most value-prone funds by an annualized return of 10.4%. In comparison, among value stocks, those held by the most value-prone funds outperform those held by the most growth-prone funds by an annualized return of 5.5%. Therefore, the underlying funds' characteristics clearly matter for stock returns. The second way is to compare the performance of the HML strategy across stocks with different underlying funds. Conditional on stocks held by the most value-prone funds, the HML strategy delivers an annualized return of 7.4%. In comparison, conditional on 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 a growth premium is particularly striking, as it potentially offers an explanation for the popularity of growth funds despite the fact that value stocks outperform unconditionally.

The documented patterns in portfolio returns remain when we examine equal-weighted portfolio returns and when we examine the CAPM alpha and a three-factor (market, size, and momentum) alpha. However, independent double-sorting raises a concern about outliers: returns for the "mismatched" portfolios, with a relatively smaller number of stocks, may be driven by a certain few stocks. To address this concern, we instead independently double-sort stocks into 9 (3×3) portfolios. With each portfolio consisting of at least 100 stocks, this largely mitigates the concern about power and outliers and we obtain qualitatively similar results.

For momentum, we perform the same set of exercises by sorting all stocks into 25 portfolios based on their past one-year returns (skipping the most recent month) and the underlying fund's momentum loadings. By and large, the results are consistent with before, albeit with a smaller magnitude. We also perform a series of subsample analyses to gain additional insights. For example, we show that the patterns for value are robust in both the first and second half of the sample, among stocks with either high or low mutual fund ownership, and among both small-cap and large-cap stocks. The strength of the pattern varies and is more pronounced in the second half of the sample, among stocks with higher mutual fund ownership, and among large-cap stocks. The patterns for momentum, however, have different subsample properties: while they are also more pronounced among stocks with higher institutional ownership, they are stronger in the first half of the sample and among small-cap stocks. Overall, the two strategies appear to be complementary (Asness et al. 2013).

We discuss alternative explanations for our results. We show that flow-induced trading is either orthogonal to or goes in the opposite direction of the observed return patterns. We argue that herding alone cannot fully account for the return patterns. We show that these abnormal returns cannot be consistently explained by their subsequent fundamentals, which casts doubt on the notion that some funds have private information about future stock fundamentals. Nonetheless, we do not fully rule out skill-based explanations. For example, it is possible that value funds specialize in value stocks while growth funds specialize in growth stocks and that their different specializations explain these differences in returns. We discuss potential challenges facing such skill-based explanations that skilled fund managers select into these outperforming stocks. Under this interpretation, funds with extreme factor exposure should have better performance. However, we find that, on average, value funds and momentum funds exhibit annualized four-factor alphas of only 28bps and -8bps, respectively. The sign and magnitude of these fund alphas seem at odds with the significant factor return spreads at the stock level, and quantitatively smaller than the findings from the mutual fund performance literature. We argue that fund manager skills, in their standard formulation, are unlikely to explain our results.

A vast literature has linked the behaviors of mutual funds to stock prices by considering a wide range of trading motives, including but not limited to 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 (Frazzini 2006; An and Argyle 2020). Our study is similar in spirit to many previous ones in that we take the prior that trading without information contents can also induce price pressure and affects equilibrium returns. However, the trading motives in our paper are fundamentally different: trading is driven by portfolio rebalancing induced by persistent factor demand. In this regard, our paper is also related to the literature on index inclusion, in which mutual funds exert price pressure on stocks to be included in a benchmark index (Harris and Gurel 1986; Shleifer 1986; Wurgler and Zhuravskaya 2002; Chang et al. 2015). Portfolio-rebalancing motives, we argue, go beyond adhering to market indexes; rather, they are prevalent at the factor level and can shed light on price dynamics and return predictability in other settings.

Our paper also contributes to the discussion on the relationship between institutional demand and asset prices. Earlier papers such as Harris and Gurel (1986) and Shleifer (1986) have shown that the demand curve is downward-sloping at the stock level. Recent literature, such as Gabaix and Koijen (2020), examines the relationship between aggregate demand and aggregate returns. The scope of our analysis is placed at the factor level by showing that factor demand can affect factor returns in similar ways.

By introducing fund-level factor betas and showing that they help forecast future stock returns, we expand the existing set of stock return predictors. The literature has primarily focused on using stocks' own characteristics to forecast returns. We bring a different perspective to the return predictability literature by showing that characteristics of the stocks' owner also have a profound effect on future stock returns. In this regard, our paper is also related to the strand of literature that compares stock-picking ability across different fund 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 examine the average stock return in the portfolio and typically find a relatively small difference in returns. However, we show that, once conditional on stocks with similar characteristics, their returns can be much more distinctive across different fund styles. Indeed, in a double-sorting approach – interacting stock characteristics with fund styles – substantially improves return predictability.

Our results have implications for the vast literature on value and momentum. Prior studies have shown that momentum seems to work better for certain kind of stocks, such as volatile stocks, growth stocks, stocks with low analyst coverage, and stocks that face less competition from other mutual funds (Daniel and Titman 1999; Hong et al. 2000; Jiang et al. 2005; Zhang 2006; Hoberg et al. 2020). There is also literature that links the time-series performance of asset pricing factors to institutional investors (e.g., Cohen et al. 2003; Daniel and Moskowitz 2017; Lou and Polk 2020.) At face value, we show that conditioning on fund characteristics substantially improves the performance of both value and momentum strategies. More profoundly, we suspect that factor rebalancing could also play a role in driving these two anomalies.

The rest of the paper proceeds as follows. Section 2 explains how we measure factor demand and shows the basic properties of these measures. Section 3 provides evidence for mutual funds' factor rebalancing behavior. Section 4 investigates return predictability and discusses its implications. Section 5 concludes.

2 Factor demand

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

2.1 Data

Our data cover all US equity mutual funds from 1980 to 2019. Quarterly fund holdings data are from the Thomson Reuters mutual fund holdings database (formerly known as the CDA/Spectrum Database). Fund-level specific characteristics such as total net assets (TNA), monthly returns, and expense ratios are from the CRSP survivor-bias-free US mutual fund database.[5] 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

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

sample size and firm size. One difference is that our sample has slightly fewer funds in earlier years, but more in later years.

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

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:

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

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

where $k = 1, 2, ..., 60$; $rret$ represents raw fund returns; MKT represents excess market returns; and HML, SMB, MOM, CMA, and RMW represent the returns for the value, size, momentum, investment, and profitability strategies, respectively. We also control for the sensitivity of fund returns to retail flows by including $flow$, where $flow_{i,t} = \frac{TNA_{i,t}}{TNA_{i,t-1}} - (1+ret_{i,t})$ and ret represents net fund returns (Dou et al. 2020). Therefore, for fund i in month t, we get seven beta coefficients: $\beta_{i,t}^{MKT}$ to $\beta_{i,t}^{flow}$. We will from now on call these coefficients fund-level factor betas or factor loadings interchangeably.[6]

In Equation (1), each $\beta_{i,t}$ (e.g., $\beta_{i,t}^{HML}$) measures the loading of fund i's return on a given factor (e.g., HML) 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 also induces a high auto-correlation in $\beta_{i,t}$, an issue we will return to in Section 2.3 when discussing the persistence of factor demand. While other approaches can also be used to measure funds' factor demand, there are two advantages to our approach. First, factor loadings are based on fund returns and therefore capture trading behaviors

[6]We include funds' retail flow $flow$ in the main specification of factor exposure estimation (1) to control for the direct impact of contemporaneous flows on fund returns. Funds' factor betas are quantitatively similar if we exclude retail flow from (1).

between two reporting dates. For instance, if we instead measure demand for value using the average B/M ratio of end-of-quarter holdings, the resulting measure would show an up-to-date snapshot of the fund's current exposure to value, but it would show little about whether the fund is actively targeting value.[7] Furthermore, the literature has shown that fund activities between the two reporting dates are informative (Kacperczyk et al. 2008). Second, compared to mutual fund classifications or investment objectives, which often rely on funds' self-reported investment objectives and can be misreported or missing, our measures are available for all funds with at least five years of return data.

We have included these seven factors—the Fama-French five factors, momentum, and retail flow—on the right-hand side of Equation (1), but our main analysis will be devoted to value and momentum; one can therefore think of the other five factors as control variables. The reasons are as follows. First, value and momentum are among the most robust asset pricing factors in both the US and global markets (Asness et al. 2013). Second – more related to our mechanism of factor rebalancing – it is reasonable to expect that mutual funds target factors such as value and momentum that are well-known and have been long established. Moreover, the underlying philosophies of value and momentum have long been known to 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 industry practitioners. Indeed, if one looks at the investment objectives reported by mutual funds, 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 (e.g., a small-cap fund), it is unlikely that there is much rebalancing induced by changes in firm size. This is because firm size is very persistent: it takes years or even decades for a small firm to grow into a medium-sized one. In comparison, for value and momentum, both the B/M ratio and past one-year return change frequently

[7] Lettau et al. (2018) examine the characteristics of the stocks held by mutual funds using their quarter-end holdings, whereas we are primarily interested in how factor rebalancing affects stock prices. Lettau et al. (2018) argue that the estimation of factor loadings may be biased due to different volatilities at the long and short legs of a given trading strategy. For our analysis, however, we rely on cross-fund variation in factor loadings at a given time, which means that a systematic bias in principle would not affect our analysis. If anything, it would only create more noise and bias against us.

at the stock level. This means that, if a fund targets either of the two strategies, it will have to rebalance regularly.

Table 2 reports the summary statistics of fund-level factor betas. We require a fund to have at least 60 months of returns data and each rolling-window estimation to have at least 24 monthly observations.[8] 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 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, an average index fund, as expected, 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, there are mandates. Many mutual funds have a specific investment objective, such as small-cap or growth, and by mandates they need to keep a relatively stable exposure to this factor. Therefore, as the set of stocks considered to be "small-cap" or "growth" changes, they will need to rebalance their portfolios. Alternatively, many mutual funds have mandates to beat or stick to a fixed benchmark, which is often a popular stock market index with constant

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

or stable exposure to certain factors. A fund manager's desire to minimize the tracking error (or maximize the "information ratio") prompts them to keep a persistent exposure to the underlying factors. Second, even mutual funds that have no specific investment objective and are thus more flexible in their choice of investment 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, a stable investment philosophy, and persistent use of similar technical analysis.

As hinted above, fund-level factor betas are estimated using overlapping windows and are therefore positively auto-correlated. To show persistence, we adopt the following strategy. In each quarter, we keep only observations of the quarter's last month and denote them by $\beta_{i,q}$. We do so because our analysis in subsequent sections relies on holdings data, which are only reliably observed at the quarterly frequency. Then, for factor X, we run the following panel regression:

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

where X represents market, value, size, and momentum—the Carhart four factors.[9] Equation (2) runs a predictive regression by lagging factor betas for 20 quarters (60 months), which ensures that the estimation windows for the two variables are non-overlapping.[10] We include quarter fixed effects and double-cluster standard errors at the fund and year-quarter levels. In Table 3, Columns (1) through (4) each represent a different factor beta. Factor betas are very persistent in time-series, suggesting that factor exposure is indeed relatively persistent at the fund level. 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

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

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

and its interaction with size beta. 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 are driving the persistence of size beta. Column (6) runs a similar regression for value beta and finds a similar pattern.

2.4 Aggregate trends

While a thorough examination of the determinants of factor betas is beyond the scope of this paper, we present some stylized facts about their aggregate trends. Figure 1 plots the evolution of aggregate factor betas. 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. Overall, the aggregate factor betas for size, value, and momentum all increase from 1980 up to the Great Recession, after which they decline. These patterns are roughly consistent with those in Lettau et al. (2018). An interesting observation is that there appears to be a lead-lag relationship between factor returns and factor betas: for example, in Subfigure 1a, HML returns peak ahead of HML betas. This suggests that mutual funds may be tilting their portfolios towards the factors that have performed well in the past, but we do not go into the details in this paper.

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 or past one-year return change, funds rebalance their portfolios to keep a persistent exposure to the value or momentum factor.

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, the funds will not need to rebalance frequently. For example, suppose that a value fund tries always to hold the top quintile of stocks sorted by B/M ratios. If the B/M ratio is very persistent at the stock level, then the set of stocks in the top quintile would remain roughly the same over time and there would be little need to rebalance. This, for example, is the case with the size strategy: because firm size is a very stable feature of a stock, funds that target size do not need to rebalance regularly. Second, factor demand must be persistent—and more persistent than stock characteristics. If factor demand changes rapidly, it reduces the need to rebalance to stick to a given factor. Third, due to institutional frictions and other constraints, funds rebalance with a delay. This would mean that even the most value-prone funds would hold some "legacy" growth stocks in their portfolios, and vice versa. In this section, we empirically confirm the first two conditions; we leave the third condition to Section 3.2.

Table 4 shows the transition probabilities of a stock moving between quintiles at the quarterly and yearly frequencies. In each panel, we primarily focus on the diagonal terms, which represent the probabilities of a stock remaining in the same quintile. Panels A and B sort stocks into quintiles based on their book-to-market ratios. Panel A shows the one-quarter transition probabilities. The diagonal terms range from 0.67 to 0.86, suggesting that, on average, a stock switches to a different quintile with a probability between 14% to 33%. Panel B shows the one-year transition probabilities. The diagonal terms range from 0.45 to 0.72, suggesting higher switching probabilities of 28% to 55%. Panels C and D show the transition probability matrix for quintiles sorted on the past one-year return (skipping the most recent month). Overall, the diagonal terms in Panels C and D have lower values than those in Panels A and B, 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.

The transition probabilities shown in Table 4 are not sufficient to generate factor rebalancing; they must be met by persistence in factor exposure at the fund level. In fact, factor exposure should be *more* persistent than stock characteristics to induce factor rebalancing. To see why, we return to the same value fund that sticks to the top quintile of stocks sorted on B/M ratio. Suppose that some stocks in its current holdings drop in their B/M ratios and presumably need to be replaced by others with a higher B/M ratio. However, if factor exposure is not sufficiently persistent, in that the value fund has now decided not to strictly stick to the top quintile but be more flexible with its choice of stocks, then it does not necessarily need to rebalance.

To compare the persistence between fund betas and stock betas, Panels A and B of Table 5 show the transition probabilities of a fund moving between different quintiles at the quarterly and yearly frequencies. The diagonal terms in these two panels are greater than those in Panels A and B of Table 4, suggesting that fund-level factor loadings are more persistent than stock-level factor loadings. Panels C and D of Table 5 show the transition probabilities between fund quintiles sorted on fund momentum betas and find a stronger pattern when compared with Panels C and D of Table 4. Therefore, we confirm that fund betas are indeed more persistent than stock betas.

3.2 Trading evidence from double-sorting

3.2.1 Mutual fund ownership

We next show how factor rebalancing induces predictable trading. We take the value strategy as an example. To understand our empirical strategy, consider two value stocks, A and B, with the same B/M ratio. Stock A has long been a value stock while stock B used to be a growth stock but recently became a value stock due to a drop in share price. As a result, stock A is currently held primarily by value funds while stock B is currently held primarily by growth funds. However, the growth funds have an incentive to sell stock B to maintain their exposure to growth stocks. This means that, compared to stock A, stock B faces more selling pressure from its current investors.

In theory, pressure can be canceled out if some value funds exhibit an equally strong demand to buy stock B. However, there are ample reasons for us to expect the selling pressure to dominate the buying pressure. The sellers have a strong incentive to sell this particular "mismatched" stock, while the buyers can choose from a large pool of other value stocks and do not specifically need to buy stock B. In fact, because stock B is not in the portfolio of many value funds, it may not even have gotten their attention and it will take time for them to realize that it is now a value stock (Barber and Odean 2008; Hartzmark 2015). Moreover, it often takes time for a fund to establish an entirely new position.

We apply this intuition to portfolio-sorting. For example, suppose that we double-sort stocks into 25 (5×5) portfolios based on their B/M ratios and the underlying fund's HML betas, as shown in the table below. The top-right corner and the bottom-left corner (both in red) represent two "mismatched" portfolios: their B/M ratios are misaligned with the demand of their underlying funds for value or growth. As a result, they are expected to face more selling pressure from the mutual fund industry as a whole in subsequent periods. The top-left corner and the bottom-right corner (both in blue) are well-matched in the stocks' characteristics and funds' factor demand and do not face the same selling pressure.

		Growth	$\longleftarrow$	*Fund*	$\longrightarrow$	Value
		1	2	3	4	5
Growth	1					
$\uparrow$	2					
Stock	3					
$\downarrow$	4					
Value	5					

Table 6 conducts this exercise. In each quarter, all stocks are sorted into 25 portfolios based on their B/M ratios and their $\overline{\beta}^{HML}$, where $\overline{\beta}^{HML}$ is calculated as the shares-weighted average β^{HML}. To address potential microstructure issues and focus on the price impact from mutual fund trading behavior, in each quarter, we exclude stocks whose price is below five dollars, whose total mutual fund ownership is less than 1%, and whose market capitalization is in the bottom decile. One concern about this double-sorting exercise is whether the number of stocks in the two "mismatched" portfolios is so small that the patterns are driven by outliers. Panel A of Table 6 immediately addresses this concern. Both corner portfolios have an average sample size above 25, which is reasonable. This also shows that even the most value-prone funds hold some growth stocks while the most growth-prone funds hold some value stocks—the third condition necessary for establishing the effects of factor rebalancing.

Panel B of Table 6 reports the total mutual fund ownership change for each portfolio. Each cell then represents the total mutual fund ownership change in the subsequent quarter, where ownership change is calculated by dividing the change in the number of shares held by all mutual funds by the total number of shares outstanding. The top-right corner and the bottom-left corner experience 0.04% and 0.28% decreases in mutual fund ownership, respectively, in the subsequent quarter. In comparison, the top-left corner and the bottom-right corner both experience an increase in mutual fund ownership. Consequently, the differences in mutual fund ownership changes between high- and low-B/M stocks (in line "HML") differ significantly: −0.35% for low $\bar{\beta}^{HML}$ stocks and 0.24% for high $\bar{\beta}^{HML}$ stocks. The results for the momentum strategy are weaker in the corner portfolios, but the pattern roughly persists when we focus on the winners-minus-losers (WML) differences.

3.2.2 Flow-induced trading

Competing with factor rebalancing is a force that similarly generates price pressure: 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 their forced purchases or sales in response to retail flows. Empirically, however, there is a concern that the two channels may be correlated, and that our factor rebalancing evidence may be therefore capturing a flow effect instead.

To rule out this concern, we calculate FIT for the 25 sorted portfolios. We follow Lou (2012) and define FIT for each stock j in each quarter q as

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

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

Panel A of Table 7 reports FIT for the 25 portfolios. For the value strategy, the FIT for the HML portfolios (in line "HML") decreases from -0.23% for the low-$\bar{\beta}^{HML}$ stocks to -0.56% for the high-$\bar{\beta}^{HML}$ stocks, a direction opposite to that of our factor-rebalancing results in Table 6. For the momentum strategy, all of he WML portfolios (in line "WML") have a positive FIT with a similar level. Therefore, FIT appears uncorrelated with factor rebalancing. To fully tease out the impact from retail flows, Panel B calculates total mutual fund ownership change adjusted for FIT by subtracting flow-induced shares. The numbers and patterns are virtually unchanged from Panel B of Table 6. We use these FIT-adjusted mutual fund ownership changes in our subsequent analysis.

3.3 Decomposition of mutual fund ownership changes

The evidence presented in Section 3.2 shows that mutual funds trade, in aggregate, in the same direction as our proposed mechanism. A closer examination of our mechanism suggests that different funds play different roles in driving the trading patterns in Panel B of Table 6. For example, the selling of the bottom-left corner should be primarily driven by growth funds and the selling of the top-right corner by value funds. We now provide a sharper test of factor rebalancing by decomposing the sources of mutual fund ownership changes. Specifically, we examine funds with low and high factor betas separately. For the value (momentum) strategy, we define value (momentum) funds broadly as funds with HML (MOM) beta higher than the cross-sectional median and growth (contrarian) funds as those with HML (MOM) lower than the cross-sectional median.

In Panel A of Table A.1, we decompose mutual fund ownership changes into those from value funds and growth funds. The left table shows the behavior of growth funds as a whole and the right table shows the behavior of value funds as a whole. In the left table, most of the actions indeed happen among the low-$\bar{\beta}^{HML}$ stocks. In aggregate, growth funds increase their ownership of the low-BM stocks by 0.35% and decrease their ownership of the high-BM stocks by 0.14%. In the right table, most of the actions happen among the high-$\bar{\beta}^{HML}$ stocks: value funds increase their ownership of the high-BM stocks 0.11% more than the low-BM stocks do. This decomposition indicates that growth and value funds indeed trade to maintain a stable factor exposure as prescribed by factor rebalancing, and they account for a significant portion of the stocks' mutual fund ownership changes. The results for the momentum strategy are shown in Panel B of Table A.1, where we find supporting evidence similar to that for the factor-rebalancing behavior from momentum and contrarian funds.

3.4 Fund-level evidence

In addition to showing evidence of factor rebalancing at the portfolio level, we deploy panel regressions to study more micro-level behavior at the fund level. Specifically, we investigate how different mutual funds rebalance their portfolios based on stock characteristics. The following fund-level regression estimates the marginal effect of a stock's past B/M ratio and past one-year return on mutual fund trading behavior in the next quarter:

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

where $trade_{i,j,q+1}$ measures the trading in stock i by fund j in quarter $q+1$. We consider two variables to measure fund-level trading activities: $\Delta Shares_{i,j,q+1}/Shrout_{i,q}$, FIT-adjusted trading in shares in quarter $q+1$ normalized by total shares outstanding as of quarter q, and $\Delta Dollars_{i,j,q+1}/ME_{i,q}$, FIT-adjusted trading in dollars in quarter $q+1$ normalized by market capitalization as of quarter q. We control for flow-induced trading to isolate the trades from mutual funds' active portfolio rebalancing from those driven by retail flows. The independent variables are stock i's characteristics in quarter q, including cross-sectionally demeaned book-to-market ratio, $B/M_{i,q}$; past one-year return (skipping the most recent month), $r_{i,q-4,q-1/3}$; market beta, $\beta_{i,q}$; and market capitalization (in billions), $ME_{i,q}$. As before, to differentiate funds with distinct trading styles, we run the above regression not only for the full sample, but also for subsamples of funds that are either high or low in their factor betas; that is, subsamples of value, growth, momentum, and contrarian funds.

Tables 8 and A.2 report the regressions results for Equation (3), using $\Delta Shares_{i,j,q+1}/Shrout_{i,q}$ and $\Delta Dollars_{i,j,q+1}/ME_{i,q}$ as the dependent variable, respectively. Panel A focuses on the B/M ratio. Columns (1) to (4) use the full sample. In the baseline specification without fixed effects and controls, the coefficient on the B/M ratio is negative and significant, suggesting that a fund, on average, buys growth stocks and sells value stocks. Adding date fixed effects and additional stock characteristics makes the coefficient closer to zero. Columns (5) to (8) estimate the same regression for the subsample of growth funds. In Column (5), as for the full sample evidence in Column (1), growth funds buy growth stocks and sell value stocks, but the coefficient more than doubles that in the full sample in magnitude. In Column (6), however, once we have controlled for other stock characteristics, especially past one-year return, the coefficient becomes less significant. As for Columns (3) and (4), the coefficients move closer to zero in Columns (7) and (8) when fixed effects and other controls are added. Next, we focus on value funds in columns (9) to (12), in which the results are more conclusive. The regression coefficients are positive and significant and the magnitude is stable across all four specifications. This pattern is in stark contrast to that of the growth funds subsample, indicating that value funds significantly buy value stocks and sell growth stocks when rebalancing their portfolios.

Panel B focuses on momentum by examining fund-level trading response to past one-year returns. In Columns (1) to (4), the coefficients on past one-year return are positive and significant, suggesting that, consistent with Grinblatt et al. (1995), an average mutual fund is buying past winners and selling past losers. Moreover, regression coefficients from the two subsample analyses have opposite signs and are all significant. As expected, contrarian funds buy loser stocks and sell winner stocks while momentum funds do the opposite. Therefore, we also show fund-level evidence of rebalancing based on the momentum factor. Table A.2 repeats the same set of regressions as in Tables 8 using $\Delta Dollars_{i,j,q+1}/ME_{i,q}$ as the dependent variable; the results offer a very similar depiction of mutual funds' trading behavior. In summary, the way that growth, value, contrarian, and momentum funds rebalance their portfolios based on stock characteristics supports factor rebalancing.

4 Factor returns

In this section, we test the asset-pricing implications of factor rebalancing. If factor rebalancing induces price pressure, then the predictable trading patterns documented in Section 3 should lead to predictable returns.

4.1 Double-sorted portfolio returns

Table 9 independently sorts all stocks into 25 (5×5) portfolios in the same way as in Table 6. As Table 6 shows, independent sorting on two highly correlated variables means that the distribution of stocks across portfolios will be uneven . We return to this issue below. Table 10 reports the pre-formation characteristics of the 25 portfolios. As desired, the two sorting variables are monotonically and evenly distributed across the portfolios.

In Panel A, each cell represents the annualized value-weighted return of that portfolio in the subsequent quarter. We interpret the table in three ways. First, we follow Section 3 and examine the four corners. 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%. Their differences in magnitude are substantial.

Second, we can read the last column in Panel A to get a sense of how stock returns depend on the HML beta of the underlying funds. Among the growth stocks sorted into the bottom B/M-quintile, those held by growth funds greatly *outperform* those held by value funds, with a difference in annualized returns of 10.4%. In contrast, among the value stocks sorted into the top B/M-quintile, those held by growth funds substantially *underperform* those held by value funds, with a difference in annualized returns of 5.5%. Therefore, a stock's future return not only depends on its own B/M ratio, but also crucially hinges on the HML beta of the underlying funds.

Third, we can read the last row (in line "HML") in Panel A to examine how the profitability of the HML strategy depends on the underlying funds. For stocks sorted into the bottom $\overline{\beta}^{HML}$-quintile—that is, stocks primarily held by growth funds—there is a "growth" premium: growth stocks outperform value stocks by 8.5% every year. Once we move away from the bottom $\overline{\beta}^{HML}$-quintile, the usual value premium reappears and reaches 7.4% in the top $\overline{\beta}^{HML}$-quintile. A straightforward implication of this result, from the perspective of portfolio management, is that it may benefit value funds to pick value stocks that are already heavily held by other value funds. More strikingly, we show that there is a growth premium once we condition on stocks held by growth funds. This may provide justification for the persistent popularity of growth funds despite the unconditional value premium.

Panels B to D establish the robustness of portfolio returns in three ways. Panel B shows that the same patterns hold for equal-weighted returns, which means that they are not driven solely by large-cap stocks. Panels C and D consider alphas from two alternative asset-pricing models: CAPM and the three-factor model of market, size, and value. In calculating the Carhart four-factor alpha, we omit the value factor. In both specifications, the alphas show a similar pattern across the 25 portfolios.

Table 11 repeats the same set of exercises as in Table 9. The only difference is that, instead of using a three-factor model of market, size, and value, we use the Fama-French three-factor model. The findings, by and large, are consistent with those in Table 11. First, the performance of the momentum strategy depends on the underlying funds. From the bottom $\overline{\beta}^{MOM}$-quintile to the top $\overline{\beta}^{MOM}$-quintile, the annualized WML return increases from 1.0% to 7.2%. Second, the patterns become stronger in Panel B, which examines equal-weighted portfolio returns. Third, the patterns of the CAPM alpha in Panel C are also consistent. However, in Panel D, the results for the Fama-French three-factor alpha become a bit weaker. Below, we show improved alphas in 3×3 sorts and in subsample analysis.

To more directly confront concern about the small number of firms in some corner portfolios, we sort stocks into 9 (3×3) portfolios instead of 25 and show that the patterns remain. Table A.3 repeats the exercises in Tables 9 and 11 by sorting stocks into 9 (3×3) portfolios. Panel A concerns the value strategy and shows that even the portfolio with the fewest stocks now has more than 100 stocks on average. Because there is less variation across stocks, the differences in portfolio returns are not as great as before, but the patterns remain. Again, results are robust to alternative asset-pricing models. Panel B concerns the momentum strategy and shows robustness for raw returns and Fama-French three-factor alpha.

4.2 Subsample analysis

To further show the robustness of and gain some insights into the return results in Section 4.1, we perform a series of subsample analyses. Table 12 reports the results for the value strategy. 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 9.

Panels A and B study two subperiods: 1980 to 1999 and 2000 to 2018. In both subperiods, the HML strategy, measured by raw returns or portfolio alphas, performs substantially better conditional on value funds. Overall, the difference doubles in the second half of the sample. Panels C and D sort stocks based on their mutual fund ownership. More specifically, in each quarter, before beginning to sort stocks into 25 portfolios, we first sort them into high or low in mutual fund ownership using the median mutual fund ownership as the cutoff. Overall, return patterns are robust in both subsamples, although, perhaps as expected, the results are stronger in the subsample of high mutual fund ownership. Panels E and F sort stocks based on their 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 A.3: 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 value strategy, in which large stocks are more profitable, the momentum strategy works better for small stocks.

4.3 Stock-level regressions

In addition to showing evidence from nonparametric portfolio sorting, we also use a regression approach to test whether the B/M ratio and past one-year return have different predictive power for stock returns conditional on different underlying funds. Specifically, we run the following panel regression:

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

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

Table 14 reports the results. Panel A shows the results for value and we focus on the coefficients of the B/M ratio across these samples. They are positive in all specifications, consistent with the value premium long known to the literature. However, their magnitude and significance vary. In the subsample of high $\bar{\beta}^{HML}$ stocks, the coefficient on the B/M ratio is 0.0044 and significant, with a magnitude that more than quadruples those in other subsamples; the coefficient for low-$\bar{\beta}^{HML}$ subsample, for instance, is significant but only 0.0010.

Panel B reports results for momentum. The coefficients on past one-year return are, on average, close to zero. Specifically, in the low- and medium-$\bar{\beta}^{MOM}$ subsamples, the coefficients are significant and negative. Although the coefficient in the high-$\bar{\beta}^{MOM}$ subsample is positive and substantially bigger, it is not statistically significant. This relatively weak evidence for momentum, we argue, stems from its weak performance in the second half of our sample, possibly due to momentum crashes (Daniel and Moskowitz 2017). Therefore, in Table A.4, we repeat the same exercise for two subperiods with the end of 1999 as the breakpoint. Consistent with the much stronger momentum premium prior to 1999, stocks with high-$\bar{\beta}^{MOM}$ in the early part of the sample show a positive and significant momentum premium, with a coefficient close to 0.02. In comparison, the other subsamples show either a smaller or a negative momentum premium. To sum up, stock-level regressions confirm that, consistent with factor rebalancing, stocks held by value (momentum) funds exhibit a stronger value (momentum) premium while stocks held by growth (contrarian) funds exhibit a zero or negative premium.

4.4 Alternative explanations

In this subsection, we discuss several explanations alternative to factor rebalancing for the stock-level evidence documented in the previous subsections. We specifically evaluate the possibilities that our evidence could be generated by flow-induced trading, stocks' subsequent fundamentals, and mutual fund herding behavior.

4.4.1 Flow-induced trading

Non-informed retail flows may prompt mutual funds to rebalance their portfolios, generating temporary price pressure on the underlying stocks. However, as we document in Table 7 , FIT is unlikely to be an explanation for our stock-level return evidence. For value, FIT is negative across all five HML long-short portfolios and is more negative for high-$\overline{\beta}^{HML}$ stocks. Since FIT is typically positively associated with contemporaneous stock returns, its prediction for cross-sectional returns goes opposite to the return dispersion that we have found for value. For momentum, FIT is positive for all WML portfolios. However, FIT is almost identical across the five WML portfolios, contrasting with the big return gap documented in Table 11. Therefore, we conclude that our results cannot be explained by flow-induced trading.

4.4.2 Subsequent stock fundamentals

In the real world, mutual funds trade for various reasons besides factor rebalancing. One such motive is that fund managers may have private information regarding the firm's future fundamentals. Stocks bought by fund managers who have such an informational advantage are more likely to have good realized fundamentals in subsequent periods. The stock return dispersion in Tables 9 and 11 may reflect fund managers' better forecasting ability for stock fundamentals.

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

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

4.4.3 Other skill-based explanations

We note that the ability to forecast future fundamentals is just one facet of fund skills. If mutual funds exhibit skills that cannot be inferred from subsequent fundamentals, then our analysis in the previous section would not capture these skills. Indeed, it is possible that value funds specialize in value stocks while growth funds specialize in growth stocks and that their specializations explain differences in returns. However, it is challenging to use this explanation to reconcile some of the more detailed patterns in portfolio returns. For example, growth funds outperform value funds by more than 10% in their selection of growth stocks, a magnitude that seems difficult to rationalize based on the literature on mutual fund performance. Indeed, prominent proxies of mutual fund skill – such as the return gap, active shares, the sensitivity to public information, herding, and active fundamental performance – have generally found a difference in returns of less than 3% per year from between the two extreme deciles (Kacperczyk and Seru 2007; Kacperczyk et al. 2008; Cremers and Petajisto 2009; Jiang and Verardo 2018; Jiang and Zheng 2018).

4.4.4 Herding

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

5 Conclusion

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

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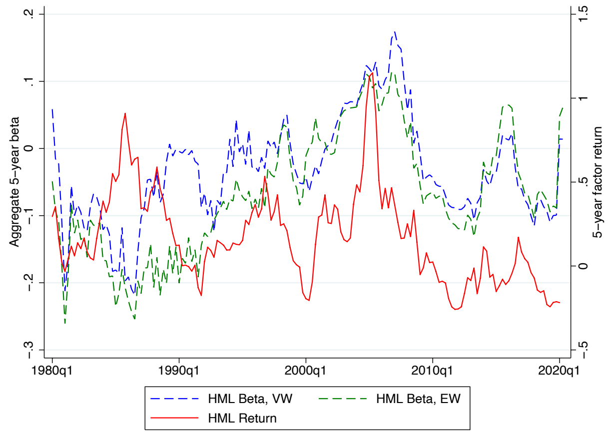
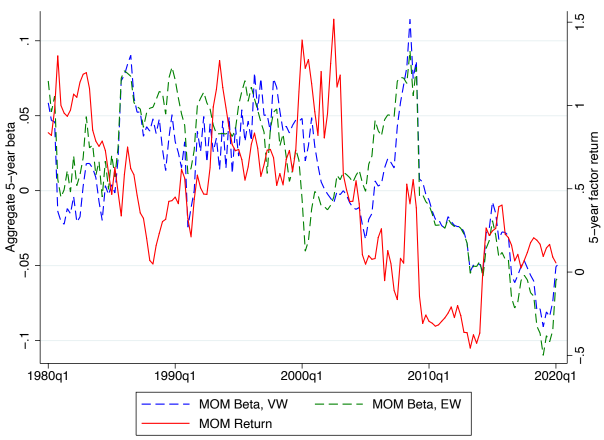
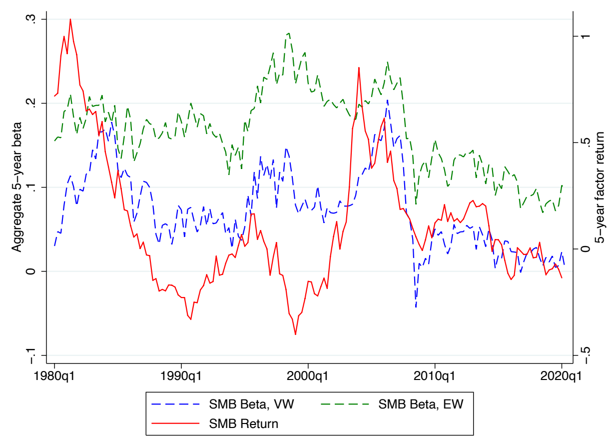


(a) Value



(b) Momentum



(c) Size

Figure 1: Aggregate factor loadings

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

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

Table 1: Summary statistics for the mutual fund sample

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

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

Table 2: Summary statistics of factor betas

Note: This table summarizes the distribution of factor betas. We require a fund to have at least 60 months of returns data and each rolling-window estimation to have at least 24 monthly observations. For each fund i in month t, we estimate factor betas by using observations from month $t-59$ to month t and running the following rolling time-series regression:

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

where $k = 1, 2, ..., 60$; $rret$ is raw fund returns; MKT is excess market returns; and HML, SMB, MOM, CMA, and RMW are returns for value, size, momentum, investment, and profitability strategies, respectively. We also control for retail flows with $flow$, where $flow_{i,t} = \frac{TNA_{i,t}}{TNA_{i,t-1}} - (1 + ret_{i,t})$ and ret represents net fund returns. In Panel A, P5, P25, P50, P75, and P95 correspond to the 5th, 25th, 50th, 75th, and 95th percentiles in the distribution. In Panel B, the classifications of growth, value, small cap, medium cap, and large cap are from the Lipper mutual fund classifications. In Panel C, the classifications of index funds are provided by CRSP.

	(1)	(2)	(3)	(4)	(5)	(6)
	$\beta_{i,q}^{MKT}$	$\beta_{i,q}^{SMB}$	$\beta_{i,q}^{HML}$	$\beta_{i,q}^{MOM}$	$\beta_{i,q}^{SMB}$	$\beta_{i,q}^{HML}$
$\beta_{i,q-20}^{MKT}$	0.348***					
	(0.019)					
$\beta_{i,q-20}^{SMB}$		0.747***			0.424***	
		(0.012)			(0.021)	
$\beta_{i,q-20}^{HML}$			0.369***			0.297***
			(0.015)			(0.021)
$\beta_{i,q-20}^{MOM}$				0.293***		
				(0.019)		
Dummy_size					0.031***	
					(0.009)	
*Dummy_size**$\beta_{i,q-20}^{SMB}$					0.469***	
					(0.024)	
Dummy_BM						-0.039***
						(0.012)
*Dummy_BM**$\beta_{i,q-20}^{HML}$						0.234***
						(0.027)
Quarter FE	✓	✓	✓	✓	✓	✓
Obs.	153,331	153,331	153,331	153,331	153,331	153,331
R-squared	0.235	0.568	0.236	0.184	0.639	0.255

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

Table 3: Persistence of factor demand

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. For funds classified as small cap, medium cap, and large cap according to the Lipper mutual fund classifications, *Dummy_size* equals 1; otherwise, it equals 0. For funds classified as value or growth funds according to the Lipper mutual fund classifications, Dummy_BM equals 1; otherwise, it equals 0. All standard errors are double-clustered by fund and quarter.

Panel A: One-quarter transition, B/M	1	2	3	4	5
1	**0.86**	0.12	0.01	0.00	0.00
2	0.10	**0.72**	0.16	0.02	0.00
3	0.00	0.14	**0.67**	0.17	0.01
4	0.00	0.01	0.16	**0.69**	0.14
5	0.00	0.00	0.01	0.14	**0.85**

Panel B: One-year transition, B/M	1	2	3	4	5
1	**0.68**	0.23	0.06	0.03	0.01
2	0.16	**0.50**	0.24	0.07	0.02
3	0.03	0.21	**0.45**	0.25	0.07
4	0.01	0.05	0.22	**0.48**	0.23
5	0.01	0.01	0.05	0.22	**0.72**

Panel C: One-quarter transition, $r_{t-12,t-2}$	1	2	3	4	5
1	**0.61**	0.23	0.09	0.05	0.02
2	0.23	**0.36**	0.25	0.12	0.04
3	0.10	0.25	**0.33**	0.24	0.08
4	0.05	0.12	0.25	**0.36**	0.21
5	0.03	0.05	0.10	0.23	**0.60**

Panel D: One-year transition, $r_{t-12,t-2}$	1	2	3	4	5
1	**0.25**	0.20	0.18	0.18	0.19
2	0.19	**0.22**	0.23	0.22	0.14
3	0.17	0.23	**0.25**	0.22	0.14
4	0.18	0.22	0.23	**0.21**	0.15
5	0.26	0.19	0.17	0.18	**0.20**

Table 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 ($r_{t-12,t-2}$, skipping the most recent month). One-quarter transition probability represents the probability of moving from one quintile to another quintile between the current quarter and the next quarter. One-year transition probability represents the probability of moving from one quintile to another quintile between the current quarter and four quarters later.

Panel A: One-quarter transition, β^{HML}					
	1	2	3	4	5
1	**0.88**	0.11	0.01	0.00	0.00
2	0.11	**0.75**	0.13	0.01	0.00
3	0.01	0.13	**0.73**	0.12	0.01
4	0.00	0.01	0.12	**0.76**	0.10
5	0.00	0.00	0.01	0.10	**0.89**

Panel B: One-year transition, β^{HML}					
	1	2	3	4	5
1	**0.74**	0.20	0.04	0.02	0.01
2	0.19	**0.53**	0.21	0.06	0.02
3	0.04	0.21	**0.51**	0.20	0.04
4	0.01	0.06	0.20	**0.56**	0.17
5	0.01	0.02	0.04	0.18	**0.75**

Panel C: One-quarter transition, β^{MOM}					
	1	2	3	4	5
1	**0.89**	0.10	0.01	0.00	0.00
2	0.09	**0.77**	0.13	0.01	0.00
3	0.01	0.12	**0.73**	0.13	0.01
4	0.00	0.01	0.13	**0.76**	0.10
5	0.00	0.00	0.01	0.10	**0.89**

Panel D: One-year transition, β^{MOM}					
	1	2	3	4	5
1	**0.75**	0.18	0.04	0.02	0.01
2	0.15	**0.56**	0.21	0.06	0.02
3	0.04	0.20	**0.51**	0.22	0.04
4	0.02	0.06	0.21	**0.54**	0.17
5	0.01	0.02	0.04	0.18	**0.74**

Table 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.

Panel A: Number of stocks in each portfolio

		Low-$\overline{\beta}^{HML}$	$\longleftarrow$	*Fund*	$\longrightarrow$	High-$\overline{\beta}^{HML}$			Low-$\overline{\beta}^{MOM}$	$\longleftarrow$	*Fund*	$\longrightarrow$	High-$\overline{\beta}^{MOM}$
		1	2	3	4	5			1	2	3	4	5
Low-B/M	1	220	132	71	41	27	Low-RET	1	131	107	98	87	70
$\uparrow$	2	124	142	110	72	45	$\uparrow$	2	124	117	104	87	63
Stock	3	61	103	122	115	92	*Stock*	3	106	116	110	95	69
$\downarrow$	4	35	67	106	134	150	$\downarrow$	4	87	102	108	108	90
High-B/M	5	26	50	92	139	184	High-RET	5	60	68	85	115	165

Panel B: Total mutual fund ownership change (%)

		Low-$\overline{\beta}^{HML}$	$\longleftarrow$	*Fund*	$\longrightarrow$	High-$\overline{\beta}^{HML}$			Low-$\overline{\beta}^{MOM}$	$\longleftarrow$	*Fund*	$\longrightarrow$	High-$\overline{\beta}^{MOM}$
		1	2	3	4	5			1	2	3	4	5
Low-B/M	1	0.07	0.02	0.03	0.12	-0.04	Low-RET	1	0.14	0.14	0.20	0.07	-0.10
$\uparrow$	2	0.02	0.00	0.10	0.05	-0.04	$\uparrow$	2	0.16	0.22	0.16	0.19	0.08
Stock	3	0.12	0.10	0.09	0.06	-0.12	*Stock*	3	0.05	0.05	0.14	0.05	0.13
$\downarrow$	4	0.00	0.10	0.11	0.18	0.14	$\downarrow$	4	-0.04	0.06	0.00	0.06	0.03
High-B/M	5	-0.28	0.12	0.15	0.20	0.20	High-RET	5	0.04	-0.07	-0.06	0.03	-0.02
HML		**-0.35**	**0.10**	**0.12**	**0.09**	**0.24**	WML		**-0.10**	**-0.21**	**-0.26**	**-0.05**	**0.08**

Table 6: Total mutual fund ownership changes

Note: This table reports the number of stocks in each portfolio and subsequent quarterly changes in total mutual fund ownership. In each quarter, stocks are first into 25 portfolios based on their B/M ratios or past one-year returns (skipping the most recent month) and on their $\overline{\beta}^{HML}$ or $\overline{\beta}^{MOM}$, calculated as the shares-weighted average β^{HML} and β^{MOM} of the underlying funds, respectively. Total mutual fund ownership change is calculated by dividing the change in the number of shares held by all mutual funds by the total number of shares outstanding.

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

		Low-$\overline{\beta}^{HML}$ 1	⟵ 2	*Fund* 3	⟶ 4	High-$\overline{\beta}^{HML}$ 5			Low-$\overline{\beta}^{MOM}$ 1	⟵ 2	*Fund* 3	⟶ 4	High-$\overline{\beta}^{MOM}$ 5
Low-B/M	1	-0.02	-0.07	0.10	0.11	0.42	Low-RET	1	-0.40	-0.42	-0.46	-0.49	-0.25
↑	2	-0.40	-0.31	-0.29	-0.05	0.17	↑	2	-0.23	-0.38	-0.35	-0.31	-0.27
Stock	3	-0.35	-0.29	-0.17	-0.04	0.18	*Stock*	3	-0.14	-0.33	-0.31	-0.22	-0.19
↓	4	-0.24	-0.27	-0.16	-0.19	0.03	↓	4	-0.07	-0.18	-0.14	-0.08	0.04
High-B/M	5	-0.25	-0.21	-0.13	-0.29	-0.14	High-RET	5	0.20	-0.10	0.06	0.10	0.42
HML		**-0.23**	**-0.14**	**-0.23**	**-0.39**	**-0.56**	WML		**0.60**	**0.32**	**0.52**	**0.59**	**0.67**

Panel B: FIT-adjusted total mutual fund ownership change (%)

		Low-$\overline{\beta}^{HML}$ 1	⟵ 2	*Fund* 3	⟶ 4	High-$\overline{\beta}^{HML}$ 5			Low-$\overline{\beta}^{MOM}$ 1	⟵ 2	*Fund* 3	⟶ 4	High-$\overline{\beta}^{MOM}$ 5
Low-B/M	1	0.15	0.06	0.04	0.11	-0.04	Low-RET	1	0.21	0.22	0.28	0.16	-0.02
↑	2	0.11	0.06	0.14	0.07	-0.06	↑	2	0.21	0.28	0.23	0.26	0.15
Stock	3	0.20	0.16	0.13	0.09	-0.12	*Stock*	3	0.09	0.11	0.19	0.11	0.20
↓	4	0.05	0.16	0.15	0.22	0.15	↓	4	-0.01	0.11	0.04	0.11	0.09
High-B/M	5	-0.22	0.17	0.20	0.26	0.23	High-RET	5	0.05	-0.04	-0.04	0.05	0.00
HML		**-0.37**	**0.11**	**0.16**	**0.15**	**0.27**	WML		**-0.16**	**-0.26**	**-0.32**	**-0.11**	**0.02**

Table 7: Flow-induced trading

Note: This table reports quarterly flow-induced trading (FIT) for each of the 25 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 $\overline{\beta}^{HML}$ or $\overline{\beta}^{MOM}$, calculated as the shares-weighted average β^{HML} and β^{MOM} of the underlying funds, respectively. Panel A reports FIT in each quarter. We follow Lou (2012) and define FIT for each stock j in each quarter q as

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

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

	Dependent variable: $\Delta Shares_{i,j,q+1}/Shrout_{i,q}$											
Panel A: Value												
	Full sample				Low-$\beta^{HML}_{j,q}$				High-$\beta^{HML}_{j,q}$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$BM_{i,q}$	-0.0080***	-0.0039*	-0.0001	0.0031*	-0.0194***	-0.0053	-0.0009	0.0089**	0.0159***	0.0116***	0.0228***	0.0152***
	(0.0025)	(0.0021)	(0.0021)	(0.0018)	(0.0071)	(0.0055)	(0.0047)	(0.0040)	(0.0037)	(0.0034)	(0.0037)	(0.0031)
$r_{i,q-4,q-1/3}$		0.0622***		0.0535***		0.1072***		0.0798***		0.0005		-0.0084
		(0.0040)		(0.0036)		(0.0065)		(0.0052)		(0.0047)		(0.0051)
$\beta_{i,q}$		0.0027		0.0333***		0.0247***		0.0260***		-0.0289***		0.0286***
		(0.0032)		(0.0035)		(0.0090)		(0.0083)		(0.0066)		(0.0037)
$ME_{i,q}$		-0.9785***		-0.8415***		-1.482***		-1.256***		-0.9863***		-0.8168***
		(0.0477)		(0.0405)		(0.0921)		(0.0794)		(0.0568)		(0.0483)
Quarter FE			✓	✓			✓	✓			✓	✓
R^2	0.0000	0.0045	0.0151	0.0185	0.0000	0.0104	0.0307	0.0362	0.0000	0.0025	0.0182	0.0200
Observations	24,268,014	24,131,968	24,268,014	24,131,968	3,615,836	3,584,211	3,615,836	3,584,211	6,575,970	6,548,231	6,575,970	6,548,231
Panel B: Momentum												
	Full sample				Low-$\beta^{MOM}_{j,q}$				High-$\beta^{MOM}_{j,q}$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$r_{i,q-4,q-1/3}$	0.0636***	0.0622***	0.0569***	0.0535***	-0.0170**	-0.0132*	-0.0320***	-0.0305***	0.1027***	0.0980***	0.0791***	0.0763***
	(0.0042)	(0.0039)	(0.0039)	(0.0035)	(0.0081)	(0.0076)	(0.0095)	(0.0089)	(0.0064)	(0.0060)	(0.0048)	(0.0046)
$BM_{i,q}$		-0.0039*		0.0031*		0.0177***		0.0218***		-0.0306***		0.0036
		(0.0021)		(0.0017)		(0.0039)		(0.0041)		(0.0059)		(0.0030)
$\beta_{i,q}$		0.0027		0.0333***		-0.0072		0.0457***		-0.0035		0.0110**
		(0.0032)		(0.0035)		(0.0080)		(0.0069)		(0.0051)		(0.0053)
$ME_{i,q}$		-0.9785***		-0.8415***		-1.51***		-1.414***		-1.286***		-1.136***
		(0.0472)		(0.0400)		(0.0947)		(0.0858)		(0.0700)		(0.0611)
Quarter FE			✓	✓			✓	✓			✓	✓
R^2	0.0018	0.0045	0.0162	0.0185	0.0000	0.0044	0.0126	0.0170	0.0049	0.0082	0.0377	0.0400
Observations	24,254,675	24,131,968	24,254,675	24,131,968	2,778,921	2,763,143	2,778,921	2,763,143	5,875,288	5,845,588	5,875,288	5,845,588

Table 8: Fund-level portfolio rebalancing: FIT-adjusted trading in shares

Note: This table reports how mutual funds rebalance their portfolios based on stock characteristics. The dependent variable, $\Delta Shares_{i,j,q+1}/Shrout_{i,q}$, is FIT-adjusted trading in shares in quarter $q+1$ normalized by total shares outstanding as of quarter q. The independent variables are stock i's characteristics in quarter q, including the book-to-market ratio (demeaned cross-sectionally), $BM_{i,q}$; past one-year return (skipping the most recent month), $r_{i,q-4,q-1/3}$; market beta, $\beta_{i,q}$; and market capitalization (in billions), $ME_{i,q}$. Panels A and B report results for value and momentum, respectively. Columns (1) to (4) use the full sample. Columns (5) to (8) use funds low in $\beta_{j,HML}$ (Panel A) or $\beta_{j,MOM}$ (Panel B), where low means being in the lowest 20th percentile of the distribution. Columns (9) to (12) use funds high in $\beta_{j,HML}$ (Panel A) or $\beta_{j,MOM}$ (Panel B), where high means being in the highest 20th percentile of the distribution. The data sample is from 1980Q1 to 2018Q4. Standard errors are clustered at quarter and fund levels.

Panel A: VW portfolio returns (annualized, %)

		Low-$\overline{\beta}^{HML}$	$\longleftarrow$	*Fund*	$\longrightarrow$	High-$\overline{\beta}^{HML}$	
		1	2	3	4	5	5−1
Low-B/M	1	17.0	11.9	8.8	10.0	6.6	-10.4
↑	2	14.5	14.3	10.6	11.2	10.1	-4.4
Stock	3	17.3	14.1	12.5	10.7	11.7	-5.5
↓	4	11.2	15.2	13.9	11.9	13.2	2.0
High-B/M	5	8.5	16.4	15.2	12.8	14.0	5.5
HML		-8.5	4.5	6.4	2.8	7.4	15.9
		[-2.02]	[1.46]	[2.43]	[0.95]	[2.72]	[3.52]

Panel B: EW portfolio returns (annualized, %)

		Low-$\overline{\beta}^{HML}$	$\longleftarrow$	*Fund*	$\longrightarrow$	High-$\overline{\beta}^{HML}$	
		1	2	3	4	5	5−1
Low-B/M	1	15.7	12.1	9.1	9.9	6.4	-9.3
↑	2	14.1	14.2	11.8	11.2	11.1	-3.1
Stock	3	17.0	15.3	13.4	12.3	13.2	-3.8
↓	4	15.2	16.3	15.0	13.2	13.4	-1.8
High-B/M	5	11.8	16.7	16.2	15.0	13.9	2.1
HML		-3.9	4.6	7.1	5.1	7.5	11.4
		[-1.04]	[1.72]	[3.06]	[2.24]	[3.42]	[2.99]

Panel C: CAPM alpha (annualized, %)

		Low-$\overline{\beta}^{HML}$	$\longleftarrow$	*Fund*	$\longrightarrow$	High-$\overline{\beta}^{HML}$	
		1	2	3	4	5	5−1
Low-B/M	1	5.0	3.0	1.0	2.8	-2.3	-7.3
↑	2	3.4	5.5	3.1	3.3	2.4	-1.0
Stock	3	7.2	5.6	5.0	3.9	5.0	-2.2
↓	4	1.2	6.9	5.9	4.8	6.5	5.3
High-B/M	5	-2.1	7.2	7.8	5.3	6.3	8.4
HML		-7.1	4.2	6.8	2.5	8.6	15.8
t-stats		[-6.59]	[5.25]	[10.02]	[3.24]	[12.48]	[13.54]

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

		Low-$\overline{\beta}^{HML}$	$\longleftarrow$	*Fund*	$\longrightarrow$	High-$\overline{\beta}^{HML}$	
		1	2	3	4	5	5−1
Low-B/M	1	1.25	0.87	-0.55	1.76	-2.51	-3.76
↑	2	2.54	5.12	2.49	2.87	1.99	-0.55
Stock	3	7.67	5.98	5.58	3.67	5.95	-1.72
↓	4	3.12	8.32	6.80	5.34	7.06	3.94
High-B/M	5	1.75	10.12	10.06	8.03	9.35	7.60
HML		0.50	9.25	10.62	6.27	11.86	11.36
t-stats		[0.46]	[13.41]	[12.27]	[9.75]	[17.81]	[9.91]

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

Note: This table reports the return and average number of stocks for each of the 25 portfolios double-sorted on B/M ratios and HML betas, $\overline{\beta}^{HML}$, where $\overline{\beta}^{HML}$is calculated as the shares-weighted average β^{HML} of the underlying funds. Data are from 1980Q2 to 2018Q4. Panel A reports value-weighted returns and Panel B reports equal-weighted returns. Panels C and D report portfolio alphas based on two asset-pricing models: CAPM and a three-factor model of market, size, and momentum, respectively.

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

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

Panel B: Pre-formation characteristics for 5 × 5 stock portfolios sorted on $r_{t-12,t-1}$ and MOM betas

		$r_{t-12,t-1}$							$\overline{\beta}^{MOM}$					
		Low-$\overline{\beta}^{MOM}$	⟵	*Fund*	⟶	High-$\overline{\beta}^{MOM}$			Low-$\overline{\beta}^{MOM}$	⟵	*Fund*	⟶	High-$\overline{\beta}^{MOM}$	
		1	2	3	4	5	5−1		1	2	3	4	5	5−1
Low-RET	1	-0.23	-0.22	-0.22	-0.23	-0.24	-0.01	1	-0.10	-0.03	0.01	0.06	0.15	0.24
↑	2	-0.02	-0.02	-0.01	-0.01	-0.01	0.00	2	-0.09	-0.03	0.01	0.06	0.14	0.23
Stock	3	0.13	0.13	0.14	0.14	0.14	0.01	3	-0.09	-0.03	0.01	0.06	0.14	0.23
↓	4	0.30	0.30	0.31	0.32	0.32	0.02	4	-0.09	-0.03	0.01	0.06	0.14	0.23
High-RET	5	0.73	0.69	0.71	0.76	0.95	0.23	5	-0.10	-0.03	0.01	0.06	0.15	0.24
WML		0.96	0.91	0.93	0.99	1.20	0.24		0.00	0.00	0.00	0.00	0.00	0.00

Table 10: Pre-formation characteristics for 5 × 5 stock portfolios

Note: This table reports the pre-formation characteristics of stocks for each of the 25 portfolios. Panel A reports results for stocks double-sorted on B/M ratios and HML betas, $\overline{\beta}^{HML}$, where $\overline{\beta}^{HML}$ is calculated as the shares-weighted average β^{HML} of the underlying funds. Panel B reports results for stocks double-sorted on one-year past return ($r_{t-12,t-1}$) and MOM betas, $\overline{\beta}^{MOM}$, where $\overline{\beta}^{MOM}$ is calculated as the shares-weighted average β^{MOM} of the underlying funds. Each panel reports the value-weighted averages of the two sorting variables and one-year mutual fund ownership change. Data are from 1980Q1 to 2018Q4.

Panel A: VW portfolio returns (annualized, %)

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

Panel B: EW portfolio returns (annualized, %)

		Low-$\overline{\beta}^{MOM}$ 1	⟵ 2	*Fund* 3	⟶ 4	High-$\overline{\beta}^{MOM}$ 5	5−1
Low-RET	1	7.8	8.3	8.0	8.3	10.2	2.4
↑	2	12.2	13.5	13.3	13.5	14.7	2.5
Stock	3	13.2	13.4	14.5	15.0	17.2	3.9
↓	4	13.4	13.6	14.8	15.7	19.5	6.0
High-RET	5	12.5	13.4	14.5	18.8	22.7	10.2
WML		4.7	5.2	6.5	10.5	12.5	7.8
		[1.53]	[1.90]	[2.41]	[3.56]	[4.27]	[3.33]

Panel C: CAPM alpha (annualized, %)

		Low-$\overline{\beta}^{MOM}$ 1	⟵ 2	*Fund* 3	⟶ 4	High-$\overline{\beta}^{MOM}$ 5	5−1
Low-RET	1	-2.6	-2.8	1.0	-1.5	0.7	3.3
↑	2	2.5	3.1	5.5	3.6	4.6	2.1
Stock	3	3.0	5.0	6.1	5.2	8.2	5.1
↓	4	2.9	4.6	4.3	6.7	7.1	4.2
High-RET	5	0.4	0.0	4.0	6.6	7.8	7.4
WML		3.0	2.9	3.0	8.1	7.1	4.2
t-stats		[2.93]	[2.84]	[3.59]	[10.02]	[7.79]	[3.44]

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

		Low-$\overline{\beta}^{MOM}$ 1	⟵ 2	*Fund* 3	⟶ 4	High-$\overline{\beta}^{MOM}$ 5	5−1
Low-RET	1	-5.9	-5.5	0.3	-0.5	3.6	9.5
↑	2	-0.8	0.5	4.1	3.8	6.1	6.9
Stock	3	0.3	3.1	5.4	5.8	9.1	8.8
↓	4	0.3	3.5	4.1	7.7	8.3	8.0
High-RET	5	0.1	0.1	4.3	8.7	11.4	11.3
WML		6.0	5.6	4.0	9.2	7.8	1.8
t-stats		[7.68]	[6.81]	[5.15]	[10.82]	[7.59]	[1.79]

Table 11: Returns and characteristics for 5×5 stock portfolios double-sorted on past one-year returns and MOM betas

Note: This table reports the return and average number of stocks for each of the 25 portfolios double-sorted on past one-year returns (skipping the most recent month) and MOM betas, $\overline{\beta}^{MOM}$, where $\overline{\beta}^{MOM}$ is calculated as the shares-weighted average β^{MOM} of the underlying funds. Data are from 1980Q2 to 2018Q4. Panel A reports value-weighted returns and Panel B reports equal-weighted returns. Panels C and D report portfolio alphas based on two asset-pricing models: CAPM and the Fama-French three-factor model, respectively.

Panel A: Pre-1999 (in %)

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

Panel B: Post-1999 (in %)

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

Panel C: High MF ownership (in %)

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

Panel D: Low MF ownership (in %)

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

Panel E: Large stocks (in %)

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

Panel F: Small stocks (in %)

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

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

Note: This table reports the raw returns and alphas for each of the 25 portfolios double-sorted on B/M ratios and HML betas, $\overline{\beta}^{HML}$, where $\overline{\beta}^{HML}$ is calculated as the shares-weighted average β^{HML} of the underlying funds. Panel A uses data from 1980Q1 to 1999Q4. Panel B uses data from 2001Q1 to 2018Q4. Panel C uses stocks that are above the median mutual fund ownership in each quarter. Panel D uses stocks that are below the median mutual fund ownership in each quarter. Panel E uses stocks that are above the median firm size in each quarter. Panel F uses stocks that are below the median firm size in each quarter. When calculating 3-factor alphas, we control for market, size, and momentum.

Panel A: Pre-1999

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

Panel B: Post-1999

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

Panel C: High MF ownership

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

Panel D: Low MF ownership

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

Panel E: Large stocks

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

Panel F: Small stocks

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

Table 13: Returns for 5×5 stock portfolios double-sorted on past returns and MOM betas, subsample analysis

Note: This table reports the return and average number of stocks for each of the 25 portfolios double-sorted on past one-year returns (skipping the most recent month) and MOM betas, $\overline{\beta}^{MOM}$, where $\overline{\beta}^{MOM}$is calculated as the shares-weighted average β^{MOM} of the underlying funds. Panel A uses data from 1980Q1 to 1999Q4. Panel B uses data from 2001Q1 to 2018Q4. Panel C uses stocks that are above the median mutual fund ownership in each quarter. Panel D uses stocks that are below the median mutual fund ownership in each quarter. Panel E uses stocks that are above the median firm size in each quarter. Panel F uses stocks that are below the median firm size in each quarter. When calculating 3-factor alphas, we control for market, size, and value.

	Dependent variable: $r_{i,q+1}$							
Panel A: Value								
	Full sample		Low-$\bar{\beta}_{i,q}^{HML}$		High-$\bar{\beta}_{i,q}^{HML}$		Medium-$\bar{\beta}_{i,q}^{HML}$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$BM_{i,q}$	0.0012	0.0011**	0.0011***	0.0010**	0.0044***	0.0044***	0.0010	0.0009
	(0.0008)	(0.0005)	(0.0004)	(0.0004)	(0.0013)	(0.0013)	(0.0007)	(0.0006)
$ME_{i,q}$		-0.1323***		-0.2037***		0.1119		-0.1280***
		(0.0137)		(0.0399)		(0.0963)		(0.0150)
$\beta_{i,q}$		-0.0072***		-0.0083***		-0.0103***		-0.0075***
		(0.0009)		(0.0024)		(0.0014)		(0.0010)
$r_{i,q-4,q-1/3}$		0.0002		0.0037**		0.0019		-0.0041***
		(0.0009)		(0.0017)		(0.0018)		(0.0012)
R^2	0.0000	0.0000	0.0000	0.0000	0.0000	0.0013	0.0000	0.0000
Observations	380,679	375,310	72,095	69,902	77,012	76,254	231,572	229,154
Panel B: Momentum								
	Full sample		Low-$\bar{\beta}_{i,q}^{MOM}$		High-$\bar{\beta}_{i,q}^{MOM}$		Medium-$\bar{\beta}_{i,q}^{MOM}$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$r_{i,q-4,q-1/3}$	-0.0002	0.0002	-0.0046*	-0.0042*	0.0015	0.0016	-0.0042***	-0.0039***
	(0.0068)	(0.0009)	(0.0024)	(0.0025)	(0.0016)	(0.0016)	(0.0013)	(0.0013)
$BM_{i,q}$		0.0011**		0.0007		0.0025*		0.0015
		(0.0005)		(0.0007)		(0.0013)		(0.0010)
$ME_{i,q}$		-0.1323***		-0.0512		-0.2883***		-0.1091***
		(0.0134)		(0.0325)		(0.0512)		(0.0154)
$\beta_{i,q}$		-0.0072***		-0.0127***		-0.0009		-0.0106***
		(0.0009)		(0.0018)		(0.0024)		(0.0010)
R^2	0.0000	0.0000	0.0000	0.0012	0.0000	0.0000	0.0000	0.0011
Observations	382,973	375,310	78,685	76,898	70,833	69,042	233,455	229,370

Table 14: Stock-level cross-sectional regressions

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

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

where the dependent variable is stock i's return in quarter $q+1$. The independent variables include the book-to-market ratio, $BM_{i,q}$; past one-year return (skipping the most recent month), $r_{i,q-4,q-\frac{1}{3}}$; market beta, $\beta_{i,q}$; and market capitalization (in billions), $ME_{i,q}$. Panel A reports the results concerning value using the full sample (Columns 1 and 2), the subsample of stocks with $\bar{\beta}_{i,q}^{HML}$ in the bottom quintile (Columns 3 and 4), the subsample of stocks with $\bar{\beta}_{i,q}^{HML}$ in the top quintile (Columns 5 and 6), and the subsample of other stocks (Columns 7 and 8). Panel B is similarly organized for momentum. Standard errors are clustered by year-quarter.

		Panel A: SUE (%), value								Panel B: CAR (%), value					
		Low-$\overline{\beta}^{HML}$	$\longleftarrow$	*Fund*	$\longrightarrow$	High-$\overline{\beta}^{HML}$				Low-$\overline{\beta}^{HML}$	$\longleftarrow$	*Fund*	$\longrightarrow$	High-$\overline{\beta}^{HML}$	
		1	2	3	4	5	5−1			1	2	3	4	5	5−1
Low-B/M	1	0.16	0.24	0.24	0.33	0.36	0.20	Low-B/M	1	0.39	0.12	-0.38	-0.31	-0.14	-0.53
↑	2	0.12	0.17	0.15	0.15	0.20	0.08	↑	2	0.37	0.15	-0.07	-0.13	-0.18	-0.55
Stock	3	-0.04	0.18	0.16	0.20	0.12	0.15	*Stock*	3	0.23	0.26	-0.03	-0.17	0.19	-0.05
↓	4	-0.15	-0.02	-0.06	0.04	0.07	0.22	↓	4	-0.14	0.30	-0.08	0.12	0.03	0.17
High-B/M	5	-0.86	-0.63	-0.45	-0.45	-0.49	0.36	High-B/M	5	-0.03	0.05	0.08	0.19	0.03	0.06
HML		-1.02	-0.87	-0.69	-0.78	-0.86	0.16	HML		-0.42	-0.06	0.46	0.50	0.17	0.59
		Panel C: SUE (%), momentum								Panel D: CAR (%), momentum					
		Low-$\overline{\beta}^{MOM}$	$\longleftarrow$	*Fund*	$\longrightarrow$	High-$\overline{\beta}^{MOM}$				Low-$\overline{\beta}^{MOM}$	$\longleftarrow$	*Fund*	$\longrightarrow$	High-$\overline{\beta}^{MOM}$	
		1	2	3	4	5	5−1			1	2	3	4	5	5−1
Low-RET	1	-1.12	-0.90	-0.64	-0.51	-0.44	0.68	Low-RET	1	0.05	-0.19	-0.06	0.26	0.20	0.15
↑	2	-0.21	-0.16	-0.07	-0.04	-0.08	0.13	↑	2	-0.01	0.06	0.20	0.14	-0.03	-0.02
Stock	3	0.04	0.10	0.09	0.14	0.14	0.10	*Stock*	3	-0.09	0.01	-0.03	0.19	0.23	0.32
↓	4	0.26	0.23	0.30	0.21	0.20	-0.06	↓	4	-0.04	-0.03	-0.09	0.13	0.47	0.51
High-RET	5	0.68	0.60	0.53	0.46	0.47	-0.21	High-RET	5	-0.49	-0.05	0.16	0.11	0.38	0.87
WML		1.79	1.49	1.17	0.98	0.90	-0.89	WML		-0.53	0.14	0.23	-0.15	0.18	0.72

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

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

	α^{CAPM}_{q+4}				α^{3F}_{q+4}				α^{4F}_{q+4}			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Intercept	0.0010**	0.0013***			0.0001	0.0003			0.0005*	0.0006**		
	(0.0004)	(0.0004)			(0.0003)	(0.0003)			(0.0003)	(0.0003)		
High $\beta_{HML,q}$	0.0006***		0.0005***		0.0009***		0.0009***		0.0007***		0.0007***	
	(0.0000)		(0.0000)		(0.0000)		(0.0000)		(0.0000)		(0.0000)	
Low $\beta_{HML,q}$	0.0004***		0.0004***		-0.0003***		-0.0003***		-0.0002**		-0.0002**	
	(0.0001)		(0.0000)		(0.0000)		(0.0000)		(0.0000)		(0.0000)	
High $\beta_{MOM,q}$		0.0000		0.0000		-0.0001		−0.0000		-0.0002***		-0.0002***
		(0.0000)		(0.0000)		(0.0000)		(0.0000)		(0.0000)		(0.0000)
High $\beta_{MOM,q}$		0.0001		0.0000		0.0000		0.0000		0.0003***		0.0003***
		(0.0000)		(0.0000)		(0.0000)		(0.0000)		(0.0000)		(0.0000)
$\log(age)_q$	-0.0002***	-0.0002***	0.0002***	0.0002***	0.0002***	0.0002***	0.0004***	0.0004***	0.0002***	0.0002***	0.0003***	0.0003***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$\log(tna)_q$	-0.0001***	-0.0001***	-0.0001***	-0.0001***	-0.0002***	-0.0002***	-0.0002***	-0.0002***	-0.0002***	-0.0002***	-0.0002***	-0.0002***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$flow_q$	0.0000	0.0000	0.0000*	0.0000*	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$expense_q$	0.0381*	0.0391*	0.0110	0.0119	-0.0037	-0.0050	-0.0165*	-0.0180**	-0.0138	-0.0147	-0.0266***	-0.0274***
	(0.0217)	(0.0222)	(0.0108)	(0.0112)	(0.0124)	(0.0119)	(0.0091)	(0.0087)	(0.0128)	(0.0124)	(0.0092)	(0.0088)
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 16: Fund factor loadings and subsequent performance

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

Appendix: additional tables

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

		Growth funds						Value funds				
		Low-$\overline{\beta}^{HML}$	$\longleftarrow$	*Fund*	$\longrightarrow$	High-$\overline{\beta}^{HML}$		Low-$\overline{\beta}^{HML}$	$\longleftarrow$	*Fund*	$\longrightarrow$	High-$\overline{\beta}^{HML}$
		1	2	3	4	5		1	2	3	4	5
Low-B/M	1	**0.35**	0.15	0.11	0.07	0.00	Low-B/M 1	0.14	0.12	0.14	0.10	**0.14**
$\uparrow$	2	**0.18**	0.08	0.07	0.07	-0.01	$\uparrow$ 2	0.13	0.12	0.18	0.18	**0.19**
Stock	3	**0.19**	0.10	0.06	0.04	-0.04	*Stock* 3	0.15	0.16	0.14	0.18	**0.15**
$\downarrow$	4	**0.09**	0.07	0.06	0.02	0.00	$\downarrow$ 4	0.08	0.19	0.16	0.23	**0.23**
High-B/M	5	**-0.14**	0.02	0.01	0.00	0.02	High-B/M 5	0.12	0.21	0.20	0.25	**0.25**
HML		**-0.50**	**-0.12**	**-0.10**	**-0.07**	**0.02**	HML	**-0.02**	**0.08**	**0.06**	**0.15**	**0.11**

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

		Contrarian funds						Momentum funds				
		Low-$\overline{\beta}^{MOM}$	$\longleftarrow$	*Fund*	$\longrightarrow$	High-$\overline{\beta}^{MOM}$		Low-$\overline{\beta}^{MOM}$	$\longleftarrow$	*Fund*	$\longrightarrow$	High-$\overline{\beta}^{MOM}$
		1	2	3	4	5		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	0.00	-0.01	**-0.06**
$\uparrow$	2	**0.15**	0.15	0.18	0.20	0.22	$\uparrow$ 2	0.02	0.06	0.06	0.07	**0.14**
Stock	3	**0.03**	0.07	0.10	0.11	0.12	*Stock* 3	0.06	0.12	0.11	0.13	**0.30**
$\downarrow$	4	**0.01**	0.01	0.04	0.10	0.11	$\downarrow$ 4	0.08	0.19	0.18	0.18	**0.37**
High-RET	5	**0.02**	-0.05	0.05	0.05	0.10	High-RET 5	0.15	0.24	0.25	0.37	**0.54**
WML		**-0.19**	-0.27	-0.18	-0.21	-0.07	WML	0.17	0.23	0.25	0.38	**0.60**

Table A.1: Decomposition of total mutual fund ownership changes

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

	Dependent variable: $\Delta Dollar_{i,j,q+1}/ME_{i,q}$											
Panel A: Value												
	Full sample				Low-$\beta_{j,q}^{HML}$				High-$\beta_{j,q}^{HML}$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$BM_{i,q}$	-0.0044**	-0.0016	0.0021	0.0043**	-0.0068	0.0000	0.0023	0.0070**	0.0185***	0.0137***	0.0251***	0.0173***
	(0.0021)	(0.0018)	(0.0018)	(0.0017)	(0.0048)	(0.0035)	(0.0033)	(0.0035)	(0.0039)	(0.0035)	(0.0039)	(0.0033)
$r_{i,q-4,q-1/3}$		0.0572***		0.0491***		0.1011***		0.0744***		-0.0032		-0.0113**
		(0.0039)		(0.0035)		(0.0064)		(0.0053)		(0.0046)		(0.0051)
$\beta_{i,q}$		0.0013		0.0308***		0.0197**		0.0203**		-0.0297***		0.0256***
		(0.0032)		(0.0034)		(0.0088)		(0.0082)		(0.0066)		(0.0036)
$ME_{i,q}$		-0.9845***		-0.8445***		-1.505***		-1.271***		-0.9802***		-0.8082***
		(0.0484)		(0.0407)		(0.0939)		(0.0803)		(0.0567)		(0.0482)
Quarter FE			✓	✓			✓	✓			✓	✓
R^2	0.0000	0.0042	0.0143	0.0175	0.0000	0.0095	0.0302	0.0352	0.0000	0.0025	0.0168	0.0184
Observations	24,305,104	24,165,118	24,305,104	24,165,118	3,622,974	3,590,458	3,622,974	3,590,458	6,584,249	6,555,659	6,584,249	6,555,659
Panel B: Momentum												
	Full sample				Low-$\beta_{j,q}^{MOM}$				High-$\beta_{j,q}^{MOM}$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$r_{i,q-4,q-1/3}$	0.0581***	0.0572***	0.0521***	0.0491***	-0.0228***	-0.0195***	-0.0380***	-0.0373***	0.0963***	0.0923***	0.0738***	0.0716***
	(0.0041)	(0.0038)	(0.0038)	(0.0034)	(0.0078)	(0.0074)	(0.0094)	(0.0090)	(0.0062)	(0.0059)	(0.0047)	(0.0045)
$BM_{i,q}$		-0.0016		0.0043**		0.0139**		0.0164***		-0.0252***		0.0067**
		(0.0017)		(0.0017)		(0.0053)		(0.0061)		(0.0051)		(0.0028)
$\beta_{i,q}$		0.0013		0.0308***		-0.0121		0.0382***		-0.0062		0.0080
		(0.0032)		(0.0034)		(0.0078)		(0.0065)		(0.0051)		(0.0053)
$ME_{i,q}$		-0.9845***		-0.8445***		-1.487***		-1.391***		-1.321***		-1.159***
		(0.0478)		(0.0401)		(0.0941)		(0.0846)		(0.0715)		(0.0623)
Quarter FE			✓	✓			✓	✓			✓	✓
R^2	0.0015	0.0042	0.0153	0.0175	0.0000	0.0043	0.0117	0.0156	0.0042	0.0075	0.0364	0.0387
Observations	24,289,628	24,165,118	24,289,628	24,165,118	2,782,034	2,766,048	2,782,034	2,766,048	5,885,403	5,855,197	5,885,403	5,855,197

Table A.2: Fund-level portfolio rebalancing: FIT-adjusted trading in dollars

Note: This table reports how mutual funds rebalance their portfolios based on stock characteristics. The dependent variable, $\Delta Dollars_{i,j,q+1}/ME_{i,q}$, is FIT-adjusted trading in dollars in quarter $q+1$ normalized by market capitalization as of quarter q. The independent variables are stock i's characteristics in quarter q, including the book-to-market ratio (demeaned cross-sectionally), $BM_{i,q}$; past one-year return (skipping the most recent month), $r_{i,q-4,q-1/3}$; market beta, $\beta_{i,q}$; and market capitalization (in billions), $ME_{i,q}$. Panels A and B report results for value and momentum, respectively. Columns (1) to (4) use the full sample. Columns (5) to (8) use funds low in $\beta_{j,HML}$ (Panel A) or $\beta_{j,MOM}$ (Panel B), where low means being in the lowest 20th percentile of the distribution. Columns (9) to (12) use funds high in $\beta_{j,HML}$ (Panel A) or $\beta_{j,MOM}$ (Panel B), where high means being in the highest 20th percentile of the distribution. The data sample is from 1980Q1 to 2018Q4. Standard errors are clustered at quarter and fund levels.

Panel A: 3×3 portfolio results for value

VW portfolio returns (annualized, %)

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

EW portfolio returns (annualized, %)

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

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

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

Number of stocks

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

Panel B: 3×3 portfolio results for momentum

VW portfolio returns (annualized, %)

		Low-$\overline{\beta}^{MOM}$	←*Fund*→	High-$\overline{\beta}^{MOM}$	
		1	2	3	3−1
Low-RET	1	9.20	11.18	11.00	
Stock↕	2	10.54	12.05	14.53	
High-RET	3	10.52	12.18	17.33	
WML		1.32	0.99	6.33	5.01
t-stats		[0.60]	[0.43]	[2.46]	[2.28]

EW portfolio returns (annualized, %)

		Low-$\overline{\beta}^{MOM}$	←*Fund*→	High-$\overline{\beta}^{MOM}$	
		1	2	3	3−1
Low-RET	1	9.81	9.92	11.31	
Stock↕	2	12.93	14.46	16.38	
High-RET	3	13.21	14.72	20.55	
WML		3.40	4.80	9.24	5.85
t-stats		[1.71]	[2.37]	[3.95]	[3.92]

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

		Low-$\overline{\beta}^{MOM}$	←*Fund*→	High-$\overline{\beta}^{MOM}$	
		1	2	3	3−1
Low-RET	1	-2.84	2.00	3.04	
Stock↕	2	1.36	4.17	7.29	
High-RET	3	1.71	4.45	9.82	
WML		4.55	2.45	6.78	2.23
t-stats		[7.79]	[4.26]	[9.28]	[3.16]

Number of stocks

		Low-$\overline{\beta}^{MOM}$	←*Fund*→	High-$\overline{\beta}^{MOM}$
		1	2	3
Low-RET	1	341	275	207
Stock↕	2	305	301	219
High-RET	3	201	263	358

Table A.3: Returns and characteristics for 3×3 stock portfolios double-sorted on stock characteristics and fund betas

Note: Panel A reports the return and average number of stocks for each of the 9 portfolios double-sorted on B/M ratios and HML betas, $\overline{\beta}^{HML}$, where $\overline{\beta}^{HML}$ is calculated as the shares-weighted average β^{HML} of the underlying funds. Panel B reports the return and average number of stocks for each of the 25 portfolios double-sorted on past one-year returns (skipping the most recent month) and MOM betas, $\overline{\beta}^{MOM}$, where $\overline{\beta}^{MOM}$ is calculated as the shares-weighted average β^{MOM} of the underlying funds. Quarterly portfolios are from 1980Q2 to 2018Q4.

	Dependent variable: $r_{i,q+1}$							
Panel A: Momentum pre-1999								
	Full sample		Low-$\bar{\beta}_{i,q}^{MOM}$		High-$\bar{\beta}_{i,q}^{MOM}$		Medium-$\bar{\beta}_{i,q}^{MOM}$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$r_{i,q-4,q-1/3}$	0.0128	0.0115***	-0.0047	-0.0037	0.0218***	0.0190***	0.0033	0.0023
	(0.0148)	(0.0018)	(0.0042)	(0.0044)	(0.0031)	(0.0032)	(0.0022)	(0.0021)
$BM_{i,q}$		0.0006*		0.0003		0.0016**		0.0008
		(0.0003)		(0.0004)		(0.0007)		(0.0006)
$ME_{i,q}$		0.1144**		-0.2304		0.2580		0.2134***
		(0.0531)		(0.2314)		(0.1854)		(0.0590)
$\beta_{i,q}$		0.0088***		-0.0012		0.0191***		0.0010
		(0.0012)		(0.0027)		(0.0029)		(0.0017)
R^2	0.0010	0.0014	0.0000	0.0000	0.0041	0.0058	0.0000	0.0000
Observations	174,225	168,650	36,231	35,045	31,638	30,309	106,356	103,296
Panel B: Momentum post-1999								
	Full sample		Low-$\bar{\beta}_{i,q}^{MOM}$		High-$\bar{\beta}_{i,q}^{MOM}$		Medium-$\bar{\beta}_{i,q}^{MOM}$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$r_{i,q-4,q-1/3}$	-0.0058	-0.0046***	-0.0051*	-0.0041	-0.0052***	-0.0040**	-0.0083***	-0.0061***
	(0.0068)	(0.0012)	(0.0027)	(0.0027)	(0.0018)	(0.0018)	(0.0015)	(0.0015)
$BM_{i,q}$		0.0066**		0.0037		0.0184***		0.0136***
		(0.0026)		(0.0025)		(0.0051)		(0.0021)
$ME_{i,q}$		-0.1101***		-0.0005		-0.2218***		-0.0971***
		(0.0119)		(0.0315)		(0.0510)		(0.0118)
$\beta_{i,q}$		-0.0156***		-0.0149***		-0.0163***		-0.0161***
		(0.0012)		(0.0024)		(0.0030)		(0.0014)
R^2	0.0000	0.0024	0.0000	0.0020	0.0000	0.0028	0.0000	0.0035
Observations	208,748	206,660	42,454	41,853	39,195	38,733	127,099	126,074

Table A.4: Stock-level cross-sectional regressions: momentum subsamples

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

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

where the dependent variable is stock i's return in quarter $q+1$. The independent variables include past one-year return (skipping the most recent month), $r_{i,q-4,q-\frac{1}{3}}$; the book-to-market ratio, $BM_{i,q}$; market beta, $\beta_{i,q}$; and market capitalization (in billions), $ME_{i,q}$. Panels A and B use observations before and after 1999. In each panel, the regressions are estimated using the full sample (Columns 1 and 2), the subsample of stocks with $\bar{\beta}_{i,q}^{MOM}$ in the bottom quintile (Columns 3 and 4), the subsample of stocks with $\bar{\beta}_{i,q}^{MOM}$ in the top quintile (Columns 5 and 6), and the subsample of other stocks (columns 7 and 8). Standard errors are clustered by year-quarter.