On the Anomaly Tilts of Factor Funds

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ABSTRACT

By analyzing portfolio holdings, we find that a significant subset of Hedged Mutual Funds (HMFs) and smart-beta Exchange-Traded Funds (ETFs) tilt their portfolios towards well-known anomaly characteristics and that such tilts are highly persistent. Short positions of HMFs are important for amplifying their factor tilts. Moreover, HMFs with large factor tilts outperform corresponding ETFs, or HMFs with contrary tilts, both before and after accounting for implementation costs and fees. We link this outperformance to the use of short positions and higher factor-related returns. Finally, we show that only HMFs achieve similar performance (net of costs) as the academic factors.

JEL Classification: G10, G11, G14, G23

Keywords: Hedged Mutual Funds, Exchange-Traded Funds, Factor Tilts, Anomalies, Short Selling, Performance.

1 Introduction

> A hedge fund manager said: *"Exotic beta is my alpha. I understand those systematic factors and know how to trade them. My clients don't." He has a point. How many investors… have the ability to program computers to execute such strategies …To an investor who has not heard of it and holds the market index, a new factor is alpha.*
> *Cochrane (2011; p. 1087)*

The core idea behind fund performance evaluation is to compare the return of a managed portfolio against the return of an investable benchmark, such as the market index (e.g., Jensen (1968)). Given the evidence of the failure of the CAPM to explain the cross section of returns, researchers often use the alpha from a multi-factor model to measure fund performance (e.g., Carhart (1997)). However, if investors cannot reproduce the same factor (or anomaly) exposure themselves, especially given the importance of real-world implementation costs[1], then we should attribute that exposure to the value-added activity that the fund provides its investors (Berk and van Binsbergen (2015)). Despite the widely recognized importance of factors in asset pricing, there is surprisingly little evidence to indicate that institutional investors make successful factor bets (Lewellen (2011), Edelen, Ince, and Kadlec (2016), Patton and Weller (2020), and Lettau, Ludvigson, and Manoel (2021)), with the notable exception of hedge funds on the long side (Calluzzo, Moneta, and Topaloglu (2019) and Cui, Kolokolova, and Wang (2023)). Institutional investment constraints—such as position limits or restrictions on tracking error, turnover, and allowed instruments—may play a part in explaining the inability of institutions to exploit anomalies (e.g., Cao, Han and Wang (2017)). In this study, we assess whether the least constrained open-end funds that are ex-ante likely to follow factor strategies tilt their portfolios sufficiently towards factors, and what the performance implications of such tilts are (both before and after implementation costs).

[1] E.g., Lesmond, Schill, and Zhou (2004), Novy-Marx and Velikov (2016), Frazzini, Israel and Moskowitz (2018), Briere, Lehalle, Nefedova and Raboun (2019), Chen and Velikov (2022), and Muravyev, Pearson, and Pollet (2023).

During the past decade, factor investing has experienced rapid growth, reaching an estimated $1.9 trillion in assets under management (AUM) in 2017 (Wigglesworth (2018)). Of the $25.4 trillion of institutional assets surveyed by Invesco (2022), 64% of respondents claim to invest more than 10% of their equity allocations to factor strategies. Many asset managers (e.g., AQR, Dimensional, Invesco, and Robeco) have embraced factor investing. Although some of these products are only available via hedge funds and separate accounts, investors can also access factor strategies via so-called Hedged Mutual Funds (HMFs) and smart-beta Exchange-Traded Funds (ETFs). Like hedge funds, HMFs are an especially good candidate for factor investing given their flexible investment mandates that permit them to use leverage and to short sell.[2]

Using a sample of 278 HMFs and 289 smart-beta ETFs over the 2010-2021 time period, we assess whether they tilt their portfolios towards the most prominent factors.[3] Furthermore, we examine the performance implications of such tilts, by comparing HMFs against smart-beta ETFs. We contrast the two fund types, because index funds/ETFs represent a more passive and significantly cheaper way to invest in factors and are widely used for benchmarking mutual fund performance both by academics (e.g., Huij and Verbeek (2009), Berk and van Binsbergen (2015), Chakraborty, Kumar, Muhlhofer and Sastry (2020)) and by investors (e.g., Sensoy (2009), Evans and Sun (2021)).

We focus on four factors that are widely used both by academics and practitioners, namely value, momentum, (conservative) asset growth, and profitability. We follow Daniel, Grinblatt, Titman, and Wermers (1997), among others, and compute characteristic (decile) scores for each

[2] The use of leverage by mutual funds is governed by Section 18(f)(1) of the Investment Company Act of the 1940 and the Federal Reserve Board's Reg-T initial margin requirements. See Appendix 2 for additional details.
[3] Our ETFs sample consists of 102 ETFs in traditional styles (e.g., standard value and growth), as well as a newer generation of 98 single-factor ETFs (e.g., momentum, and quality) and 116 active/multi-factor ETFs.

stock. Factor tilts are then constructed as the portfolio-weighted average characteristic score of the stocks held by the fund in excess of the corresponding value-weighted score of the market portfolio.[4] This method is robust to outliers, easy to interpret and is closely related to how factor strategies are typically implemented.

In our first set of results, we show that HMFs and ETFs as a group tilt significantly toward the four factors. The total factor tilt—the sum of value, momentum, (conservative) asset growth, and profitability tilts—is approximately one decile above the market portfolio and highly significant. We emphasize total rather than individual factor tilts, because most funds in our sample (whether HMFs or ETFs) target multiple factors.[5] The total factor tilt is appropriate for classifying factor funds as long as the individual tilts are not positively correlated, which they are not.[6]

To examine cross-sectional differences in factor tilts, we divide funds into four groups: large factor tilt (equivalent to academic factor benchmarks, or greater), moderate (at least halfway towards the factor benchmark), marginal, and contrary. The proportion of funds with large (large + moderate) factor tilts is substantial, at about 20% (34%) for HMFs, 17% (43%) for active/multi-factor ETFs and 7% (29%) for single-factor ETFs. By contrast, funds that bet at least moderately against factors are 9-13% of the overall sample. Importantly, these classifications are highly persistent over time. Conditional on having a large total factor tilt (≥2.0 deciles) in the current quarter, HMFs (active/multi-factor ETFs) [single-factor ETFs] have a total factor tilt that is as

[4] For HMFs, the total factor tilt is a weighted average of the long- and short-side factor tilts, with weights given by the percentage of AUM invested. For example, a 130/30 fund with a +1.0 decile value tilt (in excess of the market) on the long side, and a -1.0 decile tilt on the short side, would have a total value tilt of $1.3\times1-0.3\times(-1) = 1.6$.
[5] Among factor-based funds, as many as 80% of HMFs, 65% of active/multi-factor ETFs and, surprisingly, about 52% of single-factor labelled ETFs (based on stated investment objectives) target multiple factors. Labels are therefore misleading about the factors that an ETF is actually exposed to.
[6] Single-factor academic benchmarks (e.g., top tercile on momentum, value weighted) typically have zero or even *negative* tilts towards the other (three) factors. For a broader set of anomalies (e.g., Stambaugh, Yu, and Yuan (2012)), the correlations are in some cases highly positive (e.g., gross profitability and ROA).

much as 3.6 (2.6) [2.4] deciles above the market in the next quarter. There is very little decay in the persistence for horizons up to at least a year, despite the high turnover of our sample of funds (e.g., 235% for HMFs on average, or 97% for multi-factor ETFs).

Moreover, we find substantially greater factor tilts for the average HMF on the short side (twice as large), compared to the long side. We separately confirm that HMFs also tilt towards smaller-cap stocks, especially on the short side. Since asset pricing anomalies are generally more profitable for small-cap stocks (e.g., Hou, Xue, and Zhang (2020)) and on the short side (e.g., Stambaugh, Yu, and Yuan (2012)), these results suggest an important role played by HMFs in providing exposure to the short-leg premium for retail investors who might otherwise only have access to long-only strategies via ETFs and traditional mutual funds. This is especially important since long-only funds have been shown to be unable to achieve the on-paper performance of the academic factors (Patton and Weller (2020) and Johansson, Sabbatucci, and Tamoni (2022)).

Despite the strong evidence of economically meaningful factor tilts by both HMFs and ETFs, the results so far do not reveal the performance implications of such tilts. To answer this question, we analyze cross-sectional differences in performance between HMFs and ETFs with the same factor classification, or by the degree of the factor tilt within the same fund type. Each fund structure has its pros and cons. On the one hand, ETFs provide cheap factor exposure in a transparent wrapper, and there are no concerns with flow-induced trading (e.g., Khan, Kogan, and Serafeim (2012), Lou (2012)). On the other hand, HMFs are more flexible in pursuing factor strategies relative to passive ETFs, which are constrained to mechanically follow a pre-determined index and to disclose holdings daily. Thus, a relevant question is whether HMFs' increased flexibility and ability to short-sell lead to a performance edge over ETFs.

Depending on the factor tilt classification, we find significant differences in holdings-based performance of HMF's complete long-short portfolios vis-à-vis ETFs. Factor-based HMFs (with large or moderate factor tilts) outperform corresponding ETFs by 1.95 to 2.43% per year when measured using CAPM alphas. This outperformance can be driven by successful execution of factor strategies (especially with the use of short positions), by factor timing (e.g., Ehsani and Linnainmaa (2022)), and/or by security selection. To identify the contribution of short positions, we remove them from the holdings-based returns and find that the CAPM alphas drop by more than half, even though the size of short positions is only half of that for long positions. Short positions are therefore disproportionately important in explaining the outperformance of factor-based HMFs. To better isolate stock picking ability, we consider Fama-French 6-factor alphas (Fama and French (2018)) and DGTW characteristic-adjusted returns. In both cases the performance difference is insignificant.[7] Said differently, the large gap between CAPM and multi-factor alphas captures the value added of successful factor bets. By contrast, differences in DGTW factor timing performance are economically small and at best marginally significant. Overall, these results suggest that the holdings-based outperformance of factor-based HMFs, relative to their ETF counterparts, stems primarily from HMFs' short positions and general ability to exploit factors.

While several recent studies question whether factor strategies can survive realistic implementation costs, the outperformance of factor-based HMFs remains largely unchanged when we switch from holdings-based returns (before implementation costs) to actual (gross) returns (after implementation costs). We also confirm that HMFs do not, on average, use derivatives to

[7] If we instead compare factor-based HMFs against HMFs that bet against factor (contrary tilt), we find a performance difference of up to 3.86% per year for CAPM alpha, which falls by almost two thirds for the FF6 alpha but remains statistically significant. Any leftover multi-factor alpha may also capture the returns from anomaly-based trading strategies left unexplained by the factor model that we consider. Indeed, we find that factor-based (contrary) HMFs tilt significantly towards (against) the broader set of anomalies considered by Stambaugh et al. (2012).

alter the factor tilt profile. Dropping options-based funds altogether does not change our conclusions either. Although we focus on gross alphas because they are more informative about fund manager skill relative to net alphas (Berk and Green (2004)), we nevertheless find similar results using net returns. Our results also raise concerns about the ability of smart-beta ETFs to exploit factors. Whereas factor-based HMFs outperform contrary tilt HMF by up to 4.83% per year net of all costs and fees when measured by CAPM alpha, ETFs with large factor tilts tend to underperform contrary tilt ETFs, especially when using FF6 alphas. We also obtain similar results when benchmarking HMFs to similar ETFs in the factor space (in the spirit of Hoberg, Kumar, and Prabhala (2018)). Finally, we show that HMFs (but not ETFs) are able to achieve comparable performance as the academic factors per unit of characteristic exposure following the method by Patton and Weller (2020). Taken together, these results demonstrate the superior (market-adjusted) performance of HMFs that bet strongly on factors relative to those making contrary bets, and against factor-based ETFs, whether measured before or after implementation costs.

At a broader level, our results speak to the importance of focusing on a subset of institutions that are more likely to trade on factor strategies rather than on the aggregate portfolio of institutions. Edelen et al. (2016) actually report that institutions in aggregate trade contrary to anomalies in the period prior to the realization of anomaly returns. Cao et al. (2017) argue that investment constraints prevent institutions from fully exploiting anomalies like momentum. However, there is evidence that institutions trade in the right direction if one focuses on sophisticated investors, such as hedge funds (Cui et al. (2023)), and on the period after publication (Calluzzo et al. (2019)). Our results are complementary. We provide more direct fund-level tests that account for both leveraged long and short positions of HMFs. We also show that a subset of mutual funds can execute factor bets successfully, which contrasts with the traditional view that only hedge funds can do it.

Lettau et al. (2021) argue that virtually no mutual funds or ETFs have factor tilts that are comparable to those of the academic factors. Our differing results are primarily explained by different perspectives. First, in the case of HMFs, we account for both leveraged long and short positions, both of which amplify factor exposures. Equity HMF's observed leverage is comparable to that of equity hedge funds (Ang, Gorovyy, and van Inwegen (2011)). Second, Lettau et al. (2021) evaluate factor tilts relative to the specific Fama-French single-factor benchmark that corresponds with the fund's stated objective. By contrast, we follow Lewellen (2011) and use the market portfolio as the benchmark together with a holdings-based approach to classify factor funds. Our results suggest that most factor-based HMFs and ETFs actually target multiple factors and consequently have balanced tilts towards several factors, as opposed to having a large tilt on a single factor. Importantly, we also demonstrate the superior performance of large (multi-factor) tilts among HMFs, but not ETFs, which we attribute to their use of short position and ability to exploit factors.

Earlier studies on HMFs focus primarily on fund performance and stock return predictability. Agarwal, Boyson, and Naik (2009) find that while HMFs underperform hedge funds, they outperform traditional mutual funds. Huang and Wang (2013) find that, although HMFs do not generate alpha, they provide valuable hedging features during the 2008 financial crisis. Gao and Wang (2023) show that HMFs' aggregate short-side trades predict future stock returns, especially among securities with high dynamic short-selling risk and credit risk. Our study focuses instead on the level and persistence of factor tilts at the individual fund level, and what the performance implications of HMF's factor tilts are, relative to cheaper ETFs.

The literature on smart-beta ETFs is more recent and offers some criticisms. Huang, Song, and Xian (2023) show that the post-launch performance of smart-beta ETFs is significantly worse than the back-tested performance of smart-beta indices. Brown, Cederburg, and Towner (2021) identify a large number of dominated smart-beta ETFs with returns that are highly correlated with those of cheaper, more liquid competitors. We contribute to this literature by showing that the majority of factor-based ETFs actually target multiple factors (often in contrast to their stated objectives). Our results also raise concerns about the performance implications of their factor bets.

Finally, we contribute to the debate on the implementability of factor strategies by institutional investors. This debate has gained prominence after McLean and Pontiff (2016) documented a substantial alpha decay in anomalies post publication. While Patton and Weller (2020) show that traditional mutual funds are unable to achieve the on-paper performance of the value and momentum factors, Frazzini et al. (2018) find the opposite results when using a proprietary dataset from a single institutional asset manager (AQR). Our results for HMFs generalize the finding that long-short funds are able to successfully harvest the factor returns net of all costs. Johansson et al. (2022) create portfolios of traditional mutual funds and ETFs with large exposures to a given factor, and show that these portfolios have negative alphas relative to the corresponding academic factor. By contrast, we show that HMFs (but not ETFs) are able to achieve similar characteristic risk premia as the academic factors when using the method by Patton and Weller (2020), which is more appropriate in our setting given the prominence of multi-factor funds.[8]

[8] The tradeable factors in Johansson et al. (2022) are unlikely to include HMFs for two reasons. First, most factor-based HMFs have a multi-factor focus and are therefore unlikely to be among the top-ten funds ranked on individual tilts. Second, they exclude all funds with less than $1bn in AUM, which removes more than 92% of large tilt HMFs.

2 Data and Sample Selection

Our sample consists of U.S.-based Hedged Mutual Funds and smart-beta ETFs over the 2010-2021 time period. We identify these funds using Morningstar Direct, which contains both live and dead funds and is free of survivorship bias (e.g., Betermier, Schumacher, and Shahrad (2023)). Additional details on the sample selection are provided in Sections 2.1 and 2.2.

We collect data on fund returns, expense ratios, and assets under management (AUM) from the CRSP U.S. Mutual Fund database (henceforth CRSP MFDB). Following the procedures in Berk and van Binsbergen (2015) and Pastor, Stambaugh, and Taylor (2015), we reconcile differences in monthly returns and AUM between CRSP MFDB and Morningstar Direct (see also the Internet Appendix, Sections IA-1 and IA-2). Similar to Kacperczyk, Nieuwerburgh, and Veldkamp (2014), among others, we address the potential bias resulting from a mutual fund's incubation period by removing observations prior to its inception date, and we only include a fund in our final sample once it passes \$15 million in AUM. We apply the same \$15 million threshold to ETFs for consistency.

Portfolio holdings are collected from Morningstar Direct because it provides reliable and complete holdings on a quarterly basis (or higher).[9] In contrast to many other databases, such as Thomson Reuters, Morningstar Direct includes both U.S. and international equites, as well as non-equity positions (e.g., cash/cash equivalents, fixed-income securities, derivatives, and preferred

[9] For the ETF sample, we also compared the holdings data between Morningstar, CRSP MFDB and ETF Global (ETFG). Morningstar generally has the best coverage and most accurate holdings data. In contrast, ETF holdings are often missing in CRSP before 2012 and/or the holdings data is inaccurate. Specifically, about 5% of CRSP observations (sum(MV of holdings)/AUM) deviate more than 10%, while only 0.5% of Morningstar observations deviate more than 10%. After 02/2012 the data quality in CRSP MFDB is much better, although the proportion of outliers is still twice as high as Morningstar. We found numerous issues with ETFG, including poor coverage of position market values (only portfolio weights exist), and a substantial fraction of outliers in sum(MV of holdings)/AUM in end-of-month observations. There are visible improvements in ETFG starting only in 2017.

stock). Although we only include U.S. equity funds in our sample, some HMFs invest small amounts in non-U.S. securities as well. For completeness, we include both U.S. and international equity holdings. We obtain the data on underlying stock returns and characteristics from CRSP (U.S. firms), Compustat/North America (Canadian firms), and Compustat/Global (non-U.S. firms). (See Broman, Densmore, and Shum (2023) for additional details). Funds are required to have a minimum of two years of holdings data (e.g., as in Jiang, Yao, and Yu (2007)).

2.1 Sample Selection: HMFs

We use a combination of static and dynamic screens to identify U.S. equity-focused HMFs. For the static screens, we rely on the Morningstar Category variable to identify HMFs. Morningstar classifies mutual funds under the "alternative strategies" category based on their use of leverage, short positions, asset classes and/or derivatives. As described by Morningstar, this classification is based both on quantitative inputs (fund holdings) and a qualitative assessment (e.g., self-reported information). We then select the following sub-categories: a) long-short equity, b) equity market neutral, c) event driven, d) derivative income, f) options trading, and g) multi strategy.[10] Funds in a) through c) include funds that invest in equity markets and typically use both long and short positions extensively. Multi strategy and option-based funds [d) and f)] may also invest in fixed income (in the former case), or in derivatives (in both cases), while maintaining a substantial equity allocation. Our initial selection keeps funds in any of these categories, but we filter out non-equity funds and heavy derivative users based on several dynamic screens (discussed next). We further

[10] Funds that change strategy from standard long-only equity to alternative strategy during the sample period are deleted from the sample prior to the switch. Switches are identified by looking for changes in the historical Morningstar Category, or the Lipper Objective Name from CRSP MFDB. Any strategy changes are further confirmed by cross-checking with historical prospectuses.

exclude funds-of-funds that invest in other mutual funds as well as funds that provide leveraged/inverse exposure to an index (such as the S&P 500).

Following Ang et al. (2011), who study hedge funds' use of leverage, we define gross equity leverage as the total dollar amount invested in equity positions (long plus short) divided by AUM. The existing literature (e.g., Jordan and Riley (2015)) generally defines equity funds as having a minimum gross equity leverage of 70 to 80% on average, although some studies use a lower threshold of 50%, typically implemented period-by-period (e.g., Chen, Goldstein, and Jiang (2010) and Choi, Kahraman, and Mukherjee (2016)). We use a 50% threshold to account for the increased flexibility of HMF strategies. To account for a total gross leverage in excess of 100%, we also require that the proportion of risky assets invested in equities (gross equity leverage / total gross leverage) is at least 50%.[11] Both thresholds are applied as of *t*-1, and on average over *t*-1 to *t*-12.

In line with the existing literature (e.g., Kacperczyk et al. (2014)), we also require that all funds (HMFs and ETFs) hold at least 15 common stocks at *t*-1. When we separately analyze a fund's long or short positions, we require a minimum of 43 (7.5) percent gross equity leverage and 10 (7) common stocks on the long (short) side. Finally, to identify U.S. equity funds we only include funds that invest at least 70% of their equity portfolio in U.S. securities on average in the prior year (the average is 95%).

2.2 Sample Selection: ETFs

Morningstar is a leading fund information provider that is widely used by investors for benchmarking purposes (e.g., Ben-David, Li, Rossi, and Song (2022a)). Morningstar also has a

[11] This filter removes funds that primarily use non-equities or derivatives. Derivatives are excluded from our leverage calculations due to inconsistent reporting of their magnitude (market vs. nominal values) in Morningstar.

long track record in classifying smart-beta ETFs (Johnson (2014)), which is important because the factor vocabulary used in the academic literature does not always match with that used by practitioners. Following Ben-David, Franzoni, Kim, and Moussawi (2023), we use Morningstar's Strategic Beta category variable to identify an initial set of smart-beta ETFs. In Section 3.3, we use a holdings-based approach to obtain a more accurate factor-based classification.

Our focus is on the sample of U.S. equity ETFs that are physically replicated (i.e., no leveraged, inverse, or other derivative-based products) and belong to one of the following Strategic Beta categories: momentum, quality, value, fundamentals-weighted, dividend screened/weighted, growth, risk-oriented, and multi-factor. In contrast to the prior literature, we also include actively managed ETFs since many of them are directly named after factor strategies (e.g., WisdomTree US Quality Shareholder yield ETF).

To better align the Strategic Beta categories with the factors considered in this study, we make the following changes. First, we create a separate category for factor-based value by manually going through the strategy descriptions of all value ETFs. The reason is that standard value indices from major index provides (e.g., MSCI, S&P, Russell, or CRSP) rank stocks not just on value, but also on earnings growth. By contrast, the academic recipe for harvesting the value premium is based only on value characteristics. ETFs following such strategies are generally named "Value Factor" or "Pure Value" (e.g., iShares MSCI USA Value Factor ETF). Second, we reclassify funds targeting high dividend growth rates as Quality, since they have very similar factor tilts as other quality ETFs. Third, we re-label "risk oriented" as "low risk" and remove a few high beta/high risk funds, as well as funds that tactically switch between equities and treasuries/cash.

2.3 Descriptive Statistics

Summary statistics on the number of funds, fund size (AUM), expense ratios, turnover, and gross equity and fixed income leverage (i.e., the total market value of non-cash fixed income positions divided by AUM) are provided in Table 1, separately for HMFs (in Panel A) and ETFs (in Panel B). In total, there are 278 HMFs and 289 smart-beta ETFs. The category with the most HMFs is long-short equity (135), followed by options-based (50), multi strategy (45), market neutral (29), and event driven (19). As for ETFs, the largest categories are multi-factor (65) and actively managed (51). Funds in traditional style categories are also numerous (e.g., 42 in dividend-yielding). The newer generation of single-factor ETFs includes quality (22), fundamentally weighted (16), low risk (15), momentum (13), and factor value (9).

Long-only mutual funds have a gross equity leverage that is, by definition, less than 100% (the average is 97%, with the remaining 3% in cash, see e.g., Simutin (2014)). By contrast, gross equity leverage often exceeds 100% for HMFs. Market neutral funds, for instance, allocate on average 86% of their capital to long equity positions and 71% to short equity positions. While multi-strategy funds have the lowest gross equity leverage on average, it is still meaningful at 60% and 21% on the long- and short-side respectively. Funds in most categories hold negligible amounts (< 5%) in fixed income securities, except for multi-strategy funds (21%). Options-based funds hold large equity positions on the long-side (90% on average), but short positions are negligible (< 1%). In contrast to long-only mutual funds, ETFs in every Strategic Beta category have a higher gross equity leverage of 99-100% on average. ETFs therefore have a lower cash drag than traditional mutual funds, which have to keep cash on hand for flow management, unlike ETFs where share creations/redemptions take place in-kind.

[Table 1]

Some interesting patterns are also observed for fund size and expense ratios. In particular, average fund size is substantially larger for ETFs in traditional style categories, around \$3 to 6 billion, compared to newer single-factor categories (e.g., factor-value and momentum) that are between \$0.8 and \$3.5 billion. Multi-factor and actively managed ETFs, many of which have a multi-factor tilt as we will see later, are typically smaller at \$371 and \$868 million in AUM on average, respectively. These numbers are not all that different for HMFs, where the average size is \$609 million. Expense ratios, on the other hand, are less than a third for ETFs (generally < 0.5%) compared to HMFs (1.1-1.8% on average), indicating a distinct cost advantage for the former. These patterns are consistent with the Easley, Michayluk, O'Hara, and Putniņš (2021) equilibrium, where more "active" funds are greater in number but not in size, and they charge higher fees.

3 Factor Tilts

We construct factor tilts at the fund level based on the following stock characteristics that are robustly associated with risk premia: i) value, based on the industry-adjusted Book-to-Market ratio (e.g., Daniel et al. (1997))[12]; ii) momentum, based on *t*-2 to *t*-12 past returns (e.g., Carhart (1997)); iii) (conservative) asset growth, based on total asset growth (e.g., Cooper, Gulen, and Schill (2008) and Fama and French (2008)); and iv) operating profitability (e.g., Fama and French (2015)).

We follow Daniel et al. (1997), among others, and sort all stocks at the end of June (time *t*) based on characteristic *C* using NYSE breakpoints. For accounting-based characteristics (e.g., B/M), we use data from the prior December (*t*-6). The characteristic is assumed to be constant for

[12] Prior studies have shown that the return predictability of the value factor is primarily driven by the within-industry component (e.g., Asness, Porter, and Stevens (2000), Cohen, Polk, and Vuolteenaho (2003), and Golubov and Konstantinidi (2019)). The specific industry-adjustment that we use is based on Wermers (2003). Our results are also robust to using alternative definitions of value, such as the intangibles-adjusted B/M (Eisfeldt et al. (2022)), or a composite value index (based on B/M, E/P, S/P and CF/P) that is often used by major index providers.

each stock until the following June ($t+1$ to $t+12$). The only exception is momentum, which is recomputed monthly (e.g., as in Stambaugh et al. (2012)). Each stock j is assigned a characteristic score of $C_{j,t} = d, d \in \{1,2,3 \ldots 10\}$. These scores are then aggregated to the fund-level by taking the portfolio-weighted average of the stocks held by the fund:

$$C_{i,t} = \sum_{j=1}^{J} w_{i,j,t} C_{j,t} \tag{1}$$

where $w_{i,j,t}$ is the weight of stock j in the portfolio of fund i at time t. Using decile scores instead of continuous values has several advantages. First, it is robust to extreme values of characteristics. Second, characteristic scores have the same unit and are therefore comparable across characteristics. Third, decile scores are closely related to how factor strategies are typically implemented.

As a benchmark for the fund-level characteristic scores, we use the market portfolio. We also consider academic factor benchmarks in a later section to ensure robustness. The market portfolio is an important benchmark, because Lewellen (2011) shows that the aggregate institutional investor portfolio closely mimics the market portfolio with no meaningful tilts towards anomalies. We create fund-level factor tilts by subtracting from the fund-level characteristic score the corresponding value-weighted characteristic score of the market portfolio: $C_{i,t} - C_{M,t}$. Positive factor tilts are expected to generate outperformance relative to the market on average. As a proxy for the market portfolio representing the investment universe of HMFs and ETFs, we use iShares Russell 3000 ETF (ticker: IWV) for large/mid-cap funds and iShares Russell 2000 ETF (ticker: IWM) for small-cap funds.[13] An added benefit of doing so is that the benchmark stocks are tradeable and there are relatively few low-priced or nano-cap stocks, which mutual funds have been shown to shun because of regulatory and fiduciary constraints (e.g., Falkenstein (1996) and Del Guercio (1996)).

For HMFs we compute the characteristic scores (Eq. (1)) separately for the fund's long and short positions, with weights summing to 100% on each side. We then compute the complete long-short portfolio factor tilt at time *t* by weighting the long and short-side factor tilts by the percentage of AUM invested in long $\left(w_{i,t}^{L}\right)$ or short $\left(w_{i,t}^{S}\right)$ positions:

$$C_{i,t}^{L-S} = w_{i,t}^{L}\left(C_{i,t}^{L} - C_{M,t}\right) + w_{i,t}^{S}\left(C_{i,t}^{S} - C_{M,t}\right) \quad (2)$$

In the case of a 130/30 fund, for example, the long side receives 130% weight and the short side receives -30% weight. A positive value tilt can then arise if the long positions in the fund's portfolio have a greater value score compared to the market portfolio, and vice versa for the short positions. Moreover, factor tilts are amplified by leverage as indicated by the 130% weight in the previous example. To the best of our knowledge, we are the first to evaluate the HMFs' total factor tilts while accounting for both leveraged long and short positions.

3.1 Unconditional Factor Tilts Relative to the Market Portfolio

Table 2 summarizes the unconditional fund-quarter average factor tilts separately for HMFs in Panel A, and smart beta ETFs in Panels B and C. We cluster standard errors by funds since the factor tilts are expected to be highly persistent for a given fund over time.[14] In contrast to Edelen

[13] For ETFs we use the Morningstar 3×3 size-valuation box to determine whether a fund has a small-cap orientation. For HMFs we instead use the average of the long- and short-side size characteristic score over the prior two years. Small-cap ETFs have a decile score below six for 97.5% of observations. We use the same cut-off for HMFs. Alternatively, we get similar results when using Vanguard's Total Stock market ETF (> 4,000 stocks).
[14] We obtain nearly identical results when clustering instead by fund and time.

et al. (2016) who find that institutions on average trade *against* anomalies, our results suggest that HMFs tilt significantly towards value (by 0.37 deciles), momentum (0.18 deciles), and conservative asset growth (0.27 deciles). The individual tilts may at first glance appear economically small, but this is partly expected since the average fund targets multiple factors (more in Section 3.3). The total factor tilt is in this case more informative, and it is about 0.86 deciles away from the market portfolio on average when using all four factors. As we will show later, a one decile total factor tilt is roughly halfway towards academic factor benchmarks. Importantly, these averages hide a substantial degree of cross-sectional variation with a meaningful subset of funds betting as strongly as the academic factors do, which we explore in Section 3.2. Our initial results are therefore more consistent with Calluzzo et al. (2019), who show that hedge funds trade on anomalies, as identified by changes in 13-F (long-side) portfolio holdings.

[Table 2]

The factor tilts of multi-factor and fundamentally-weighted ETFs are very similar to those of HMFs with meaningful tilts on multiple factors (around 0.85 and 1.12 deciles in total, respectively, above the market, see Panel B). Among the single-factor labelled ETFs, we see especially large value tilts among factor value ETFs (+2.07 deciles), and momentum tilts for momentum ETFs (+1.40 deciles). Although quality ETFs also load meaningfully on the profitability factor (+0.93 deciles), these funds typically target other stock characteristics as well, such as low leverage or low earnings volatility. As a result, we also see meaningful asset growth tilts for these ETFs (+0.56 deciles).[15] Among the older-generation of value-oriented funds

[15] We do not focus on the low-risk anomaly here, because it is correlated with the profitability and asset growth anomalies (Novy-Marx and Velikov (2021)). We do report the results for low-vol tilts of HMFs and ETFs in the Internet Appendix, Table IA-1. Low risk ETFs tilt significantly towards the low-vol characteristic, but HMFs do not. Low risk ETFs are included in all remaining tests, though the results are not sensitive to excluding them.

(standard value, dividend-yielding and growth), we see at most moderate value tilts (e.g., +0.93 deciles for standard value), combined with offsetting tilts (momentum and/or profitability) that result in a small total factor tilt.

3.2 Persistence and the Cross-Section of Factor Tilts

The previous results suggest that a significant factor exposure is available to investors in these funds. However, can investors identify factor-based funds ex-ante?[16] It is not at all obvious in light of the high reported turnover (see Table 1) of not only HMFs (235% per year), but also actively managed ETFs (156%) and multi-factor ETFs (97%). As a simple yet revealing test, we divide funds into four groups based on their total factor tilts (*VAL+MOM+CAG+PROF*) at *q*-1 (or *q*-4). A *large* factor tilt is a portfolio with a total factor tilt ≥ 2.0 deciles. A *moderate* factor tilt is a portfolio with 1.0 ≤ total factor tilt < 2.0 deciles. A *marginal* tilt corresponds to a small factor tilt (0.0 < total factor tilt ≤ 1.0 deciles). We refer to negative factor tilts as *contrary*, and for some tests we further split them into marginal (between −1.0 and 0.0 deciles) and at least moderate (< −1.0 deciles).

The fixed cut-off for *large* is similar to what we observe for academic factor benchmarks—a value-weighted portfolio targeting stocks in the top tercile on a particular characteristic— similar to Fama-French and others. Specifically, the total factor tilts of academic factors are centered around two deciles above the market. This is true both for single-factor benchmarks (e.g., momentum), as well as for multi-factor benchmarks (results available upon request). Consequently, the scales of individual factor tilts and the total factor tilt are comparable, and we can use the latter even for single-factor funds.

[16] Morningstar has started disseminating characteristic scores for value, dividend-yield, momentum, quality, liquidity and size. This classification is, however, currently available only for long-only funds (including ETFs).

The results in Table 3 provide strong evidence of persistence in factor tilt classifications. In particular, HMFs with large (moderate) factor tilts in the previous quarter have, on average, a total factor tilt of 3.6 (1.3) deciles above the market in the next quarter. Nearly identical results are obtained when lagging the factor tilt classification by four quarters instead of one. The factor tilts are also highly persistent for smart-beta ETFs. In particular, active/multi-factor (single-factor labelled) ETFs with large factor tilts at q-1 have a total factor tilt of 2.6 (2.4) deciles above the market in the next quarter.

[Table 3]

Moreover, the total factor tilts of HMFs are substantially greater on the short side (about twice as large among funds with large/moderate factor tilts), compared to the long side. Even among funds with contrary tilts (for the overall long-short portfolio), we find significant evidence that the short side is tilted towards factors (by 0.5 deciles). Thus, it is exceedingly rare for HMFs to bet against factors on the short side. In Table IA-1 in the Internet Appendix, we also show that HMFs tilt significantly towards small-cap stocks, especially on the short side. Since asset pricing anomalies are more profitable for small-cap stocks (e.g., Hou et al. (2020)) and on the short side (e.g., Stambaugh et al. (2012) and Drechsler and Drechsler (2023)), HMFs are instrumental in providing exposure to the short-leg premium for retail investors who might otherwise only have access to long-only strategies via ETFs and traditional mutual funds. These results complement those by Gao and Wang (2023), who show that HMFs trade on several anomalies on the short side.

Our focus is different because we examine the *level* of factor tilts at the individual *fund level* rather than changes in factor tilts for the aggregate short-side HMF stock portfolio.[17]

Almost as important as the magnitude of factor tilts is the proportion of funds with meaningful factor tilts and, in the case of HMFs, how much leverage they use. Table 4 shows that around 20% (34%) of the sample of HMFs have large (large + moderate) factor tilts. If we separately examine the long- and short-side sub-portfolios, we can see that about 30% and 56% of funds have large or moderate factor tilts. Importantly, funds with large factor tilts also have high gross equity leverage, at 108% and 52% for long and short positions respectively, compared to 86% and 26% for funds with moderate tilts.[18] For ETFs, the proportion of funds with large (large + moderate) factor tilts is very high for active/multi-factor ETFs at 17% (43%), but lower for single-factor labelled ETFs at 7% (29%). Although a sizeable fraction of funds have negative (i.e., contrary) factor tilts—about 30% of HMFs, 36% of single-factor labelled ETFs, and 26% of active/multi-factor ETFs—the proportion of funds that bet *at least* moderately against factors (i.e., large plus moderate contrary tilts) is substantially lower (between 9% and 13%).

[Table 4]

We also compare the persistence of individual vs. total factor tilts using a simple autoregressive (AR) model. Individual factor tilts may be lower for HMFs given their high turnover and because they may engage in factor timing. Indeed, the results in Tables IA-3 and IA-

[17] In Table 2, Gao and Wang (2023) also report the level of anomaly tilts for the aggregate HMF portfolio. However, they do not use actual portfolio weights when computing these tilts, but instead use market-capitalization weights. Thus, the portfolio represents the "market portfolio" of the HMF's investment universe. This may also explain why they find that long-side tilts are several times stronger than short side tilts, which is inconsistent with our results.

[18] A potential concern with the results for HMFs is that the complete portfolio factor tilts are mechanically amplified by leverage, since the long and short-side factor tilts are multiplied by a leverage factor (see Eq. (2)). To address this concern, we show in Table IA-2 in the Internet Appendix that gross equity leverage also predicts higher long- and the short-side factor tilts independently, before the leverage adjustment.

4 show that for HMFs with large/moderate factor tilts, the total factor tilt is far more persistent than any individual tilt, while the opposite is true for ETFs. Thus, the factor strategies used by HMFs appear to be more dynamic. Nevertheless, the total factor tilts of HMFs remain more persistent than for ETFs, indicating that HMFs are more active in maintaining large factor exposures in total.

3.3 Benchmarking Single vs. Multi-Factor Funds

Next, we evaluate more formally how close actual portfolios are to academic factor benchmarks considered in the existing literature. In the case of value funds, Lettau et al. (2021) compare a fund's value tilt relative to the value tilt of the long leg of the HML factor. In our case, a single-factor benchmark is typically not appropriate because most funds in our sample have significant exposures to multiple factors.

To provide further justification, we compute the proportion of funds with a single- or multi-factor focus. A portfolio is designated as having a single-factor focus if the largest (smallest) single-factor tilt accounts for more than 75% of the total factor tilt when the total tilt is positive (negative); otherwise, we classify it as a multi-factor portfolio. By comparison, academic single-factor benchmarks typically have ratios in excess of 100%, i.e., the largest single-factor tilt is actually *larger* than the total factor tilt. Based on this definition, we find that the vast majority, or 95% (19.4 divided by 20.4; see Table 4), of HMFs with a large factor tilt have a multi-factor focus, compared with 58% for HMFs with a moderate tilt. A similar pattern is observed for active/multi-factor ETFs. Surprisingly, we find that 52% single-factor labelled ETFs with large or moderate factor tilts actually have a multi-factor holdings-based designation.

Next, we analyze the factor tilts of HMFs and ETFs relative to academic factor benchmarks. Here, we focus only on multi-factor funds (based on our holdings-based analysis), given the small sample size of single-factor funds with meaningful factor tilts. We seek a benchmark with balanced tilts on all four factors, since the average factor-based HMF or ETF has roughly equal tilts on all four factors (unreported for conciseness). Hence, we assign equal weight to each of the four single-factor academic benchmark portfolios (a single-factor benchmark corresponds to a value-weighted portfolio that targets the top tercile on a given characteristic). This is sometimes referred to as a mix of stand-alone factor sleeves in the industry.

We summarize the pooled fund-quarter average total factor tilts, where each individual tilt is calculated relative to its counterpart in the multi-factor benchmark (e.g., the fund-level value score minus the corresponding value score of the benchmark), in Table IA-5 in the Internet Appendix. The full sample results indicate that the average HMF is far from its multi-factor benchmark. However, funds with large factor tilts have a total factor tilt that is significantly greater than that of the multi-factor benchmark, while HMFs with moderate tilts are 0.8 deciles below the multi-factor benchmark. We also take a closer look at the long- and the short-side of these funds' portfolios. While the long-side factor tilt is only marginally above the multi-factor benchmark (by 0.1 deciles) for large-tilt funds, the short side is actually tilted more towards anomalies by a significant 2.0 deciles. Even funds with moderate tilts bet on factors on the short side as strongly as the academic multi-factor benchmark. This result is consistent with our previous finding on the aggressiveness of HMFs in targeting factors on the short side.

Similar results are also observed for active/multi-factor ETFs. Interestingly, even ETFs that are labelled as "single factor", but have a multi-factor designation based on our holdings analysis, have factor tilts that are insignificantly different from those of the multi-factor benchmark. Overall, these results speak to the importance of properly benchmarking factor tilts, because stated objectives (or fund names) of ETFs can be misleading.

Overall, the results in this and the previous section confirm that the factor tilts are highly persistent for both HMFs and ETFs, and that a significant subset of funds have factor tilts that are comparable to the academic factors. By comparison, Lettau et al. (2021) show that only 7 out of 2,657 mutual funds and 4 out of 575 ETFs have value tilts that are comparable to the academic value factor. The authors provide similarly weak evidence on the profitability and asset growth tilts. The differences with our findings are primarily explained by different perspectives. First, we focus on the total factor tilt, rather than individual factor tilts, since most funds in our sample target multiple factors. In the case of HMFs, we account for both leveraged long and short positions which results in substantially stronger tilts, especially on the short side. Second, we measure factor tilts relative to the market portfolio, or relative to a multi-factor academic benchmark. By contrast, Lettau et al. (2021) evaluate factor tilts relative to the specific Fama-French factor benchmark that corresponds with the fund's stated investment objective, as inferred from the fund's name. However, Johansson et al. (2022), among others, caution that fund names and prospectuses can be misleading, and they advocate using fund holdings instead to classify factor funds.

3.4 Robustness: Factor Loadings (*β's*) vs. Factor Tilts (characteristics)

In comparison to factor loadings (or betas) from an asset pricing model, factor tilts (based on characteristics) are robust to outliers, easy to interpret with a clear benchmark (see also Lettau et al. (2021)) and perhaps most importantly, they can be computed from a single holdings snapshot. By contrast, factor loadings need to be estimated over a rolling window spanning a few years, typically with monthly data. This is a problem when either stock-, or fund-level factor exposures are time-varying, as shown in Section 3.2. Using daily data together with a shorter window can address this issue, but it is not obvious how to control for stale pricing and microstructure issues when using multi-factor models, or how to account for the fact that factor loadings themselves vary systematically across sampling frequencies (e.g., Gilbert, Hrdlicka, Kalodimos, and Siegel (2014), Kamara, Korajczyk, Lou, and Sadka (2016), Bandi, Chaudhuri, Lo, and Tamoni (2021)). Equally weighting the large and small-cap portfolios used to construct factor returns may also be inappropriate (Grinblatt and Saxena (2018)), especially in practice when funds face constraints (e.g., tracking error) that limit how much they can invest in smaller-capitalization stocks.

To ensure robustness, we nevertheless replicate our main results using factor loadings. As the counterpart to the total factor tilt, we estimate the Fama-French 6-factor model and compute the sum of the value, momentum, investment, and profitability factor loadings. The results, in the Internet Appendix Table IA-6, show that the total factor loadings increase monotonically with the factor tilt classification (contrary, marginal, moderate, and large).

4 Holdings-Based Performance

Our results suggest that many HMFs and ETFs have economically meaningful factor tilts. For HMFs, we also document the importance of short positions as a way to increase factor exposures. Nevertheless, the results so far do not reveal the performance implications of these tilts.

Each fund structure has its pros and cons. On the one hand, ETFs provide factor exposure at low cost, in a transparent wrapper, and there are no concerns with the negative externalities associated with fund flows (e.g., Chen et al. (2010), Lou (2012)). Incentives are also better aligned in passively managed ETFs, where the manager has no discretion to try to beat the benchmark by, for instance, buying high-beta stocks (e.g., Buffa, Vayanos, and Woolley (2022), Christoffersen and Simutin (2017)), which is contrary to the low-risk anomaly. On the other hand, HMFs have more flexibility to pursue factor strategies relative to passive ETFs. This is not only about their ability to short sell securities, but also because HMFs are not constrained to mechanically follow a pre-determined index. Indeed, concerns have been raised both by academics (Johansson et al.

(2022) and Huang et al. (2023)) and practitioners (e.g., Malkiel (2014) and Arnott and Kalesnik (2017)) about whether smart-beta ETFs can successfully trade on the underlying factors. In general, the trading strategies of HMFs can be modified more quickly to account for the latest developments relative to ETFs which rarely, if ever, change their benchmark index after inception (Boyde (2021)). HMFs may also be able to take advantage of the higher returns on anomaly strategies surrounding information events (Bowles, Reed, Ringgenberg, and Thornock (2023)), in contrast to passive ETFs which typically have to rebalance on a fixed schedule.

Thus, a relevant question is whether HMFs' increased flexibility and ability to short sell leads to a performance edge over ETFs. An investor seeking exposure to factor strategies is arguably expecting to earn positive market-adjusted returns on average when measured over a long period of time. In light of the short sample period, however, we focus on cross-sectional differences in performance between ETFs and HMFs.

We focus initially on holdings-based performance measures, but later we also consider the fund's actual performance to shed light on the importance of implementation costs, within-quarterly trades, and non-equity positions. A fund can deliver positive market-adjusted returns by successfully executing factor strategies (with a significant risk premium), by factor timing (e.g., Ehsani and Linnainmaa (2022)), or by engaging in security selection. We start with the CAPM alpha, which captures both security selection and factor-related returns. To control for the performance of factor tilts, we report Fama-French 6-factor alphas. We estimate betas using daily data in the previous quarter (t-1 to t-3). This is to ensure that we are capturing time-series variations in factor loadings at the same frequency as the factor tilts (from quarterly holdings).[19] We also consider DGTW characteristic-adjusted returns and characteristic timing (Daniel et al. (1997)), which do not require the estimation of the betas. The original DGTW methodology uses benchmarks based on size, value, and momentum. To account for the asset growth and profitability factors that are also included in our analysis, we extend the DGTW approach to include all five factors.[20]

For long-short HMFs, we compute the holdings-based return as the weighted average of long- and short-side portfolio returns, with weights given by the percentage of AUM invested in long ($w_{i,t-1}^{L}$) and short ($w_{i,t-1}^{S}$) positions, respectively:

$$R_{i,t}^{L-S} = w_{i,t-1}^{L} R_{i,t}^{L} + w_{i,t-1}^{S} R_{i,t}^{S} \qquad (3)$$

where $R_{i,t}^{L}$ ($R_{i,t}^{S}$) is the buy-and-hold portfolio return of the fund's long (short) positions based on its previously reported holdings, with weights summing to 100% on a given side. We calculate the long-short DGTW returns by replacing the raw return in Eq. (2) with the characteristic-adjusted or characteristic-timing return (Eq. (1) and (2) in Daniel et al. (1997)).

4.1 Regression Results

In Table 5, we estimate pooled OLS regressions of fund performance on lagged factor tilt dummies—contrary, marginal, and large + moderate (combined to preserve sample size)—

[19] In the case of the CAPM, we use the Dimson (1979) adjustment with one lead and lag for the market return to account for stale pricing. For the FF6 model, we instead rely on value-weighting to mitigate the impact of stale pricing. As shown in Table IA-6, factor tilts and factor loadings are significantly and positively related. The results for FF6 are nonetheless similar if we use the Dimson adjustment estimated on one year of daily returns. In the Internet Appendix, Table IA-7 Panel A, we also report results with betas estimated using monthly returns in (*t*-1, *t*-36), or using full sample betas (to preserve the sample size given the large number of young funds).

[20] The original DGTW method has 5x5x5 = 125 benchmark portfolios. For the extended DGTW, we only consider two size portfolios (large and small), and terciles for the remaining factors. This results in 2x3x3x3x3 = 162 benchmarks.

interacted with a HMF dummy. The omitted (benchmark) group includes smart-beta ETFs with marginal factor tilts. We include time fixed effects in all specifications in order to focus on cross-sectional differences in performance. Our primary focus is on the performance difference between HMFs and ETFs with a particular factor tilt (e.g., large/moderate), or between large/moderate and contrary tilt funds of the same fund type.[21]

[Table 5]

The results in Panel A are reported for the complete long-short portfolios of HMFs (vs. ETFs) in the first four columns, followed by only the long-side HMF portfolios (vs. ETFs) in the next two columns to assess the contribution of the (omitted) short positions (i.e., we drop $w_{i,t-1}^{S} R_{i,t}^{S}$ from Eq. (3)). When measured by CAPM alpha, we find that factor-based HMFs—with large or moderate factor tilts—outperform corresponding ETFs by a highly significant 16 bps per month (see the last coefficient of column (1)), and by 20 bps for the sub-sample of multi-factor funds (column (2)). This sub-sample provides more of an apples-to-apples comparison since multi-factor funds tend to have balanced tilts on all four factors. After we remove short positions from the holdings-based returns, the HMF-ETF performance difference drops to 3-5 bps per month and is no longer significant (columns (5) and (6)). This decline is economically even more meaningful if we consider the fact that the weight invested in short positions is only about half of that for long positions (see Table 4). Hence, short positions largely explain the outperformance of factor-based HMFs perform relative to their ETF counterparts.

[21] To account for important determinants of performance (such as fees or implementation costs), we directly adjust the dependent variable (e.g., by using gross or net returns in Section 5). Nevertheless, our results are robust, or even stronger, if we include a standard set control variables in the regression (see Table IA-7, Panel C).

Aside from capturing the returns to factor tilting, the differences in CAPM alphas may be attributed stock picking and/or factor timing. As a first test of stock picking, we consider Fama-French 6-factor alphas, which are reported in columns (3) and (4). The outperformance of factor-based HMFs vs. ETFs tilts disappears, regardless of specification, when using FF6 alphas. Estimation issues with the factor loadings (see Section 3.4) may play a part, however. As an alternative measure that is not subject to estimation error, we consider DGTW-adjusted returns in Panel B. In this case, the performance gap between factor-based HMFs and ETFs is also insignificant, except for the sub-sample of multi-factor funds when we use the extended (five-factor) DGTW alpha. The point estimate of +7 bps per month (significant at the 5% level) is economically relatively small, however, since it corresponds to a two-thirds decline from the CAPM alpha. Said differently, the large performance gap between CAPM and multi-factor alphas (whether FF6 or DGTW) is driven by successful factor bets. By contrast, we find at best only marginally stronger characteristic-timing performance (of up to 3 bps) for factor-based HMFs over ETFs.

If the market-adjusted outperformance of factor-based HMFs, relative to their ETF counterparts, is truly due to superior ability to execute factor strategies, then we would also expect to find evidence of outperformance relative to HMFs that bet against factors (contrary tilts). Indeed, that is what we find for the full sample of funds (+14 bps per month in column (1) of Panel A), and especially for the sub-sample of multi-factor funds (+32 bps in column (2)). For multi-factor funds we even find evidence of significant outperformance on the long side (+19 bps in column (5)), suggesting that while short positions are crucial for generating factor-related returns, long positions do matter as well. Moreover, we find at least marginally significant evidence of outperformance (of 11-13 bps per month) by multi-factor funds when measured by FF6 or DGTW alphas. Aside from capturing the value added of security selection, any leftover multi-factor alpha may also reflect the returns from anomaly-based trading strategies left unexplained by the specific factor model that we use (Fama and French (2015)). Indeed, we show in the Internet Appendix, Table IA-8, that factor-based (contrary) funds have significant tilts towards (against) the set of anomalies considered by Stambaugh et al. (2012), and this result is especially strong among multi-factor funds. Nevertheless, the substantial performance gap in CAPM alphas between factor-based and contrary tilt HMFs confirms that the outperformance is primarily due to factor tilting. We also confirm that contrary tilt HMFs are not simply factor timers. In fact, their factor timing performance is significantly negative, while factor-based HMFs have some positive timing performance, and the gap between the two is around 5 bps per month (significant at the 5% level, see last column of Table 5 Panel B).

Our results also raise concerns about the ability of factor-based ETFs (with large or moderate tilts) to make factor bets. They actually underperform by a highly significant 8 to 12 bps per month, relative to the marginal tilt ETFs (the omitted group), when measured by CAPM alphas (though FF6 alphas are insignificant). Moreover, the performance gap between factor-based and contrary tilt ETFs is consistently negative for multi-factor funds (between 10 and 15 bps), although statistically significant at the 5% level only for FF6 alphas.[22] The inflexibility of factor-based ETFs in trading on the underlying factors and the underweighting of smaller-capitalization stocks (see Table IA-1 in the Internet Appendix), compared to HMFs, may explain the poor performance of these funds.

[22] This sub-sample result should be taken with a grain of salt, however, given the very small sample size of contrary tilt multi-factor ETFs (see Table 4).

5 The Impact of Non-Equity Positions and Implementation Costs

So far, we have used quarterly equity holdings to assess factor tilts and measure fund performance. If a fund uses non-equity positions, such as fixed income securities or options, to alter the exposure to risk factors, then drawing conclusions based only on the equity portfolio may be inaccurate. In practice, HMFs hold negligible amounts in (non-cash) fixed income securities (< 5%, see Table 1). Futures or options on broad-based market indices are less of a concern, since they are more likely to be used to dynamically adjust the fund's market risk exposure (Natter, Rohleder, Schulte, and Wilkens (2016)), which we can account for by using time-varying betas (estimated using daily net returns within a quarter). Single-stock options arguably represent a bigger concern since their use may alter the fund's factor tilt profile, whether intentionally or not. HMFs in the Derivative Income category, and to a lesser extent in the Options Trading category, frequently use single-stock options, e.g., for covered call strategies. To be comprehensive, we also manually identify funds that use single-stock options based on their reported holdings.[23] We refer to funds screened by these two filters as options-based funds, and they account for about 34% (18% + 16%) of the full sample of HMF-quarters. Importantly, while the proportion of option users is substantially lower among factor-based funds (17%) compared to other HMFs (44%), it is clearly not zero. We therefore assess the impact of single-stock option use on factor exposures (Section 5.1) and performance (Section 5.2) using sub-sample analysis by excluding options-based funds.

Moreover, actual fund performance is influenced not only by fees, but also by the unobserved actions of fund managers, such as within-quarterly trades and implementation costs, that are not reflected in the reported holdings (Kacperczyk, Sialm, and Zheng (2008)). We evaluate

[23] We define option use based on the most recently reported holdings. We obtain comparable results if we instead define it based on a longer window of four quarters.

the impact of these actions on performance in Section 5.2. To ensure robustness, we also directly assess the performance of HMFs against an investable benchmark based on ETFs (Section 5.3). Finally, in Section 5.4, we evaluate whether HMFs can achieve comparable performance as the academic factors using the methodology in Patton and Weller (2020).

5.1 Actual vs. Holdings-Based Factor Exposures

To assess the impact of derivative and other non-equity positions on factor exposures, we start by evaluating the *difference* between actual factor loadings (obtained from net fund returns) and holdings-based loadings (obtained from the holdings-based returns of the fund's equity positions), estimated using daily data within a quarter. We find that HMFs in all sub-samples, except large/moderate tilt multi-factor funds, have significantly *lower* actual than holdings-based CAPM betas by between 0.06 and 0.16 (see Table 6, column (1)). Thus, consistent with Natter et al. (2016), derivative positions are likely used for hedging market risk, which would explain the lower CAPM betas of net returns. In the performance analysis we focus primarily on large/moderate and contrary tilt funds. These two categories have relatively small actual-minus-holdings-based beta differences of -0.035 and -0.077, respectively. As for the Fama-French 6-factor model, the differences in total factor loadings (*VAL+MOM+CAG+PROF*) are not economically meaningful for any sub-sample (column (3)). After excluding options-based funds, the beta differences (both CAPM and FF6) are, if anything, smaller (see columns (2) and (4)). Hence, HMFs do not seem to use derivatives to exploit (non-market) factor returns. Our emphasis on funds with large/moderate or contrary factor tilts is therefore appropriate and we can indeed draw conclusions about the total factor tilts of these funds even if we only observe their equity portfolios.

[Table 6]

5.2 Actual Performance, Unobserved Actions, and Fees

To assess the actual performance of factor-based funds, and in particular the importance of unobserved actions, we shift away from a holdings-based performance analysis to one based on the fund's gross returns (i.e., net return plus 1/12 of the annual expense ratio), or net returns, in Table 7. We focus primarily on gross alphas because they are more informative about manager skill, rather than net alphas which should be zero in equilibrium (Berk and Green (2004)). Overall, we continue to find nearly identical results on the (gross) outperformance of around 15 to 20 bps per month (CAPM alpha) of factor-based HMFs compared to their ETF counterparts (see column (1) for the full sample and (2) for multi-factor funds). The corresponding difference between factor-based and contrary tilt HMFs is also similar to before. To properly interpret this finding, it is important to remember that gross returns incorporate the net effect of implementation costs, fixed income, derivatives, and within-quarterly trades. As shown in Sections 5 and 5.1, fixed income positions are generally small for HMFs, and derivatives are unlikely to meaningfully affect a fund's factor tilt profile. Nevertheless, we drop options-based funds from the sample (column (3)) to ensure robustness, and we find nearly identical results that remain statistically significant, despite the reduction in sample size. Finally, we confirm that factor-based ETFs underperform by a highly statistically significant 5 to 15 bps per month, relative to marginal tilt ETFs, regardless of whether we use CAPM or FF6 alphas. Factor-based ETFs also underperform contrary ETFs with a significant difference for FF6 alphas.[24]

[24] In additional tests reported in the Internet Appendix (see Table IA-9), we construct calendar-time portfolios, where we take long positions in factor-based HMFs and short positions in corresponding ETFs, or contrary tilt HMFs. Despite the short time-series and the equal weighting of time periods, we confirm that factor-based HMFs outperform 2.56% per year (relative to contrary tilt HMFs) and between 1.49-2.20% (relative to factor-based ETFs) using holdings-based returns and CAPM alpha to measure performance. The performance difference with gross returns remains similar although is statistically significant only for the multi-factor sample.

We therefore conclude that the net effect of implementation costs, the presence of fixed income/derivatives, and within-quarterly trades does not explain the performance difference between large factor tilt HMFs and ETFs, or between factor-based and contrary tilt HMFs. While HMFs do incur additional implementation costs relative to ETFs (e.g., the cost of shorting or borrowing on margin), they may compensate by having lower liquidity costs or by executing profitable trades within the quarter. Indeed, Puckett and Yan (2011) show that institutional investors in general earn significant abnormal returns from their within-quarterly trades. By contrast, ETFs typically rebalance only quarterly or semi-annually (e.g., Johnson (2021)).

[Table 7]

The holdings-based analysis is useful for examining the overall performance of factor strategies and stock selection before implementation costs, while gross returns are useful to gauge the extent of implementation costs, within-quarterly trades, and derivatives. Ultimately, however, investors care about net returns and, in particular, whether some of the outperformance is passed on to them (Berk and van Binsbergen (2015)). When using net returns, the performance differential—as measured by CAPM alpha between factor-based HMFs and ETFs—drops by almost half, but remains significant for multi-factor funds (columns (5) and (6)). These HMF managers are therefore able to extract a good portion (but not all) of the factor-related performance, which is included in the CAPM alpha, for themselves, via higher fees compared to ETFs. Our results are consistent with both sides (investors and fund managers) having market power, which is in line with Pástor and Stambaugh (2012) and Pedersen (2015), but inconsistent with Berk and Green (2004) where fund managers extract all rents. Interestingly, the performance gap between large and contrary HMFs is similar, or even stronger, with net returns. Better performing factor-based funds therefore do not reap commensurately higher fees, despite the fact that investors do not seem to differentiate between factor and non-factor-related performance (e.g., Ben-David, Li, Rossi, and Song (2022b)). A possible explanation is that HMFs with contrary tilts charge relatively higher fees because they are more likely to use 'complex' strategies that require more time and effort (Calluzzo, Moneta, and Topaloglu (2021)), or because their clientele is less sophisticated. By contrast, factor strategies are likely to be relatively cheaper to implement, which would explain the lower fees charged by factor-based HMFs relative to those with contrary tilt.

5.3 Robustness: Investable benchmarks

As an alternative to factor-based risk-adjustment, we evaluate HMFs against an investable single-factor benchmark in the spirit of Berk and van Binsbergen (2015), who use index funds instead of hypothetical benchmark indices. Our single-factor alternative is also related to the commonly used benchmark-adjusted return (e.g., Pástor, Stambaugh, and Taylor (2015)), except that we use OLS to estimate the beta w.r.t. the benchmark rather than setting it to equal one. In particular, for each HMF, we compute the return on the investable benchmark as the average returns of ETFs in the same factor tilt category (*contra*, *marginal*, or *large* + *moderate*) at q-1. Similarity in total factor tilts does not, however, guarantee similarity in individual factor tilts. To improve comparability, we overweight ETFs with similar factor tilts. Specifically, we set the weight equal to the inverse of the Euclidean spatial distance in factor tilts between a HMF and its peer ETF at q-1, following Hoberg et al. (2018), Eq. (1). (Results remain similar even if we equally or value weight all ETFs in a given factor tilt category). We then estimate pooled OLS regressions of excess HMF returns on the excess return of the investable ETF benchmark, with separate coefficients (α, β) for each factor tilt category. Results are reported in Table 8.

[Table 8]

When using holdings-based returns, the average benchmark-adjusted alpha of factor-based HMFs is +14.3 bps per month, while that of contrary tilt HMFs is an insignificant -3.9 bps per month. The difference between the two is 18.1 bps per month and it is significant at the 1% level. The corresponding difference remains significant when using gross returns (10.4 bps), or net returns (10.9 bps). Remarkably, the performance difference is greater by a factor of two to four if we restrict the sample to multi-factor funds only. For example, factor-based HMFs outperform contrary tilt HMFs by as much as 47.3 bps per month net of all costs and fees, after risk adjusting HMF returns based on the investable ETF benchmark. These results confirm that a group of HMFs are successful in harvesting the factor-related returns, but investors should be careful in identifying those HMFs that provide the right factor exposure.

5.4 Ability to Harvest Factor Risk Premia

To further assess the ability of fund managers to harvest the underlying factor risk premia, we follow Patton and Weller (2020) and analyze whether, for a given level of factor exposure, managers achieve similar performance as the academic factors. They propose a method, based on Fama-MacBeth regressions, to measure the gap between the risk premia earned by mutual funds in practice and that earned by test assets on paper. They find that mutual funds, for a given level of risk exposure, earn lower returns than the academic value and momentum factors. Using our sample, we estimate cross-sectional Fama-MacBeth regressions of performance on characteristics (see Eq. (8) in Patton and Weller (2020)), separately for HMFs, ETFs, and test assets (S):

$$Perf_{i,t} = \sum_k \lambda_{k,t}^{HMF} C_{i,k,t-1}^{HMF} 1_{i \in HMF} + \sum_k \lambda_{k,t}^{ETF} C_{i,k,t-1}^{ETF} 1_{i \in HMF} + \sum_k \lambda_{k,t}^{S} C_{i,k,t-1}^{S} 1_{i \in S} + \epsilon_{i,t} \qquad (4)$$

As in Section 3.3 on the proper benchmarking of factor tilts, we use academic single-factor benchmarks as test assets (S).[25] We measure factor exposures by characteristic (decile) scores ($C_{i,k,t-1}$), see Eq. (2). The time-series average of the slope (λ) coefficients represents the average return per unit of characteristic exposure. Given our prior results on the superior performance of factor-based HMFs relative to corresponding ETFs, we conjecture that HMFs achieve similar factor performance as the test assets ($\lambda^{HMF} - \lambda^{S} = 0$), while ETFs perform worse ($\lambda^{ETF} - \lambda^{S} < 0$).[26] We use gross CAPM alphas as the dependent variable to control for the markedly lower CAPM betas of long-short HMFs (full sample average of 0.4) vs. long-only ETFs (1.0).

Table 9 reports the difference between the characteristic risk premia achieved by HMFs (or ETFs) relative to the test assets. The results for HMFs in Panel A indicate that they achieve comparable market-adjusted performance (or better in the case of Profitability) as the test assets per unit of characteristic exposure. By contrast, ETFs earn lower risk premia on Value, Momentum and Conservative Asset Growth compared to the test assets (between -6 to -13 bps per month), although they are mostly statistically insignificant. However, the differences in risk premia between HMFs and ETFs are both economically and statistically highly significant. To illustrate, HMFs earn 32.7 bps per month higher market-adjusted returns (with a *t*-stat of 2.37), compared to ETFs, per decile of total characteristic exposure (i.e., 0.25 deciles above the market for each of the four characteristics, see the last column of Panel C). As before, the results are even stronger if we

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[25] Specifically, for each of the four factors, we create two value-weighted benchmark portfolios (top and bottom) using tercile cut-offs, separately for large- and small-cap investment universe (Russell 3000 vs. Russell 2000). In total, we have $4 \times 2 \times 2 = 16$ benchmark portfolios.

[26] Johansson et al. (2022) focus on the alpha that is estimated from regressions of tradeable factor returns (constructed from mutual funds and ETFs) on the corresponding academic factor. Such a single-factor approach is not appropriate for in our setting where multi-factor funds are the dominant type.

drop single-factor funds from the sample (44.2 bps per month, *t*-stat = 2.98). Thus, the findings confirm the inability of factor-based ETFs to achieve comparable risk premia as the test assets.

[Table 9]

We emphasize characteristic scores since they are directly observed and therefore accurate, which is especially important in our setting given the relatively short sample period. By contrast, estimated factor betas can be noisy especially when a using short estimation window to account for time-variation in factor exposures (see the discussion in Sections 3.2 and 3.4). Nevertheless, we also report results with characteristic scores in Eq. (4) replaced by betas relative to the Fama-French six factor model (estimated, as before, using daily data over the prior quarter). In this case, we use gross returns on the left-hand side, and we omit the intercept as is standard practice (see Patton and Weller (2020)). The results, reported in Table IA-10 in the Internet Appendix, suggest that HMFs achieve higher non-market risk premia overall, especially for multi-factor funds, though the differences vis-à-vis the test assets or ETFs are statistically insignificant. The lack of statistical significance is not surprising, given the noisy beta estimates and the short sample period (cross-sectional regressions equal weight all time periods, including those with a limited number of funds).

As a final test, we create long-short synthetic factors based on the aggregate (i.e., dollar-weighted) holdings of factor-based HMFs in extreme anomaly stocks (top or bottom 30%), and compare them with the academic factors (reported in Table IA-11 in the Internet Appendix). We regress each synthetic long-short factor return (e.g., HML) on the corresponding academic factor (HML), or against the full set of factors in Fama-French six-factor model. In the former case, we find insignificant intercepts and betas that deviate from one (for HML and RMW only). In the latter case, we observe positive and at least marginally significant intercepts for CMA and RMW.

Moreover, each synthetic factor loads not just on its own academic counterparts (the RMW beta of the synthetic RMW factor is 1.02), but also on other factors (e.g., the HML and CMA betas of the synthetic RMW factor are 0.35 and 0.37, respectively). We therefore conclude that the factor bets made by HMFs achieve similar, or better, performance as the academic factors, while obtaining exposure to multiple factors simultaneously. This further reinforces our message that HMFs truly are multi-factor funds.

6 Conclusions

We assess whether Hedged Mutual Funds (HMFs) tilt their portfolios to exploit factor strategies and what the performance implications of these tilts are, relative to smart-beta Exchange-Traded Funds (ETFs). HMFs are prime candidates to study factor strategies because they are permitted to use leverage and engage in short selling, both of which are important for boosting the return contribution of factors at the expense of market returns. Smart-beta ETFs, on the other hand, are specifically designed to mimic factor strategies, but their long-only mandate leaves much of the market risk intact and profits from short positions on the table.

We measure factor tilts using characteristic decile scores, which are direct and up-to-date measures of factor exposures unlike factor loadings that need to be estimated over an extended period of time. We show that HMFs and many smart-beta ETFs have significant factor tilts towards four well-known factors—value, momentum, (conservative) asset growth, and profitability. Moreover, the total factor tilts are extremely persistent indicating that investors can choose these funds ex-ante. Our results are particularly strong on the short-side, which suggests an important role played by HMFs in providing exposure to the short-leg premium for retail investors who might otherwise only have access to long-only strategies via ETFs and traditional mutual funds.

As for the performance implications of factor tilts, we show that factor-based HMFs outperform ETFs with corresponding tilts when using holdings-based returns. We attribute this outperformance to the factor-related returns, especially on the short side. There is also some limited evidence of positive multi-factor alphas among factor-based HMFs, though this may be explained by their large exposures to (other) anomalies that are not accounted for by the factor model that we use. The results remain strong using gross returns, suggesting that implementation costs do not eliminate the returns to trading on factor strategies. HMFs also achieve similar performance as the academic factors per unit of factor exposure. On the flip side, our results suggest that smart-beta ETFs with meaningful factor tilts underperform substantially even before implementation costs or fees are taken into account. Investors therefore appear to be worse off from investing in factor-based ETFs over other ETFs. These results call into question the ability of smart-beta ETFs to successfully execute factor strategies. Overall, our study is the first to provide evidence that a significant subset of mutual funds with the ability to short sell can make successful factor bets. This finding is important given the rise of factor-based investing and the ongoing debate about the ability of mutual funds and ETFs to provide factor exposures to investors.

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Table 1: Summary Statistics

This table presents summary statistics for Hedged mutual funds (HMFs) and smart-beta Exchange-Traded Funds (ETFs). *#Funds* is the number of unique funds, Assets Under Management (*AUM*) is the total fund size in $millions, %*Exp. Ratio* is the annual expense ratio, *%Turnover* is the reported turnover in CRSP. %*Gross Eq. Levg.* is the sum of the market value of long or short positions divided by AUM, %*Fixed Inc. Levg* is the sum of the market value of risky (i.e., non-cash) fixed income positions divided by AUM. Expense ratios, turnover and leverage ratios are in percentages. Panel A summarizes the results for HMFs by Morningstar Categories. Panel B provides the results by Morningstar's Strategic Beta category (with the additional Factor Value category) and separately for actively managed ETFs. The sample period from 01/2010 to 12/2021.

		AUM ($millions)		*%Exp. Ratio*	*%Turnover*	*%Gross Eq. Levg.*		*%Fixed Inc. Levg.*
	#Funds	Avg	Med	Avg	Avg	Long - Avg	Short - Avg	Avg
Panel A: Hedged Mutual Funds (HMFs)								
Morningstar Category								
Market Neutral	29	695.85	148.15	1.51	283.55	86.24	70.53	6.04
Long-Short Equity	135	517.89	90.40	1.60	251.64	94.84	29.24	1.99
Event driven	19	876.62	200.20	1.55	297.67	77.59	21.27	12.91
Options based	50	760.19	86.60	1.09	82.68	89.58	0.87	4.02
Multi strategy	45	470.42	98.25	1.80	300.19	60.32	20.89	20.95
Full sample	278	608.91	102.30	1.52	234.67	87.84	27.37	5.74
Panel B: Smart-beta Exchange-Traded Funds (ETFs)								
Strategic Beta Category								
Momentum	13	929.19	115.95	0.39	94.40	99.83		
Quality	22	3531.80	241.13	0.34	50.85	99.80		
Factor Value	9	847.42	156.15	0.27	42.56	99.54		
Standard Value	27	6547.20	1349.60	0.19	33.48	99.98		
Dividend yielding	42	2964.94	688.92	0.36	46.21	99.54		
Fund. weighted	16	989.12	369.82	0.38	28.29	99.81		
Growth	29	7032.62	1513.08	0.21	38.86	99.75		
Low Risk	15	2380.28	250.11	0.26	55.01	99.72		
Multi-Factor	65	371.39	145.10	0.47	96.90	99.70		
Actively managed	51	868.48	80.10	0.62	156.52	96.63		
Full sample	289	3022.22	341.30	0.36	65.11	99.47		

Table 2: Average Factor Tilts Relative to the Market Portfolio

This table presents fund-quarter average factor tilts. Factor tilts are based on the following characteristics: i) value (B/M), ii) momentum (t-2, t-12), iii) (conservative) asset growth, and iv) operating profitability. For each security, we first compute the stock characteristic at the end June (time t) based on accounting information from the prior December (t-6). The stock-level characteristic is assumed to be constant until the following June ($t+1$ to t+12). The only exception is the momentum characteristic, which is recomputed monthly using t-2 to t-12 past returns. Each stock is then assigned a decile score based on NYSE breakpoints. These are aggregated to the fund-level by taking the portfolio-weighted average of the stocks held by the fund, e.g., the B/M ratio of fund i at time t is the portfolio-weighted average of the B/M ratio decile score of all stocks in the fund's portfolio: $C_{i,t} = \sum_{j=1}^{J} w_{i,j,t}\, C_{j,t}$. For HMFs we compute this separately for the fund's long and short positions. Factor tilts are then constructed by subtracting from the fund-level characteristic score the corresponding value-weighted characteristic score of the market portfolio: $\left(C_{i,t} - C_{m,t}\right)$. We reverse the order for asset growth, so that higher values indicate conservative (lower) asset growth (and higher expected returns). The complete (long-short) factor tilt is calculated by weighting the long and short-side factor tilts by the percentage of AUM invested in long or short positions: $w_{i,t}^{L}\left(C_{i,t}^{L} - C_{m,t}\right) + w_{i,t}^{S}\left(C_{i,t}^{S} - C_{m,t}\right)$. E.g., for a 130/30 fund, the long side receives 130% weight and the short side receives -30% weight. Panel A (B) [C] presents the results for HMFs (newer generation of smart-beta ETFs) [older generation of smart-beta ETFs]. The sample period is 01/2010 to 12/2021. */**/*** denotes statistical significance at the 10, 5, and 1 percent levels. Standard errors are clustered by fund (t-statistics in brackets).

Panel A: Hedged mutual funds

	VAL	MOM	CAG	PROF	Total Factor tilt
	(1)	(2)	(3)	(4)	(1-4)
Average	0.373***	0.177***	0.274***	0.053	0.859***
	(9.017)	(3.533)	(6.760)	(1.174)	(7.086)
Nobs	4,957	4,957	4,957	4,957	4,957

Panel B: Newer generation of smart-beta ETFs

	VAL	MOM	CAG	PROF	Total Factor tilt
Actively managed					
Average	0.265**	0.114	0.156	0.003	0.539*
	(2.278)	(1.525)	(1.044)	(0.025)	(1.808)
Nobs	691	691	691	691	691
Multi Factor					
Average	0.609***	0.056	0.189**	-0.009	0.846***
	(4.769)	(0.448)	(2.239)	(0.098)	(6.290)
Nobs	1,557	1,557	1,557	1,557	1,557
Fundamentally weighted					
Average	0.776***	-0.390***	0.479***	0.258	1.123***
	(5.522)	(10.655)	(5.539)	(1.732)	(6.116)
Nobs	502	502	502	502	502
Momentum					
Average	-0.536***	1.403***	-0.534***	-0.016	0.318
	(4.291)	(6.285)	(4.826)	(0.114)	(1.214)
Nobs	388	388	388	388	388
Quality					
Average	-0.426***	-0.331***	0.552***	0.927***	0.723***
	(3.980)	(3.323)	(7.655)	(6.105)	(3.393)
Nobs	537	537	537	537	537
Factor value					
Average	2.072***	-0.865***	0.793***	-0.362	1.639***
	(7.142)	(6.952)	(11.427)	(1.460)	(5.970)
Nobs	202	202	202	202	202

Panel C: Older generation of smart-beta ETFs					
	VAL	MOM	CAG	PROF	Total Factor tilt
	(1)	(2)	(3)	(4)	(1-4)
Standard value					
Average	0.929***	-0.469***	0.426***	-0.384***	0.501***
	(8.587)	(8.529)	(5.268)	(3.337)	(3.404)
Nobs	1,119	1,119	1,119	1,119	1,119
Dividend yielding					
Average	0.364***	-0.733***	0.481***	0.154*	0.267**
	(4.481)	(12.189)	(8.675)	(1.712)	(2.076)
Nobs	1,212	1,212	1,212	1,212	1,212
Growth					
Average	-0.853***	0.569***	-0.400***	0.454***	-0.230*
	(13.656)	(11.120)	(8.679)	(4.634)	(1.715)
Nobs	1,217	1,217	1,217	1,217	1,217

Table 3: Persistence in Factor Tilt Classifications

This table presents fund-quarter average total factor tilts in a given quarter conditional on the extent of a fund's factor tilt in the previous quarter. We designate each fund into one of four mutually exclusive groups at q-1: *contrary*, *marginal*, *moderate*, or *large* factor tilt. A portfolio is designated as *contrary* if the total factor tilt is negative; a *marginal* factor tilt is a portfolio with a total factor tilt < 1.0 deciles; a *moderate* factor tilt is a portfolio with 1.0 ≤ total factor tilt < 2.0 deciles; a *large* factor tilt is a portfolio where the total factor tilt ≥ 2.0. The total factor tilt is calculated as the sum of a fund's value, momentum, (conservative) asset growth, and profitability factor tilts relative to the market portfolio: $\left(C_{i,t}^{VAL} - C_{M,t}^{VAL}\right) + \left(C_{i,t}^{MOM} - C_{M,t}^{MOM}\right) + \left(C_{i,t}^{CAG} - C_{M,t}^{CAG}\right) + \left(C_{i,t}^{PROF} - C_{M,t}^{PROF}\right)$. Factor tilts are determined for the fund's complete portfolio by weighting the long and short-side factor tilts by the percentage of AUM invested in long and/or short positions. Panel A summarizes the results for HMFs for the complete portfolio, and separately for the fund's long and short positions. Panel B summarizes the results for factor-based ETFs. The sample period is 01/2010 to 12/2021. */**/*** denotes statistical significance at the 10, 5, and 1 percent levels. Standard errors are clustered by fund (t-statistics in brackets).

Panel A: Hedged Mutual Funds

	Contrary Factor Tilt (q-1)			Marginal Factor Tilt (q-1)		
	Portfolio	Long	Short	Portfolio	Long	Short
Average	-0.735***	-1.015***	-0.545***	0.437***	0.395***	-0.692***
	(6.927)	(7.505)	(3.281)	(17.631)	(10.360)	(5.473)
Nobs	1,360	1,317	916	1,650	1,584	820
	Moderate Factor Tilt (q-1)			**Large Factor Tilt (q-1)**		
	Portfolio	Long	Short	Portfolio	Long	Short
Average	1.325***	1.058***	-1.740***	3.568***	1.758***	-3.542***
	(30.170)	(16.067)	(9.588)	(21.926)	(22.371)	(20.589)
Nobs	639	622	444	988	985	907

Panel B: Factor-based ETFs

	Active/multi-factor ETFs				Single-factor (labelled) ETFs			
	Contrary	Marginal	Moderate	Large	Contrary	Marginal	Moderate	Large
Average	-0.914***	0.561***	1.489***	2.570***	-0.686***	0.505***	1.248***	2.356***
	(4.197)	(16.474)	(35.476)	(22.102)	(12.135)	(19.756)	(33.082)	(30.562)
Nobs	549	683	548	343	1,994	1,910	1,167	351

Table 4: Factor Classifications and Single- vs. Multi-Factor Portfolios

This table summarizes the frequency of observations and the gross equity leverage associated with a particular factor classification. Factor tilts are determined either for the fund's complete (long-short) portfolio, or separately for the fund's long and short sub-portfolios. A portfolio is designated as *large* if the total factor tilt ≥ 2.0 deciles; a *moderate* factor tilt is a portfolio with 1.0 ≤ total factor tilt < 2.0 deciles; a *marginal* factor tilt is a portfolio with a total factor tilt between 0 and 1.0 deciles. For negative total factor tilts (*contrary*), we report results separately for marginal and large/moderate. The total factor tilt is calculated based on the sum of value, momentum, conservative asset growth, and profitability tilts. Portfolios with a meaningful factor tilt are further classified as either single-, or multi-factor. A single-factor portfolio is defined as one where the largest (smallest) single-factor tilt accounts for more than 75 % of the total factor tilt when the total factor tilt is positive (negative). Note that this holdings-based classification is different from the single-factor ETF classification used in the last column, which is based on Morningstar's Strategic Beta category variable that reflects the fund's stated objective. The sample period is 01/2010 to 12/2021. %Obs is the percentage of fund-month observations by factor tilt designation (**bolded** numbers add up to 100%). Gross Eq. Levg. is the sum of the fund's long or short positions divided by AUM (in %).

	Hedged mutual funds					Active / Multi ETFs	Single-Factor ETFs
	Complete portfolio			Long	Short		
	%Obs	%Gross Eq. Levg.		%Obs	%Obs	%Obs	%Obs
		Long – Avg.	Short – Avg.				
Factor tilts							
Large	**20.43**	107.99	51.91	**11.30**	**38.49**	**17.26**	**7.12**
Single (>75%)	1.00	108.86	53.90	1.38	4.09	3.31	1.95
Multi (≤75%)	19.43	107.95	51.81	9.92	34.41	13.95	5.17
Moderate	**13.63**	86.39	26.37	**19.01**	**17.17**	**25.70**	**21.49**
Single (>75%)	5.74	91.30	29.08	8.00	7.93	11.92	11.66
Multi (≤75%)	7.88	82.81	24.39	11.01	9.25	13.77	9.83
Marginal	**36.29**	81.31	16.78	**35.28**	**21.14**	**31.43**	**34.90**
Contrary tilts							
Marginal	**20.33**	79.96	21.53	**20.83**	**15.36**	**16.95**	**23.51**
Large/Mod.	**9.32**	88.78	25.32	**13.58**	**7.83**	**8.65**	**12.98**

Table 5: Holdings-Based Performance of Factor Funds

This table reports the results for pooled OLS regressions of fund performance (HMF and ETF) on dummies that capture the extent of a fund's factor tilt at q-1 (*contrary*, *marginal*, and *large* + *moderate*), interacted with a dummy for HMFs. The omitted (benchmark) group consists of ETFs with marginal factor tilts. Columns (1), (3), and (5) in Panel A and columns (1), (3), (5) and (6) in Panel B are estimated for the full sample of funds, while columns (2), (4) and (6) in Panel A and columns (2), and (4) in Panel B include multi-factor funds (based on holdings data, see Table 4). The results are reported separately for the complete long-short portfolios of HMFs (vs. ETFs) in the first four columns, followed by only the long-side HMF portfolios (vs. ETFs) in the last two columns. Performance is measured by CAPM (columns (1), (2), (5), and (6)) and Fama-French 6-factor alpha (columns (3) and (4)) for holdings-based returns in Panel A (with betas estimated using daily data in the prior quarter), and by the DGTW characteristic-adjusted returns (columns (1), (2), (3) and (4)), or DGTW characteristic timing (columns (5) and (6)) in Panel B. Calendar time fixed effects are included in all specifications. The sample period is from 01/2010 to 12/2021. */**/*** denotes statistical significance at the 10, 5, and 1 percent levels. Standard errors are clustered by fund (t-statistics in brackets).

Panel A: Factor-based alphas

	Complete equity portfolio				Long-side sub-portfolio	
	CAPM		FF6		CAPM	
Variables	(1)	(2)	(3)	(4)	(5)	(6)
Contrary tilt	-0.071**	-0.023	0.018	0.127*	-0.072**	-0.026
	(2.202)	(0.265)	(0.947)	(1.903)	(2.228)	(0.295)
× HMF	0.018	-0.216*	-0.032	-0.244***	0.017	-0.231**
	(0.431)	(1.929)	(1.063)	(2.680)	(0.429)	(2.179)
Marginal tilt						
× HMF	0.017	0.014	-0.007	-0.010	0.032	0.033
	(0.529)	(0.439)	(0.325)	(0.473)	(1.027)	(1.067)
Large/Moderate tilt	-0.075**	-0.120***	0.005	-0.024	-0.074**	-0.116***
	(2.235)	(2.874)	(0.245)	(0.977)	(2.190)	(2.818)
× HMF	0.162***	0.202***	0.025	0.041	0.032	0.053
	(4.518)	(4.564)	(0.843)	(1.201)	(0.947)	(1.300)
Difference between coefficient estimates						
Lrg/Mod – Contra (ETF)	-0.004	-0.097	-0.013	-0.151**	-0.002	-0.090
Lrg/Mod – Contra (HMF)	0.140**	0.321***	0.044	0.134*	0.013	0.194***
Omitted group	Marginal tilt	Marginal tilt	Marginal tilt	Marginal tilt	Marginal tilt	Marginal tilt
Sample	Full	Multi factor	Full	Multi factor	Full	Multi factor
Fixed effects						
Time	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R2	0.172	0.157	0.071	0.074	0.211	0.200
N	37,645	23,891	37,645	23,891	37,097	23,477

Panel B: DGTW characteristic-adjusted returns and characteristic timing

	Char-adj Return				Timing Return	
	Original (ME, BE/ME, MOM)		Extended (+ CAG + PROF)		Original	Extended
Variables	(1)	(2)	(3)	(4)	(5)	(6)
Contrary tilt	0.002	0.096	-0.000	0.100	0.014	0.018
	(0.108)	(1.285)	(0.016)	(1.367)	(1.333)	(1.460)
× HMF	-0.011	-0.169*	-0.006	-0.181**	-0.032**	-0.041**
	(0.392)	(1.914)	(0.196)	(2.059)	(2.025)	(2.371)
Marginal tilt						
× HMF	-0.015	-0.017	0.004	0.002	0.008	-0.028**
	(0.731)	(0.830)	(0.174)	(0.086)	(0.823)	(2.380)
Large/Moderate tilt	0.036*	0.000	0.014	-0.037	0.002	0.013
	(1.739)	(0.003)	(0.683)	(1.573)	(0.266)	(1.262)
× HMF	-0.007	0.034	0.022	0.072**	0.034**	0.019
	(0.256)	(1.045)	(0.748)	(2.279)	(2.492)	(1.255)
Difference between coefficient estimates						
Lrg/Mod – Contra (ETF)	0.033	-0.096	-0.014	-0.136*	-0.012	-0.005
Lrg/Mod – Contra (HMF)	0.038	0.107*	0.042	0.117**	0.054***	0.056***
Omitted group	Marginal tilt	Marginal tilt	Marginal tilt	Marginal tilt	Marginal tilt	Marginal tilt
Sample	Full	Multi factor	Full	Multi factor	Full	Full
Fixed effects						
Time	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R2	0.071	0.081	0.039	0.049	0.041	0.026
N	39,326	25,054	39,326	25,054	36,961	36,961

Table 6: Actual vs. Holdings-Based Factor Exposures

This table examines the impact of derivatives and other non-equity positions by reporting the results for pooled OLS regressions of fund-quarter total factor exposures on factor classification dummies at q-1 (see Table 4 for additional details). The total factor exposure is measured by the *difference* in factor loadings of actual and holdings-based returns, based on the CAPM or the Fama-French 6-factor model. In the latter case, we report the difference between the sum of value, momentum, investment and profitability factor loadings. Results are reported for the full sample (columns (1) and (3)), and for the sub-sample that excludes option-based funds. The sample period is from 01/2010 to 12/2021. */**/*** denotes statistical significance at the 10, 5, and 1 percent levels. Standard errors are clustered by fund (t-statistics in brackets).

Y = Actual-minus-Holdings-based Factor Loading				
	CAPM (β^{MKT})		FF6 ($\beta^{HML}+\beta^{WML}+\beta^{INV}+\beta^{RMW}$)	
Variables	(1)	(2)	(3)	(4)
Contrary × Single	-0.078***	-0.043***	0.016*	0.010
	(5.246)	(3.526)	(1.753)	(0.866)
Contrary × Multi	-0.063***	-0.034*	0.039*	0.022
	(2.936)	(1.684)	(1.696)	(0.907)
Marginal	-0.159***	-0.087***	0.002	0.020**
	(7.105)	(3.857)	(0.239)	(1.972)
Large/moderate × Single	-0.120***	-0.073	-0.024	0.003
	(3.231)	(1.613)	(1.585)	(0.208)
Large/moderate × Multi	-0.037	-0.024	0.014	0.021
	(1.277)	(0.736)	(1.060)	(1.535)
Sample	Full	≠ Options	Full	≠ Options
Adj. R^2	0.151	0.047	0.004	0.003
Nobs	4,732	3,105	4,680	3,073

Table 7: Actual Performance of Factor Funds

This table reports the results for pooled OLS regressions of fund performance (HMF and ETF) on dummies that capture the extent of a fund's factor tilt and single/multi-factor focus at q-1 (*contrary*, *marginal*, and *large* + *moderate*), interacted with a dummy for HMFs. The omitted (benchmark) group consists of ETFs with marginal factor tilts. Columns (1), (2), (3), (7), and (8) are estimated for gross returns, while columns (4), (5), and (6) are for net returns. Performance is measured by CAPM and Fama-French 6 factor alphas (with betas estimated using daily data in the prior quarter). Results are reported for the full sample (columns (1), (4), and (7)), for multi-factor funds (columns (2), (5), and (8)), and for the sub-sample that excludes options-based funds in columns (3) and (6). Calendar time fixed effects are included in all specifications. The sample period is from 01/2010 to 12/2021. */**/*** denotes statistical significance at the 10, 5, and 1 percent levels. Standard errors are clustered by fund (t-statistics in brackets).

	CAPM alpha						FF6 alpha	
	Gross returns			Net returns			Gross returns	
Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Contrary tilt	-0.089***	-0.050	-0.047	-0.069**	-0.041	-0.038	-0.017	0.103
	(2.864)	(0.527)	(0.488)	(2.230)	(0.446)	(0.406)	(0.783)	(1.366)
× HMF	0.022	-0.292**	-0.293**	-0.078	-0.406***	-0.416***	-0.011	-0.306***
	(0.427)	(2.140)	(2.070)	(1.500)	(2.972)	(2.910)	(0.273)	(2.869)
Marginal tilt								
× HMF	-0.036	-0.029	-0.072*	-0.107***	-0.122***	-0.177***	-0.062**	-0.039
	(1.109)	(0.820)	(1.710)	(3.204)	(3.342)	(4.133)	(2.451)	(1.502)
Large/Moderate tilt	-0.120***	-0.147***	-0.143***	-0.106***	-0.152***	-0.148***	-0.059***	-0.052**
	(3.686)	(3.466)	(3.361)	(3.273)	(3.593)	(3.485)	(2.841)	(2.148)
× HMF	0.151***	0.196***	0.179***	0.063	0.108**	0.090**	0.011	0.024
	(3.772)	(4.361)	(4.044)	(1.583)	(2.420)	(2.036)	(0.349)	(0.737)
Difference between coefficient estimates								
Lrg/Mod – Contrary (ETF)	-0.031	-0.097	-0.097	-0.038	-0.111	-0.111	-0.042*	-0.155**
Lrg/Mod – Contrary (HMF)	0.098*	0.392***	0.376***	0.103**	0.403***	0.395***	-0.020	0.175**
Omitted group	Marginal tilt	Marginal tilt	Marginal tilt	Marginal tilt	Marginal tilt	Marginal tilt	Marginal tilt	Marginal tilt
Sample	Full	Multi factor	Multi factor & MC ≠ Options	Full	Multi factor	Multi factor & MC ≠ Options	Full	Multi factor
Fixed effects								
Time	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R2	0.144	0.141	0.157	0.143	0.138	0.154	0.056	0.061
N	42,241	24,397	20,818	42,378	24,478	20,899	42,244	24,399

Table 8: Benchmark-adjusted alphas

This table reports the results for pooled OLS regressions of excess HMF returns on the excess returns of the investable ETF benchmark. The benchmark includes all ETFs in the same factor tilt category (*contra*, *marginal*, or *large* + *moderate*). Each ETF is weighted by the inverse Euclidian spatial distance between the factor tilts of the HMF and the ETF. Given the dynamic nature of factor tilts, we estimate separate coefficients (α, and β) for each factor tilt category. We require a minimum of five "mature" ETFs (> $50million in AUM) to compute the benchmark return. */**/*** denotes statistical significance at the 10, 5, and 1 percent levels. The sample period is from 01/2010 to 12/2021. Standard errors are clustered by fund (*t*-statistics in brackets).

	Holdings-based return		Actual (gross) return		Actual (net) returns	
	(1)	(1)	(2)	(2)	(3)	(3)
Intercepts:						
Contrary tilt	-0.039	-0.272***	0.006	-0.331**	-0.000	-0.339**
	(0.841)	(3.256)	(0.107)	(2.338)	(0.005)	(2.405)
Large/Moderate tilt	0.142***	0.157***	0.110**	0.132***	0.109**	0.134***
	(3.330)	(3.661)	(2.402)	(2.903)	(2.383)	(2.937)
Difference between coefficient estimates						
Lrg/Mod – Contrary	0.181***	0.429***	0.104*	0.463***	0.110*	0.473***
Betas:						
Inv. ETF BMK return	0.658***	0.658***	0.478***	0.478***	0.478***	0.478***
	(21.816)	(21.814)	(18.006)	(18.005)	(18.018)	(18.016)
× Contrary	-0.060*	-0.011	0.034	0.092	0.034	0.093
	(1.869)	(0.204)	(1.026)	(1.255)	(1.040)	(1.257)
× Large/Moderate	-0.159***	-0.166***	-0.018	-0.013	-0.018	-0.013
	(3.679)	(3.516)	(0.436)	(0.296)	(0.431)	(0.290)
Omitted group	Marginal tilt	Marginal tilt	Marginal tilt	Marginal tilt	Marginal tilt	Marginal tilt
Sample	Full	Multi-factor	Full	Multi-factor	Full	Multi-factor
Adj. R^2	0.583	0.594	0.458	0.463	0.458	0.463
N	15,377	11,021	15,240	10,926	15,240	10,926

Table 9: Characteristic Risk Premia in Practice vs. on Paper

This table reports the results for cross-sectional Fama-MacBeth regressions of performance on lagged characteristic (decile) scores (see Eq. (2)), estimated separately for HMFs, ETFs, and test assets. The test assets correspond to 16 academic single-factor benchmarks. Specifically, for each of the four factors (Value, Momentum, Conservative Asset Growth, and Profitability), we create two value-weighted benchmark portfolios using tercile cut-offs (top and bottom), separately for a large- and small-cap investment universe. This yields a total of $4 \times 2 \times 2 = 16$ test assets. Performance on the left-hand side is measured by the gross CAPM alpha to account for differences in market risk exposure between long-short HMFs and (long-only) ETFs. We report the time-series average of the estimated coefficients (λ's) for HMFs (λ^{HMF}), or ETFs (λ^{ETF}), relative to the test assets (λ^{S}). The first specification is estimated with the full sample of funds, while the second excludes single-factor funds (as in Tables 5 and 7). The risk premia are expressed in percentages per month. Standard errors are based on the Newey-West adjustment with three lags (*t*-statistics in brackets). The sample period is from 01/2010 to 12/2021.

	Intercept	1. VAL	2. MOM	3. CAG	4. PROF	Sum(1-4)
Panel A: Difference in risk premia between HMFs and test assets ($\lambda^{HMF} - \lambda^{S}$)						
Full sample	0.080	0.033	0.033	-0.041	0.078	0.104
	(0.681)	(0.681)	(0.858)	(0.932)	(1.478)	(1.432)
Excl. single-factor funds	0.049	0.016	0.089	-0.065	0.113*	0.153*
	(0.412)	(0.335)	(1.654)	(1.074)	(1.943)	(1.958)
Panel B: Difference in risk premia between ETFs and test assets ($\lambda^{ETF} - \lambda^{S}$)						
Full sample	0.132*	-0.132	-0.063	-0.090	0.062	-0.223
	(1.664)	(1.374)	(1.497)	(1.070)	(0.643)	(1.649)
Excl. single-factor funds	0.125	-0.151	-0.102**	-0.093	0.056	-0.289**
	(1.486)	(1.327)	(2.300)	(0.959)	(0.480)	(2.027)
Panel C: Difference in risk premia between HMFs and ETFs ($\lambda^{HMF} - \lambda^{ETF}$)						
Full sample	-0.052	0.166*	0.096**	0.049	0.016	0.327**
	(0.752)	(1.909)	(2.265)	(0.517)	(0.186)	(2.367)
Excl. single-factor funds	-0.076	0.167	0.191***	0.027	0.056	0.442***
	(1.043)	(1.554)	(3.727)	(0.229)	(0.458)	(2.982)

Appendix 1: Institutional Details on Hedged Mutual Funds

The use of leverage and short-selling by mutual funds is regulated by the Securities and Exchange Commission (SEC) under the Investment Company Act of the 1940 (henceforth the "Act"), as well as subsequent amendments to the Act. Since short selling involves borrowing, it is treated by the SEC similar to leverage. Section 18(f)(1) of the Act states that an open-end fund can use leverage as long as it maintains an asset coverage ratio (i.e., assets under management (AUM) plus market value of liabilities divided by the latter) of at least 300%. Said differently, this rule restricts a fund's liabilities (short positions plus margin loans) to no more than 50% of the fund's AUM.

However, SEC Release IC-10666 in 1970 clarifies that a mutual fund is compliant with the Act if it holds a sufficient amount of liquid assets, such as cash or treasuries, in segregated accounts to undo the liability. A fund would therefore be compliant under Section 18 if it held an amount sufficient to cover the current market value of the security sold short, or the market value of the margin loan (for leveraged long positions). In 1996, the SEC allowed mutual funds to hold liquid securities, including equity security, in segregated accounts. In 1997, the SEC went a step further by allowing a fund to designate securities as segregated assets based solely on the fund records and not on the fund's custodian's records (see Chen, Desai, Krishnamurthy (2013) for additional details).

In addition, U.S.-based investment funds are covered by the Federal Reserve Board's Regulation T (known as "Reg T") margin requirements, which allows investors to borrow up to a maximum 50% of the asset's market value on margin. For short positions, Reg T requires the short seller to deposit 50% of the market value of the short position as cash collateral with the broker.

To illustrate the regulatory limits on leverage, let us consider two examples. Fund A is a long-only leveraged fund, while fund B is a long-short equity fund. Both have \$100 in equity capital provided by the fund's investors (also known as assets under management, or AUM). Fund A can invest up to $200 in long equity positions by taking a margin loan for $100 and by paying for the remaining $100 using its own equity capital, in line with Reg-T. The fund is compliant with Section 18 of the Act if it segregates $100 worth of stocks. Next, if fund B takes a short position of $75, then the cash proceeds from the short sale must be kept as collateral with the broker. The fund also needs to deposit an additional $37.5 (or 50%*$75) with the broker as initial margin, as per Reg-T. In addition, Section 18 of the Act requires that the fund undoes the leverage by segregating additional collateral worth 100% of the *current* market value of securities sold short. If the market value of the shorted securities declines from $75 to $70, then the fund would need to segregate additional collateral for $70 less the initial cash margin of $37.5, or $32.5. This could come from the fund's existing long equities positions, for example.

As the previous examples illustrate, segregating assets is necessary for funds with a high degree of leverage. Assets that are segregated cannot be traded while the liability is outstanding, which is a disadvantage for funds that rebalance frequency. However, this is less likely to be a concern for factor-based funds since they typically rebalance less frequently (e.g., once per quarter).

Anomaly Tilts by Factor Funds

Internet Appendix

The Internet Appendix (IA) provides additional details on the data construction and cleaning, as well as additional results.

IA.1 Reconciling Returns

Following Berk and van Binsbergen (2015) and Pastor, Stambaugh and Taylor (2015), we reconcile the data on mutual fund returns and assets under management (AUM) between CRSP MFDB and Morningstar Direct. We link CRSP MFDB to Morningstar Direct by CUSIP and ticker. To verify the accuracy of the matches, we compare fund names and inception dates (and liquidation dates, if applicable) between the two databases.

Pastor et al. (2015) find that 3.1% of all monthly returns are "inconsistent" during the 1979 to 2011 period, in the sense that the fund returns from Morningstar Direct and CRSP MFDB differ by more than 10 bps per month. In our raw sample of hedged mutual funds, the proportion of monthly returns that are inconsistent is only 0.47%. The lower proportion of inconsistent returns is likely a consequence of greater data accuracy in more recent years (our sample starts in 2010). Nevertheless, we follow Berk and Binsbergen (2015), and Pastor et al. (2015) and apply the following procedures to fix any inconsistent returns.

First, we compute two sets of monthly returns based on the reported NAVs and dividends paid in Morningstar Direct and CRSP MFDB.

$$imp\_CRSP\_RET_{i,t} = \frac{CRSP\_NAV_{i,t} + CRSP\_DIV_{i,t} - CRSP\_NAV_{i,t-1}}{CRSP\_NAV_{i,t-1}}$$

$$imp\_MS\_RET_{i,t} = \frac{MS\_NAV_{i,t} + MS\_DIV_{i,t} - MS\_NAV_{i,t-1}}{MS\_NAV_{i,t-1}}$$

In cases where the dividend data are missing, we apply the following set of rules to fill in the dividend data.

1. If dividend is missing in one database (either Morningstar Direct or CRSP MFDB), but not the other, then we fill in the dividend value for that database using the dividend value of the other database.

2. If (1) cannot resolve the missing dividend problem, we assume that the dividend paid is zero for that observation.
3. If under the assumption in (2), we find that the difference between the reported return in CRSP (*rep_CRSP_RET*) and the implied return (*imp_CRSP_RET*) is equivalent to the difference between the reported return in Morningstar Direct (*rep_MS_RET*) and the implied return (*imp_MS_RET*), and the reported returns are greater than implied returns (*rep_CRSP_RET- imp_CRSP_RET>0, and rep_MS_RET> imp_MS_RET)*, then we can infer that the difference is caused by dividends. In such cases we replace the implied returns by the reported returns.

Then for a given observation with inconsistent returns, we apply the following set of rules:

1. If *rep_CRSP_RET* is consistent with both *imp_CRSP_RET* and *imp_MS_RET*, then we accept *rep_CRSP_RET* as the correct monthly return.
2. If *rep_MS_RET* is consistent with both *imp_CRSP_RET* and *imp_MS_RET*, then we accept *rep_MS_RET* as the correct monthly return.
3. If *rep_CRSP_RET* is consistent with *imp_CRSP_RET*, but not with *imp_MS_RET*, and *rep_MS_RET* is not consistent with *imp_MS_RET*, we accept *rep_CRSP_RET.*
4. If *rep_MS_RET* is consistent with *imp_MS_RET*, but not with *imp_CRSP_RET*, and *rep_CRSP_RET* is not consistent with *imp_CRSP_RET*, we accept *rep_MS_RET.*
5. If *rep_CRSP_RET* is consistent with *imp_CRSP_RET*, and both *rep_MS_RET and imp_MS_RET* are missing, then we use *rep_CRSP_RET.*
6. If *rep_MS_RET* is consistent with *imp_MS_RET*, and both *rep_CRSP_RET and imp_CRSP_RET* are missing, then we use *rep_MS_RET.*

IA.2 Reconciling Assets Under Management (AUM)

We use CRSP MFDB as our primary source of Assets Under Management (AUM) data. To obtain fund-level AUM, we sum up the share-class level AUM data.

There are instances of extreme reversals in the AUM that likely reflect decimal-place mistakes. We perform the following procedure to fix these extreme reversals separately in AUM data from Morningstar Direct and CRSP MFDB. First, we create a variable for the fraction change from last month to the current month,

$$dAUM = (AUM_{i,t} - AUM_{i,t-1})/AUM_{i,t-1}$$

Second, we create a reversal variable to capture the reversal pattern,

$$rev\_next = (AUM_{i,t+1} - AUM_{i,t})/(AUM_{i,t} - AUM_{i,t-1})$$

This variable will be approximately –1 if it is a reversal (e.g., 20m, 2m, 20m). If $abs(dAUM) \geq 0.5$, $-0.75 > rev\_next > -1.25$, and $AUM_{i,t-1} \geq \$10m$, then we assign missing value to both AUM and $dAUM$.

We define an inconsistent AUM observation as one where the relative deviation between CRSP and Morningstar AUM is greater than 5% and the absolute deviation is greater than $0.75 million. In contrast to Berk and van Binsbergen (2015), we only set inconsistent AUM observations to missing if in addition to the above, the relative deviation between CRSP AUM and the sum of the market value portfolio holdings exceeds 10%, and the relative deviation between MS AUM and the sum(MV of holdings) exceeds 10%. If instead the relative deviation between MS AUM and the sum of the market value portfolio holdings is below 10 %, then we use MS AUM instead. Moreover, if CRSP AUM is missing, but MS AUM is within 10 % of sum(MV of holdings), or the absolute difference is less than $1.5 million, then we use MS AUM.

IA.3 Persistence in Individual Factor Tilts among Multi-Factor Funds

We formally assess the persistence in individual factor tilts by regressing the factor tilt (a = value, momentum, asset growth, profitability, or the total) on its own lag one to four quarters earlier ($k \in [1,4]$):

$$Factor\ Tilt_{i,q}^{a} = a_0 + b_1 Factor\ Tilt_{i,q-k}^{a} + \varepsilon_{i,q}^{a} \quad \text{(IA1)}$$

Our focus is on multi-factor funds with large/moderate factor tilts, because this is arguably the more relevant sample for studying variations across factor tilts. As shown in Table IA-3 for HMFs, the total factor tilt is far more persistent than any individual tilt. At the four-quarter horizon, for example, the b_1 coefficient on the total factor tilt is 0.93, while it ranges from 0.82 for momentum to 0.88 for profitability. The simple average of b_1, across the four individual tilts, is 0.86. By contrast, the individual factor tilts of ETFs are on average equally persistent (b_1 between 0.86 and 0.97 with an average of 0.91) as the total factor tilt (0.90). It is therefore less likely that ETFs engage in factor timing, compared to HMFs. Factor timing can arise intentionally (e.g., from bets on factors that are expected to outperform), or it could arise unintentionally from an exposure to the stock momentum factor, which itself is a bet on factor momentum (i.e., buying factors that have recently outperformed and selling those that have underperformed, see Ehsani and Linnainmaa (2022)).

We also check the persistence in factor tilts by using a contingency table (4x4) based on the rank of a particular factor (1 = highest for a given fund *i*; 4= lowest for the same fund) in the current quarter (q) vs. four quarters earlier (q-4). As the results in Table IA-4 show, the off-diagonal elements are in most cases more larger for HMFs compared to ETFs, indicating that the individual factor tilts of HMFs exhibit more time-series variation.

Table IA-1: Size and Low Risk Tilts

This table presents fund-quarter average size and low risk characteristic tilts, measured in deciles, in quarter q. These are aggregated to the fund-level by taking the portfolio-weighted average of the stocks held by the fund. For HMFs we compute this separately for the fund's long and short positions. Factor tilts are then constructed by subtracting from the fund-level characteristic score the corresponding value-weighted characteristic score of the market portfolio: $(C_{i,t} - C_{m,t})$. When measuring the size tilt (higher values indicate larger size), we use iShares Russell 3000 ETF (ticker: IWV) as the proxy for the market portfolio for all funds, including small-cap ones. For the low-risk tilt we use iShares Russell 2000 ETF (ticker: IWM) for small cap funds. The low-risk characteristic is measured by the average decile score based on the CAPM beta and idiosyncratic risk (with higher values indicating less risk). The results are summarized by sub-sample based on the extent of a fund's factor tilt at q-1 (see Table 3 for additional details). The sample period is from 01/2010 to 12/2021. */**/*** denotes statistical significance at the 10, 5, and 1 percent levels. Standard errors are clustered by fund (t-statistics in brackets).

Panel A: Long sub-portfolio

			Moderate Factor tilt q-1		Large Factor tilt q-1	
	Full sample	Marginal tilt q-1	Single-factor	Multi-factor	Single-factor	Multi-factor
Average	-0.912***	-0.415***	-1.132***	-0.984***	-1.495***	-1.651***
	(10.09)	(4.23)	(6.80)	(5.24)	(4.59)	(10.84)
Nobs	4,957	1,650	270	369	49	939

Panel B: Short sub-portfolio

			Moderate Factor tilt q-1		Large Factor tilt q-1	
	Full sample	Marginal tilt q-1	Single-factor	Multi-factor	Single-factor	Multi-factor
Average	-1.513***	-0.991***	-1.480***	-1.630***	-1.735***	-2.357***
	(13.86)	(8.63)	(4.76)	(6.89)	(4.47)	(14.80)
Nobs	3,277	820	189	255	42	865

Panel C: Low Risk Tilts for HMFs

	Low Risk (LVOL) Tilt				Total Factor tilt (VAL + MOM + CAG + PROF + LVOL)			
	Portfolio	Long-Short	Long	Short	Portfolio	Long-Short	Long	Short
Average	-0.090***	0.307***	-0.369***	-0.752***	0.696***	1.487***	-0.068	-2.349***
	(2.87)	(4.52)	(8.74)	(10.20)	(5.47)	(8.19)	(0.70)	(12.97)
Nobs	4,957	3,120	4,800	3,277	4,957	4,957	4,800	3,277

Panel D: Low Risk ETFs

	VAL	MOM	CAG	PROF	LVOL	Total Factor Tilt (1-4)	Total Factor Tilt (1-5)
	(1)	(2)	(3)	(4)	(5)		
Average	-0.117	-0.228***	0.258***	-0.057	1.150***	-0.144	1.006***
	(1.40)	(6.45)	(3.90)	(0.53)	(8.39)	(0.90)	(4.50)
Nobs	383	383	383	383	383	383	383

Table IA-2: Factor Tilts and Fund characteristics

This table reports the results for pooled OLS regressions of fund-quarter total factor tilts (value, momentum, conservative asset growth, and profitability) in columns (1) through (4), or the average anomaly tilt (relative to the list of anomalies in Stambaugh et al. (2012)) in columns (5) through (8), on lagged fund characteristics. *Gross Eq. Levg.* is the gross leverage from equity positions (total market value of long + short positions scaled by *AUM*), *Exp. Ratio* is the net expense ratio, *AUM* is the assets under management, *AGE* is fund age since inception, *Net flow* is growth in AUM adjusted for returns averaged over the prior year and *Turnover* is min($buys, $sells) divided by the average AUM over the year, as reported in CRSP MFDB. Calendar time fixed effects are included in all specifications. The sample period is from 01/2010 to 12/2021. */**/*** denotes statistical significance at the 10, 5, and 1 percent levels. Standard errors are clustered by fund (*t*-statistics in brackets).

	Total Factor tilt (VAL + MOM + CAG + PROF)				Average Anomaly Tilt			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Portfolio	Long-Short	Long	Short	Portfolio	Long-Short	Long	Short
Gross Eq. Levg.	2.218***	2.665***	0.688***	-1.304***	0.546***	0.743***	0.176***	-0.377***
	(7.36)	(7.35)	(4.07)	(4.78)	(8.59)	(9.04)	(3.97)	(5.21)
Net Flow	0.015	0.019	0.007	-0.015	0.005	0.005	0.001	-0.005
	(1.21)	(1.23)	(0.62)	(1.03)	(1.42)	(1.26)	(0.30)	(1.09)
Exp. Ratio.	-0.296*	-0.209	-0.336**	0.376	-0.147***	-0.180***	-0.160***	0.226***
	(1.69)	(0.85)	(2.23)	(1.36)	(3.45)	(3.06)	(3.50)	(3.04)
ln(*AUM*)	-0.050	-0.058	-0.018	0.205**	-0.016	-0.019	-0.010	0.061**
	(0.92)	(0.72)	(0.41)	(2.42)	(1.12)	(0.94)	(0.72)	(2.57)
ln(*AGE*)	0.287*	0.503**	0.265**	-0.311	0.026	0.062	0.012	-0.051
	(1.91)	(2.28)	(2.15)	(1.36)	(0.69)	(1.10)	(0.34)	(0.76)
Turnover	-0.003	-0.024	-0.002	0.095**	-0.000	-0.008	-0.007	0.025**
	(0.09)	(0.58)	(0.05)	(2.18)	(0.04)	(0.77)	(0.72)	(2.03)
Fixed Effects								
Time	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.228	0.184	0.062	0.143	0.233	0.215	0.061	0.163
Nobs	4,646	4,646	4,511	3,089	4,646	4,646	4,511	3,089

Table IA-3: Persistence in Individual vs. Total Factor Tilts

This table reports results from regressions of the factor tilt (value, momentum, asset growth, profitability, or the total) on its own lag one to four quarters earlier ($k \in [1,4]$) in columns 1 to 4. Panel A (B) provides the results for HMFs (ETFs) with large/moderate factor tilt and a multi-factor focus at lag-length k. For ETFs we do not report results for persistence in the momentum exposure, because this subset of ETFs has an insignificant exposure to momentum in the first place. The sample period is from 01/2010 to 12/2021. */**/*** denotes statistical significance at the 10, 5, and 1 percent levels. Standard errors are clustered by fund (t-statistics in brackets).

Panel A: Hedged Mutual Funds

	(1)	(2)	(3)	(4)
Total Factor tilt	0.934***	0.886***	0.847***	0.837***
	(50.32)	(29.50)	(22.83)	(20.02)
Adjusted R^2	0.733	0.610	0.536	0.512
N	1,308	1,263	1,224	1,191

	Value tilt				Momentum tilt			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Average	0.860***	0.759***	0.739***	0.725***	0.823***	0.739***	0.674***	0.646***
	(37.01)	(24.82)	(23.31)	(23.80)	(35.04)	(22.77)	(13.88)	(11.52)
Adj. R^2	0.698	0.542	0.494	0.459	0.638	0.462	0.368	0.336
N	1,308	1,263	1,224	1,191	1,308	1,263	1,224	1,191
	Conservative Asset Growth				Profitability			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Average	0.874***	0.796***	0.734***	0.696***	0.881***	0.827***	0.774***	0.769***
	(44.78)	(24.26)	(15.15)	(11.24)	(44.90)	(32.72)	(29.28)	(23.57)
Adj. R^2	0.702	0.549	0.452	0.396	0.696	0.546	0.488	0.455
N	1,308	1,263	1,224	1,191	1,308	1,263	1,224	1,191

Panel B: Exchange-Traded Funds

	(1)	(2)	(3)	(4)
Total Factor tilt	0.901***	0.836***	0.734***	0.672***
	(25.26)	(12.49)	(9.23)	(7.99)
Adjusted R^2	0.557	0.349	0.238	0.193
N	1,351	1,261	1,216	1,201

	Value tilt				Momentum tilt			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Average	0.965***	0.959***	0.941***	0.921***	0.860***	0.729***	0.624***	0.610***
	(57.86)	(33.35)	(24.04)	(20.02)	(27.36)	(10.65)	(6.36)	(5.92)
Adj. R^2	0.841	0.753	0.683	0.645	0.568	0.351	0.248	0.237
N	1,351	1,261	1,216	1,201	1,351	1,261	1,216	1,201
	Conservative Asset Growth				Profitability			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Average	0.899***	0.861***	0.824***	0.797***	0.922***	0.918***	0.885***	0.856***
	(31.70)	(22.31)	(18.58)	(16.04)	(48.95)	(29.25)	(21.54)	(18.17)
Adj. R^2	0.713	0.602	0.514	0.455	0.766	0.658	0.564	0.510
N	1,351	1,261	1,216	1,201	1,351	1,261	1,216	1,201

Table IA-4: Persistence in Factor Rankings

This table presents a contingency table for factor ranks (1 = largest factor tilt at the fund level; 4 = lowest factor tilt) in quarter q against the corresponding ranks in q-4. Numbers in the diagonal (bolded) represent no change in factor ranking from quarter q to q-4. The first (last) four columns provide the results for factor-based HMFs (ETFs) with a multi-factor designation in q-4. The sample period is from 01/2010 to 12/2021.

		Sample: HMFs				Sample: ETFs			
		Value (q-4)				Value (q-4)			
		1	2	3	4	1	2	3	4
Char. (q)	1	**15.6%**	6.0%	3.2%	3.0%	**23.0%**	6.1%	2.1%	0.8%
	2	5.2%	**7.5%**	3.8%	3.9%	5.6%	**12.5%**	4.2%	1.8%
	3	3.3%	3.5%	**6.7%**	7.3%	2.2%	3.7%	**15.5%**	9.0%
	4	1.2%	3.2%	6.9%	**19.7%**	0.2%	0.7%	2.3%	**10.4%**
		Momentum (q-4)				Momentum (q-4)			
		1	2	3	4	1	2	3	4
Char. (q)	1	**12.8%**	5.2%	3.8%	3.7%	**5.7%**	1.4%	1.2%	0.7%
	2	6.6%	**6.3%**	5.3%	1.8%	2.6%	**2.0%**	1.3%	1.1%
	3	5.4%	4.6%	**10.0%**	5.7%	2.1%	2.9%	**6.9%**	4.5%
	4	3.7%	4.3%	7.4%	**13.3%**	3.3%	3.7%	14.2%	**46.3%**
		Conservative Asset Growth (q-4)				Conservative Asset Growth (q-4)			
		1	2	3	4	1	2	3	4
Char. (q)	1	**12.9%**	9.8%	4.4%	1.1%	**26.6%**	8.9%	2.2%	0.4%
	2	9.1%	**18.4%**	8.5%	2.1%	9.7%	**21.5%**	7.2%	1.2%
	3	4.1%	8.4%	**11.1%**	3.0%	1.7%	5.6%	**10.2%**	1.4%
	4	1.0%	1.3%	2.9%	**1.8%**	0.2%	0.8%	1.5%	**0.7%**
		Profitability (q-4)				Profitability (q-4)			
		1	2	3	4	1	2	3	4
Char. (q)	1	**8.6%**	5.4%	3.4%	1.1%	**10.8%**	6.7%	3.0%	0.3%
	2	5.1%	**7.9%**	6.1%	2.4%	4.3%	**16.7%**	5.3%	2.9%
	3	3.5%	5.6%	**9.6%**	8.1%	1.2%	5.2%	**18.8%**	9.2%
	4	1.9%	2.7%	6.7%	**21.9%**	0.7%	1.6%	4.2%	**9.1%**

Table IA-5: Factor Tilts Relative to Factor Benchmarks

This table presents average factor tilts relative to academic factor benchmarks. Fund-level characteristics are constructed by value-weighting the stocks in a fund's portfolio, e.g., the B/M ratio of a fund is the portfolio-weighted average of the B/M ratio decile score of all stocks in the fund's portfolio. Factor tilts are then constructed by subtracting from the fund-level characteristic score the corresponding value-weighted characteristic score of the factor benchmark portfolio. We use a multi-factor benchmark that assigns equal weight to the four factors (VAL, MOM, CAG, PROF). In this case, we summarize the total factor tilt. Sub-sample results are provided based on the extent of a fund's factor tilt (*contrary*, *marginal*, *moderate*, and *large*) and by single- vs. multi-factor designation (see Table 4 for additional details). The sample period is 01/2010 to 12/2021. */**/*** denotes statistical significance at the 10, 5, and 1 percent levels. Standard errors are clustered by fund (t-statistics in brackets).

	Full sample	Moderate tilt		Large tilt	
		Single (max tilt >75%)	Multi (max tilt ≤75%)	Single (max tilt >75%)	Multi (max tilt ≤75%)
HMF complete portfolio: Expected sign (+)					
Average	-1.568***	-1.165***	-0.790***	-1.073***	0.344***
	(14.99)	(9.90)	(9.00)	(3.90)	(2.65)
Nobs	4,957	295	391	46	975
HMF long sub-portfolio: Expected sign (+)					
Average	-1.401***	-0.700***	-0.478***	-0.266*	0.114
	(15.87)	(8.29)	(5.58)	(1.98)	(1.45)
Nobs	4,800	292	378	46	974
HMF short sub-portfolio: Expected sign (-)					
Average	0.041	-0.204	-0.252	-0.432	-2.004***
	(0.27)	(0.91)	(1.03)	(0.96)	(11.44)
Nobs	3,277	203	262	39	907

	Active/multi-factor labelled ETFs				
	Full sample	Moderate tilt		Large tilt	
		Single (max tilt >75%)	Multi (max tilt ≤75%)	Single (max tilt >75%)	Multi (max tilt ≤75%)
Expected sign (+)					
Average	-1.333***	-0.752***	-0.635***	0.100	0.593***
	(10.95)	(14.10)	(8.24)	(0.94)	(4.00)
Nobs	2,248	267	309	74	313
	Single-factor labeled ETFs				
	Full sample	Moderate tilt		Large tilt	
		Single (max tilt >75%)	Multi (max tilt ≤75%)	Single (max tilt >75%)	Multi (max tilt ≤75%)
Expected sign (+)					
Average	-1.751***	-0.774***	-0.701***	0.354***	0.208**
	(24.99)	(16.79)	(13.17)	(3.68)	(2.11)
Nobs	5,560	648	549	109	287

Table IA-6: Total Factor Loadings

This table presents fund-quarter average total factor loadings conditional on the extent of a fund's factor tilt in the previous quarter (*contrary*, *marginal*, *moderate*, or *large*). Total factor loadings refer to the sum of the fund's value, momentum, investment, and profitability betas from the Fama-French six-factor model. Factor loadings are estimated using daily fund returns in a given quarter (t, t-2). A portfolio is designated as having a *contrary* factor tilt if the total factor tilt is negative; a *marginal* factor tilt is a portfolio where 0.0 < total factor tilt < 1.0 deciles; a *moderate* factor tilt is a portfolio with 1.0 ≤ total factor tilt < 2.0 deciles; a large factor tilt is a portfolio with a total factor tilt ≥ 2.0. The total factor tilt is calculated as the sum of a fund's value, momentum, (conservative) asset growth, and profitability factor tilts relative to the market portfolio. See Table 3 for additional details. Panels A summarizes the results for HMFs complete portfolio holdings-based returns, separately for the fund's long and short returns, and based on the fund's actual (net) return; Panels B summarizes the results for smart-beta ETFs. The sample period is from 01/2010 to 12/2021. */**/*** denotes statistical significance at the 10, 5, and 1 percent levels. Standard errors are clustered by fund (t-statistics in brackets).

Panel A: HMF total factor loadings

	Holdings-based Returns							
	Contrary Factor Tilt				Marginal Factor Tilt			
	Portfolio	Long-Short	Long	Short	Portfolio	Long-Short	Long	Short
Average	-0.146***	-0.170***	-0.161***	0.020	0.056***	0.069***	0.080***	0.014
	(5.27)	(4.69)	(3.80)	(0.28)	(4.51)	(2.98)	(5.45)	(0.33)
Nobs	1,327	1,326	1,288	910	1,637	1,637	1,560	806
	Moderate Factor Tilt				Large Factor Tilt			
	Portfolio	Long-Short	Long	Short	Portfolio	Long-Short	Long	Short
Average	0.185***	0.262***	0.165***	-0.152**	0.473***	0.648***	0.227***	-0.457***
	(8.58)	(5.97)	(7.77)	(2.59)	(16.18)	(11.58)	(9.30)	(6.59)
Nobs	650	650	635	435	991	991	988	913

	Actual (net) Returns			
	Contrary	Marginal	Moderate	Large
Average	-0.143***	0.060***	0.193***	0.494***
	(5.01)	(4.91)	(9.83)	(16.20)
Nobs	1,388	1,738	670	1,011

Panel B: Smart-beta ETF total factor loadings

	Holdings-based return: Active/multi-factor ETFs				Holdings-based return: Single-Factor ETFs			
	Contrary	Marginal	Moderate	Large	Contrary	Marginal	Moderate	Large
Average	-0.032	0.222***	0.382***	0.515***	0.071	0.269***	0.396***	0.534***
	(0.47)	(9.21)	(20.17)	(15.65)	(1.62)	(10.40)	(18.05)	(13.65)
Nobs	549	680	553	373	1,999	1,899	1,164	381

	Net return: Active/multi-factor ETFs				Net return: Single-Factor ETFs			
	Contrary	Marginal	Moderate	Large	Contrary	Marginal	Moderate	Large
Average	-0.038	0.220***	0.379***	0.505***	0.063	0.266***	0.391***	0.536***
	(0.58)	(9.19)	(20.00)	(15.94)	(1.45)	(10.37)	(18.45)	(14.50)
Nobs	554	686	561	381	2,009	1,915	1,176	388

Table IA-7: Performance of Factor Funds

This table reports the results for pooled OLS regressions of fund performance (HMF or ETF) on sub-sample dummies for the extent of a fund's factor tilt at q-1 (*contrary*, *marginal*, and *large* + *moderate*) interacted with a dummy for HMFs. The omitted (benchmark) group consists of ETFs with marginal factor tilts. In Panel A, we report results with factor loadings estimated over the prior 36 months (columns (1) to (3)), or with full sample betas (columns (4) to (8)). In Panel B, we estimate CAPM or FF6 alphas with control variables that are cross-sectionally standardized to mean zero, variance one, separately for HMFs and ETFs. Calendar time fixed effects are included in all specifications. The sample period is from 01/2010 to 12/2021. */**/*** denotes statistical significance at the 10, 5, and 1 percent levels. Standard errors are clustered by fund (t-statistics in brackets).

Panel A: Monthly betas

	Rolling window betas (t-1, t-36)			Full sample betas				
	CAPM			CAPM			FF6	FF6+LIQ
	Gross		Net	Gross		Net	Gross	
Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Contrary	-0.0651**	-0.0528	-0.0539	-0.0165	0.0791	0.0763	0.0713	0.0704
	(1.99)	(0.64)	(0.66)	(0.58)	(0.94)	(0.93)	(1.50)	(1.49)
× HMF	0.0171	-0.3210*	-0.4221**	-0.0137	-0.3342***	-0.4358***	-0.2565***	-0.2091**
	(0.26)	(1.95)	(2.55)	(0.26)	(2.60)	(3.39)	(2.76)	(2.32)
Marginal tilt								
× HMF	-0.0092	-0.0101	-0.0995**	-0.0284	-0.0310	-0.1226***	-0.0495*	-0.0402
	(0.24)	(0.25)	(2.42)	(0.84)	(0.86)	(3.34)	(1.89)	(1.55)
Large/Moderate tilt	-0.1652***	-0.2111***	-0.2166***	-0.1317***	-0.1782***	-0.1829***	-0.0400*	-0.0402**
	(4.67)	(4.80)	(4.93)	(4.22)	(4.75)	(4.90)	(1.93)	(1.97)
× HMF	0.1677***	0.2091***	0.1224**	0.1699***	0.2170***	0.1288***	0.0305	0.0319
	(3.92)	(4.38)	(2.57)	(4.47)	(5.40)	(3.23)	(1.02)	(1.08)
Lrg/Mod – Contrary (ETF)	-0.1001*	-0.1588*	-0.1627***	-0.1152***	-0.2574***	-0.2592***	-0.1113**	-0.1105**
Lrg/Mod – Contrary (HMF)	0.0505	0.3718**	0.3817***	0.0684	0.2937***	0.3054***	0.1756**	0.1304*
Omitted group	Marginal tilt	Marginal tilt	Marginal tilt	Marginal tilt	Marginal tilt	Marginal tilt	Marginal tilt	Marginal tilt
Sample	Full	Multi factor	Multi factor	Full	Multi factor	Multi factor	Multi factor	Multi factor
Fixed effects								
Time	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R2	0.130	0.136	0.134	0.121	0.125	0.124	0.072	0.071
N	34,101	19,678	19,723	42,346	24,440	24,503	24,440	24,440

Panel B: Performance regressions with control variables						
	Holdings-based Ret		Gross Ret			Net Ret
	CAPM		CAPM		FF6	CAPM
Variables	(1)	(2)	(3)	(4)	(5)	(6)
Contrary tilt	-0.0683**	-0.0334	-0.0721**	-0.0444	0.1064	-0.0415
	(2.12)	(0.38)	(2.17)	(0.47)	(1.46)	(0.44)
× HMF	0.0190	-0.2064*	0.0254	-0.2950**	-0.3020***	-0.3924***
	(0.45)	(1.84)	(0.49)	(2.17)	(2.85)	(2.86)
Marginal tilt						
× HMF	0.0235	0.0178	-0.0163	-0.0197	-0.0308	-0.1109***
	(0.74)	(0.55)	(0.47)	(0.56)	(1.22)	(3.16)
Large/Moderate tilt	-0.0599*	-0.1155***	-0.0836**	-0.1303***	-0.0403	-0.1262***
	(1.79)	(2.67)	(2.47)	(2.94)	(1.61)	(2.85)
× HMF	0.1539***	0.2038***	0.1363***	0.1907***	0.0176	0.0949**
	(4.15)	(4.41)	(3.30)	(4.02)	(0.54)	(2.01)
Turnover	-0.0212	-0.0107	-0.0412***	-0.0364**	-0.0269**	-0.0350**
	(1.57)	(0.64)	(2.81)	(2.24)	(2.18)	(2.16)
Net Flow	-0.0233*	-0.0058	-0.0140	0.0007	0.0061	0.0013
	(1.66)	(0.37)	(1.03)	(0.04)	(0.55)	(0.08)
Exp. Ratio	0.0013	0.0088	-0.0022	0.0052	0.0205	-0.0238
	(0.09)	(0.49)	(0.13)	(0.27)	(1.28)	(1.22)
ln(*AUM*)	0.0188	0.0264*	0.0427***	0.0539***	0.0391***	0.0526***
	(1.44)	(1.78)	(2.76)	(3.31)	(3.19)	(3.21)
ln(*AGE*)	-0.0351**	-0.0333*	-0.0443***	-0.0472**	-0.0072	-0.0459**
	(2.51)	(1.88)	(2.80)	(2.44)	(0.50)	(2.36)
Lrg/Mod – Contra (ETF)	0.0084	-0.0820	-0.0115	-0.0858	-0.1467**	-0.0847
Lrg/Mod – Contra (HMF)	0.1433***	0.3281***	0.0994*	0.3998***	0.1728**	0.4026***
Omitted group	Marginal tilt	Marginal tilt	Marginal tilt	Marginal tilt	Marginal tilt	Marginal tilt
Sample	Full	Multi factor	Full	Multi factor	Multi factor	Multi factor
Fixed effects						
Time	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R2	0.174	0.160	0.153	0.143	0.062	0.143
N	37,361	23,707	38,082	23,996	23,996	24,007

Table IA-8: Total Anomaly Tilt

This table presents fund-quarter average total anomaly tilts, based on the list of anomalies from Stambaugh et al. (2012), conditional on the extent of a fund's factor tilt in the previous quarter (*contrary*, *marginal*, and *large* + *moderate*). A portfolio is designated as having a *contrary* factor tilt if the total factor tilt is negative; a *marginal* factor tilt is a portfolio where total factor tilt ≤ 1.0 deciles; a *moderate* factor tilt is a portfolio with 1.0 ≤ total factor tilt < 2.0 deciles; a large factor tilt is a portfolio with a total factor tilt ≥ 2.0. The total factor tilt is calculated as the sum of a fund's value, momentum, (conservative) asset growth, and profitability factor tilts relative to the market portfolio. See Table 3 for additional details. Panels A summarizes the results for HMFs complete long-short portfolios, while Panels B summarizes the results for ETFs. The sample period is from 01/2010 to 12/2021. */**/*** denotes statistical significance at the 10, 5, and 1 percent levels. Standard errors are clustered by fund (*t*-statistics in brackets).

Panel A: Hedged Mutual Funds

	Average anomaly tilt (Stambaugh et al. (2012))						
	Contrary		Marginal	Moderate		Large	
	Single factor	Multi factor	Full sample	Single factor	Multi factor	Single factor	Multi factor
Average	-0.245***	-0.474***	0.021	0.089**	0.219***	0.234***	0.709***
	(10.73)	(7.82)	(1.61)	(2.40)	(9.70)	(3.58)	(17.84)
Nobs	1,040	402	1,808	295	391	46	975

	Average anomaly tilt excluding Asset Growth & Momentum (Stambaugh et al. (2012))						
	Contrary		Marginal	Moderate		Large	
	Single factor	Multi factor	Full sample	Single factor	Multi factor	Single factor	Multi factor
Average	-0.252***	-0.437***	-0.012	0.006	0.137***	0.066	0.578***
	(9.21)	(6.46)	(0.76)	(0.14)	(5.41)	(0.68)	(14.65)
Nobs	1,040	402	1,808	295	391	46	975

Panel B: Smart-beta ETFs

	Average anomaly tilt (Stambaugh et al. (2012))						
	Contrary		Marginal	Moderate		Large	
	Single factor	Multi factor	Full sample	Single factor	Multi factor	Single factor	Multi factor
Average	-0.251***	-0.480***	0.034*	0.197***	0.208***	0.194***	0.389***
	(7.77)	(12.31)	(1.70)	(6.61)	(14.18)	(3.37)	(13.23)
Nobs	2,186	423	2,643	915	858	183	600

	Average anomaly tilt excluding Asset Growth & Momentum (Stambaugh et al. (2012))						
	Contrary		Marginal	Moderate		Large	
	Single factor	Multi factor	Full sample	Single factor	Multi factor	Single factor	Multi factor
Average	-0.239***	-0.493***	0.047*	0.199***	0.222***	0.089	0.360***
	(6.27)	(10.31)	(1.85)	(5.08)	(11.45)	(1.07)	(8.89)
Nobs	2,186	423	2,643	915	858	183	600

Table IA-9: Calendar Time Portfolios

This table reports the results using holdings-based (gross) returns in Panel A (B) for calendar time long-short portfolios in HMFs or ETFs with large/moderate or contrary factor tilts. Funds in each leg are equally weighted (with a minimum of five funds). The CAPM and Fama-French six-factor model is estimated once for each strategy using the full sample of observations. Standard errors are based on the Newey-West adjustment with 12 lags (*t*-statistics in brackets). The sample period is from 01/2010 to 12/2021.

Panel A: Holdings-based returns

CAPM		FF6						
α	MKT	α	MKT	SMB	HML	WML	CMA	RMW
Full sample: Large/Moderate HMF – Large/Moderate ETF								
1.49*	-0.51***	0.64	-0.44***	-0.32***	-0.02	-0.04	-0.01	-0.03
(1.64)	(16.11)	(0.92)	(22.92)	(8.60)	(0.77)	(1.60)	(0.21)	(0.55)
Multi-factor: Large/Moderate HMF – Large/Moderate ETF								
2.20**	-0.51***	0.79	-0.42***	-0.37***	-0.05	-0.01	0.00	-0.06
(1.98)	(9.75)	(0.97)	(15.08)	(5.54)	(0.99)	(0.36)	(0.02)	(0.76)
Full sample: Large/Moderate HMF – Contrary HMF								
2.56*	-0.10***	1.40*	-0.06**	-0.03	0.13***	0.11***	0.23***	0.26***
(1.82)	(2.84)	(1.73)	(1.99)	(0.77)	(5.51)	(3.65)	(3.70)	(4.73)

Panel B: Actual (gross) returns

CAPM		FF6						
α	MKT	α	MKT	SMB	HML	WML	CMA	RMW
Full sample: Large/Moderate HMF – Large/Moderate ETF								
1.08	-0.56***	0.00	-0.48***	-0.32***	-0.02	-0.01	0.01	-0.02
(1.25)	(21.63)	(0.01)	(25.08)	(11.6)	(0.6)	(0.23)	(0.22)	(0.44)
Multi-factor: Large/Moderate HMF – Large/Moderate ETF								
2.23**	-0.55***	0.65	-0.46***	-0.35***	-0.06	0.01	0.04	-0.05
(2.10)	(10.29)	(0.91)	(13.44)	(6.46)	(1.02)	(0.31)	(0.41)	(0.59)
Full sample: Large/Moderate HMF – Contrary HMF								
1.39	-0.04	0.18	-0.01	-0.04	0.17***	0.14***	0.22***	0.27***
(0.86)	(1.14)	(0.21)	(0.20)	(1.24)	(7.42)	(5.10)	(5.52)	(6.44)

Table IA-10: Factor Risk Premia in Practice vs. on Paper

This table reports the results for factor risk premia estimated from the two-step Fama-MacBeth method by Patton and Weller (2020). In the first step (omitted), we estimate betas relative to the Fama-French six-factor model using daily data from the previous quarter. In the second step, we estimate cross-sectional Fama-MacBeth regressions of gross returns on the estimated betas, separately for HMFs, ETFs and the test assets (without an intercept). The test assets correspond to 16 academic single-factor benchmarks (top or bottom tercile on a given characteristic, value weighted), see Table 9. We report the time-series average of the estimated coefficients (λ's) for HMFs (λ^{HMF}), or ETFs (λ^{ETF}), relative to the test assets (λ^{S}). The first specification is estimated with the full sample of funds, the second excludes single-factor funds (as in Tables 5 and 7). The risk premia are expressed in percentages per month. Standard errors are based on the Newey-West adjustment with three lags (*t*-statistics in brackets). The sample period is from 01/2010 to 12/2021.

	MKT	SMB	HML	MOM	CMA	RMW
Panel A: Difference in risk premia between HMFs and test assets ($\lambda^{HMF} - \lambda^{S}$)						
Full sample	-0.163***	0.114	0.356*	-0.104	-0.099	-0.105
	(3.55)	(0.58)	(1.96)	(0.39)	(0.63)	(0.76)
Excl. single-factor funds	-0.169***	0.263	0.374*	0.036	-0.134	-0.117
	(3.65)	(1.24)	(1.95)	(0.13)	(0.80)	(0.60)
Panel B: Difference in risk premia between ETFs and test assets ($\lambda^{HMF} - \lambda^{S}$)						
Full sample	-0.012	0.044	0.235	-0.115	-0.066	-0.061
	(0.47)	(0.81)	(1.52)	(0.42)	(0.54)	(0.45)
Excl. single-factor funds	-0.035	0.093	0.217	-0.094	-0.096	-0.059
	(1.18)	(1.41)	(1.29)	(0.32)	(0.66)	(0.37)
Panel B: Difference in risk premia between HMFs and ETFs ($\lambda^{HMF} - \lambda^{ETF}$)						
Full sample	-0.151***	0.071	0.122	0.011	-0.033	-0.044
	(3.47)	(0.39)	(0.70)	(0.06)	(0.25)	(0.30)
Excl. single-factor funds	-0.134***	0.171	0.157	0.130	-0.038	-0.058
	(2.63)	(0.91)	(0.76)	(0.57)	(0.23)	(0.30)

Table IA-11: Synthetic Long-Short Factors

This table reports the results from regressions of synthetic long-short factor returns on the corresponding academic factor (Panel A), or against the full Fama-French six-factor model (Panel B). Synthetic long-short factor returns are calculated as the aggregate (i.e., market-value weighted) holdings of large/moderate tilt HMFs in extreme anomaly positions (top or bottom 30%). Academic Factor (self) refers to the academic factor that corresponds with the column header. Returns are expressed in percentages per month. *t*-statistic are computed using standard errors based on the Newey-West adjustment with 12 lags. The *t*-statistic tests whether the coefficient is different from zero (all except for the academic factor (self)) or one (only for the academic factor (self)). The sample period is from 01/2010 to 12/2021. */**/*** denotes statistical significance at the 10, 5, and 1 percent levels.

Panel A: Single-factor regression

	(1) HML	(2) WML	(3) CMA	(4) RMW
Intercept	-0.1899	-0.1991	0.0580	-0.1516
	(0.76)	(0.62)	(0.18)	(0.66)
Academic Factor (self)	0.6946***	0.9244	1.0679	1.3499***
t-test: $\beta = 1$	(2.97)	(0.99)	(0.41)	(2.77)
N	144	144	144	144

Panel B: Fama-French six-factor model

	(1) HML	(2) WML	(3) CMA	(4) RMW
Intercept	-0.0140	0.1028	0.3092**	0.2396*
	(0.08)	(0.50)	(2.51)	(1.84)
Academic Factor (self)	0.7143**	0.8818***	0.5556**	1.0221
t-test: $\beta = 1$	(2.16)	(3.41)	(2.45)	(0.19)
MKT	-0.1755	-0.2434***	-0.2025*	-0.1941***
	(1.26)	(3.71)	(1.82)	(3.23)
SMB	-0.0824	-0.3260***	-0.3444***	-0.4557***
	(1.16)	(3.91)	(4.97)	(7.04)
HML		0.2578***	0.5410***	0.3479***
		(5.08)	(4.43)	(6.41)
WML	0.0214		0.1125*	0.0823**
	(0.29)		(1.86)	(2.01)
CMA	0.2088	0.2089*		0.3740***
	(1.29)	(1.68)		(2.73)
RMW	0.1619	0.3140***	0.5163***	
	(1.35)	(3.70)	(4.30)	
N	144	144	144	144